Skill Dispersion and Trade Flows

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First Draft: June 2009

This Draft: May 2011

Abstract

Is skill dispersion a source of comparative advantage? In this paper we use microdata from the International Adult Literacy Survey to show that the effect of skill dispersion on trade flows is quantitatively similar to that of the aggregate endowment of human capital. In particular we investigate, and find support for, the hypothesis that countries with a more dispersed skill distribution specialize in industries characterized by lower complementarity of workers' skills. The result is robust to the introduction of controls for alternative sources of comparative advantage, as well as to alternative measures of industry-level skill complementarity.

JEL Classification codes: F12, F16, J82.

We would like to thank Paul Beaudry, David Green, Patrick Francois, Keith Head, Thomas Lemieux, Vadim Marmer, Francesco Trebbi, Jonathan Vogel and seminar participants at CIFAR, EIIT, EPGE-Fundação Getulio Vargas, Queen's University, Ryerson University, University of Alberta, University of Auckland, UC Davis, UC San Diego, University of Chicago Booth, Universidad de Chile and University of Sydney for helpful comments.

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1 Introduction

One of the mainstays of the theory of comparative advantage is that countries' factor endowments determine the pattern of trade. An established theoretical framework, the Heckscher-Ohlin-Samuelson factor proportion theory, and numerous related empirical studies,[1] identify quantities such as the stocks of human and physical capital of countries as primary sources of comparative advantage. This paper provides evidence supporting an alternative, and empirically sizeable, source of comparative advantage: the dispersion of skills (human capital) in the working population.[2]

A first glance at the data reveals that cross-country differences in skill dispersion are larger than differences in the average skills of workers. We employ the distribution of scores in the International Adult Literacy Survey (IALS), an internationally comparable measure of work-related skills, as a proxy for the distribution of skills. Figure 1 plots the mean against the standard deviation of IALS scores for 19 countries during 1994-1998 (Figure A-1 in the Appendix reports the distribution of IALS scores for each country vis-à-vis the US). The coefficient of variation of the standard deviation of scores is 1.6 times larger than that of the average scores, highlighting substantial cross-country differences in the second moments.

The reasons why countries at similar stages of development differ in their skill distributions are beyond the scope of this study;[3] such differences may be due to the degree of centralization in the education system and curricular control (Stevenson and Baker, 1991), the existence of elite schools,

[1] Recent studies, primarily Romalis (2004), testing the predictions of the theory about commodity trade, have detected larger effects compared to tests based on factor content, namely Bowen et al. (1987), Trefler (1993), Trefler (1995), and Davis and Weinstein (2001).

[2] Human capital is determined by many factors, among which formal education, family upbringing, underlying ability and on-the-job training. Throughout this paper we refer to human capital or skills, terms that we use interchangeably, as a set of attributes that are of productive use in the workplace.

[3] What is not beyond the scope of this study is a discussion of how the endogeneity of skill dispersion might affect our empirical results. See Section 4.4.

sorting and segregation,[4] early tracking,[5] local school financing (Benabou, 1996) and the shares of private and public schools (Takii and Tanaka, 2009).[6]

In the absence of previous empirical research linking skill dispersion to comparative advantage, we start by showing that relative trade flows of manufacturing goods vary with skill dispersion, i.e. countries with higher skill dispersion export relatively more in some sectors. This analysis is performed by means of a simple 'atheoretical' exercise which also shows that the effect of skill dispersion is quantitatively similar to that of average skill endowments, a usual suspect in the empirical trade literature.

Although this exercise cannot explain why some industries benefit from skill dispersion, it provides a useful motivation for the next step, in which we discipline our analysis by focusing on a specific sector characteristic which interacts with skill dispersion to generate comparative advantage. In particular, we exploit cross-industry variation in the degree of complementarity of workers' skills across production tasks. In some industries, such as aerospace or engine manufacturing, production requires completing a long sequence of tasks and poor performance at any single stage greatly reduces the value of output. These are industries with high skill complementarity (or *O-Ring*, as in Kremer, 1993), where teamwork is crucial and efficiency is higher if workers of similar skills are employed at every stage of production. On the contrary, in other industries, such as apparel, teamwork is relatively less important, skills are more easily substitutable and therefore poor performance in some tasks can be mitigated by superior performance in others. The question we pose is whether countries with greater skill dispersion specialize in sectors characterized by

[4] The existence of peer effects, as documented for example by Hanushek et al. (2003) and Hoxby and Building (2000), implies that segregation and sorting might result in even higher inequality of educational outcomes. An example of this amplification mechanism is provided by Friesen and Krauth (2007).

[5] Tracking refers to the practice of grouping students in different schools according to their ability. Woessmann et al. (2006) show that when grouping happens before age 10, inequality in education outcomes increases at the country level.

[6] James (1993) argues that the mix of public and private educational services is due, for example, to the degree of religious heterogeneity within a country.

higher substitutability of skills across tasks.

The hypothesis that skill dispersion may lead to specialization has been the object of theoretical work by Grossman and Maggi (2000), henceforth GM. They show that in a two-country, two-sector model with perfectly observable talent and competitive labor markets, the country with a relatively more dispersed skill distribution specializes in the sector that benefits from matching workers of different skill levels. In related work we build on this insight and propose a multi-country, multi-sector model where skill dispersion generates testable implications for the pattern of international trade (Bombardini, Gallipoli and Pupato, 2010, henceforth BGP2). Section 3 shows that the key difference between the two approaches resides in the role of observable (the focus in GM) versus unobservable skills (our focus), that is, the portion of skills which is not ex-ante observable during hiring. While in GM comparative advantage emerges as the result of perfect assortative (or cross) matching, we explore the alternative case of imperfect matching due to unobservability of certain skill dimensions. In the absence of sorting in unobservable skills between firms and workers, firms in every sector inherit the country's unobservable skill distribution.[7] Then, comparative advantage emerges from the combination of a sector's degree of skill complementarity and a country's skill dispersion.

A stylized example with two countries and two sectors, depicted in Figure 2, clarifies the intuition for our mechanism. Each sector employs only two workers, who perform symmetric tasks in the production process, and whose skills (a_1 and a_2) are measured on the axes. Technologies in the two sectors are represented by isoquants. For simplicity assume one of the sectors to be the limit case of perfect skill substitutability, corresponding to a linear isoquant Q_{PS}. Isoquant Q_{IS} represents a sector with imperfect substitutability of skills. Each country corresponds to one point: country C

[7] This assumption is consistent with evidence, in Altonji and Pierret (2001), that firms take time to learn about many dimensions of workers' skills and that sorting, both across industries and occupations, does not seem to depend, for the most part, on unobservable worker characteristics, as documented by Blackburn and Neumark (1992).

has two workers with the same average skills as country C' (they both lie on a line with constant mean skills). Skills in country C, however, are more dispersed relative to country C'. One can immediately verify that output in sector PS is the same for both countries because only aggregate skills matter in the presence of perfect skill substitutability. However, in the sector with skill complementarity (IS) output is higher in the country with lower skill dispersion, C'. The less dispersed country has a comparative advantage in the sector with higher skill complementarity.

The empirical counterpart of unobservable skills can be residually approximated by purging IALS scores of the effect of a variety of observable individual characteristics, such as education, age and gender, to create what we refer to as 'residual' skill dispersion. We investigate empirically the prediction that countries with more dispersed residual skill distributions specialize in sectors with lower skill complementarity in production. We adapt the empirical approach of Helpman et al. (2008) to industry-level bilateral trade flows and augment it with our variable of interest. The analysis shows that the interaction of exporter skill dispersion with sectoral measures of skill substitutability is a significant and economically large determinant of exports, while controlling for bilateral trade barriers, exporter and importer-industry fixed effects. We also include determinants of comparative advantage based on aggregate factor endowments, in the spirit of Romalis (2004), and institutional quality as in Nunn (2007) and show that their effects on trade flows are of the same statistical magnitude as that of skill dispersion.

The main focus of the paper is on residual skill dispersion. One reason for this choice is that, in the median country in our sample, residual dispersion accounts for 70% of overall dispersion. The second reason is that data constraints do not allow us to implement a theory-based test of GM (see section 4.4.2). However, we expand the analysis by also assessing the effect of predicted skill dispersion, a proxy for variation in observable skills, on trade flows. Although not formally grounded in GM's theory, this exercise confirms the significance and robustness of the effect of skill dispersion on comparative advantage.

As the degree of substitutability of skills is not directly observable, we take two distinct approaches to its measurement. First, we exploit a theoretical result - established in BGP2 - linking the unobservable degree of complementarity to the observed dispersion of residual wages within industries. In a setting with labor market frictions and random matching on residual skills, residual wage dispersion within industries increases in the degree of skill substitutability. Sectors with higher complementarity are characterized by a more compressed wage distribution because, for example, workers with higher-than-average skills contribute relatively less to surplus, a fact reflected in their wage. As with IALS scores, in order to bring the empirical analysis in line with this theory, we use US Census data to construct a measure of residual wages by purging the effect of observable characteristics from individual wages. In order to mimic random matching, we spend considerable effort addressing the possible non-random selection in unobservable characteristics across industries using a method proposed in Dahl (2002). Furthermore, in view of substantial evidence linking firm size and wages (e.g. Oi and Idson, 1999), we filter out sector-specific firm heterogeneity from our residual wage dispersion measures.

Second, we use an alternative set of proxies for skill substitutability based on data from the Occupational Information Network (O*NET), which allow us to quantify the degree of teamwork, communication and interdependence between co-workers' labor inputs. These measures do not rely on the theoretical structure of BGP2 and provide a direct and intuitive way to proxy for complementarity.

Our findings relate to recent work emphasizing less traditional sources of comparative advantage. In this literature the endowment of a country, interpreted in its broadest sense, includes institutional features, such as the ability to enforce contracts (Levchenko, 2007, and Nunn, 2007), the quality of the financial system (Manova, 2008a; 2008b) and the extent of labor market frictions (Helpman and Itskhoki, 2010, Cuñat and Melitz, 2010, Tang, 2008). We view our contribution as related to this 'institutional endowment' view of comparative advantage because human capital dispersion in a country is to a large extent the result of the prevailing educational system and social make-up. These, in turn, can be considered, if not immutable, a slow-moving attribute of a country.[8]

The paper is organized as follows. Section 2 provides preliminary evidence that skill dispersion matters as much as average skills in determining trade flows. Section 3 describes the theoretical background. Section 4 and 5 inspect the mechanism put forward in Section 3. Section 6 concludes. A detailed data description can be found in the Appendix.

2 Preliminary Evidence: the Importance of Second Moments

This section provides preliminary evidence that skill dispersion within a country shapes its pattern of international trade. We present an atheoretical exercise that aims at quantifying the overall effect of IALS dispersion on comparative advantage without the need to specify any particular mechanism driving specialization, a task that will be the concern of following sections in the paper. Importantly, the impact of skill dispersion is assessed against that of skill abundance, the first moment of the skill distribution, which is a natural benchmark in the trade literature.

More specifically, the question addressed in this section is: what is the effect of marginal changes in skill dispersion (as well as skill mean) on the relative exports of any two manufacturing industries? The exercise is implemented through an OLS regression of export volumes on interactions of the

[8] Glaeser et al. (2004) show that education is significantly more persistent than several other institutional features, such as the form of government.

first and second moments of an exporter's skill distribution with a full set of industry dummies:

$$\log X_{HFi} = \sum_{i\in S} \alpha_i^{mean} I_i \times SkillMean_H + \sum_{i\in S} \alpha_i^{disp} I_i \times SkillDisp_H + \gamma d_{HF} + \delta_H + \delta_{Fi} + \varepsilon_{HFi} \quad (1)$$

where $\log X_{HFi}$ is the logarithm of the value of exports from country H to country F in industry i; $SkillMean_H$ and $SkillDisp_H$ are the mean and standard deviation of the distribution of log IALS scores in exporter H, and the I_i's are dummy variables for each of the S sectors (except an excluded baseline industry). Although not explicitly derived, the fixed effects included in this specification can be rationalized in a model of monopolistic competition with trade frictions, where bilateral trade flows depend on: the industry's price index and total expenditure level in the importing country (captured by importer-industry fixed effects, δ_{Fi}), the exporter's size (accounted for by exporter fixed effects, δ_H) and bilateral trade barriers (represented by d_{HF}, a vector of observable bilateral trade frictions).[9] We estimate (1) employing the value of bilateral trade flows from 19 exporters to 145 importers in 63 industries in the year 2000. A detailed data description is provided in Section 4.2 and the Appendix. For comparability, average skill and skill dispersion are standardized across exporters. Estimation of (1) allows us to gauge the impact of mean skill and skill dispersion on the relative exports of any two exporting countries, say H and G, to an average third country F in industries i and j. For example, focusing on skill dispersion, we can write:

$$E\left[\log\left(\frac{X_{HFi}}{X_{GFi}}\right) - \log\left(\frac{X_{HFj}}{X_{GFj}}\right)\right] = (\alpha_i^{disp} - \alpha_j^{disp})\Delta_{HG} SkillDisp \quad (2)$$

where $\Delta_{HG} SkillDisp \equiv SkillDisp_H - SkillDisp_G$. Regardless of its sign, the larger the difference $\alpha_i^{disp} - \alpha_j^{disp}$ (in absolute value), the stronger the impact of skill dispersion on relative exports of i and

[9] The estimation framework is analogous to Manova (2008b) and, with the exception of our focus on a breakdown of trade flows by sectors, to Helpman et al. (2008).

j.[10] Reporting $\left|\alpha_i^{disp} - \alpha_j^{disp}\right|$ for each possible industry pair and for both moments is cumbersome (there are two sets of 62 α coefficients), therefore we summarize the estimation results by providing an average of those differences across *all* possible industry pairs. In this sense, the mean difference $MD\left(\alpha^{disp}\right) \equiv \frac{1}{S(S-1)} \sum_{i \in S} \sum_{j \in S} \left|\alpha_i^{disp} - \alpha_j^{disp}\right|$ captures the average effect of skill dispersion.

Within this framework we perform three different exercises. The first evaluates the importance of within-country skill dispersion vis-a-vis skill mean. Table 1 reports the bounds of 95% confidence intervals for $MD\left(\alpha^{mean}\right)$ and $MD\left(\alpha^{disp}\right)$, the estimated mean difference of the effects of mean and standard deviation of log IALS scores.[11] Column 1 indicates that both moments contribute to shaping the pattern of specialization across industries, with quantitatively similar effects.

The second exercise extends the specification in equation (1) by including standardized measures of the thickness of the left and right tails of the skill distribution in country H. Each of these measures is interacted with a full set of industry dummies, just like we do for the mean and standard deviation of skills. These "thickness-of-tails" measures correspond to the shares of the country's population that belong, respectively, to the top and bottom quintiles of the *world* IALS distribution.[12] The goal is to verify that the estimated effect of skill dispersion in column 1 is not solely driven by the tails of the distribution. In addition, we can assess whether cross-country differences in the sets of very (un)skilled individuals have an independent effect on trade (beyond their contribution to skill dispersion and mean).[13] The results in column 2 of Table 1 confirm this

[10] Notice that, while the choice of baseline industry clearly affects the individual estimates of the α's, it is inconsequential in terms of the object of interest, $\alpha_i^{disp} - \alpha_j^{disp}$, which is the pairwise difference in those estimated coefficients.

[11] Confidence intervals are computed using the Delta method.

[12] The top and bottom quintiles of the world IALS distribution define two thresholds. For each country we compute the share of individuals above the top and below the bottom threshold. Notice that, in any country, these shares can be higher or lower than 20%.

[13] This exercise is particularly important in light of our analysis in Appendix section G, where we decompose the cross-country variation in skill dispersion and assess the importance of various parts of the skill distribution. Because we find that differences in the left tail of the distribution are the largest driver of the variation in skill dispersion, it is particularly important to verify, as we do in column 2 of Table 1, that, holding the thickness of the left tail constant, skill dispersion still has the same effect on trade flows.

and show that confidence intervals of $MD\left(\alpha^{disp}\right)$ and $MD\left(\alpha^{mean}\right)$ overlap, pointing to statistically equivalent impacts of the first two moments of the skill distribution.

The third exercise employs the same approach to quantify and compare the impact on trade of two sources of skill dispersion, namely dispersion in observable skills and dispersion in unobservable skills. This exercise attempts to capture the role of variation due to easily observable 'credentials', like education, as opposed to those residual skills that employers find harder to identify before a worker has been hired. This atheoretical framework allows us to assess the importance of both sources of skill dispersion (the decomposition of predicted and residual skills is discussed in Section 4.2.1). In this exercise, we interact each of three moments, average skills, the standard deviation of predicted skills and that of residual skills, with a full set of industry dummies and again report the MD's associated with each set of estimated coefficients. Column 3 of Table 1 shows that both types of skill dispersion matter for specialization and their effects have similar magnitude. Column 4 also shows that, whether or not predicted skill dispersion is included, the coefficients on residual dispersion are unaffected.

3 Theoretical Background: Why Dispersion Matters

The previous section shows that skill dispersion has an impact on trade flows, but does not explain why. This section highlights a mechanism through which skill dispersion matters for specialization, hinging on the degree of complementarity of skills across tasks in the production process. In related work (BGP2) we develop a monopolistic competition model with variable transport costs in which countries are characterized by different skill distributions. All sectors feature symmetric supermodular production functions, but vary in the degree of complementarity of skills across tasks. More specifically, output y depends on the skill a of employed workers, the mass $h\left(a\right)$ of workers with given skill a, and a parameter λ measuring skill complementarity, so that $y = \left(\int a^{\lambda} h\left(a\right) da\right)^{\frac{1}{\lambda}}$ with $\lambda < 1$. Sectors with low λ benefit relatively more from a less dispersed skill distribution. The model in BGP2 features labor market frictions in the spirit of Helpman and Itskhoki (2010). Workers decide to look for a job in an industry only knowing the average industry wage and its unemployment rate. By definition, any residual skill is not ex-ante observable to hiring firms. As a result, the distribution of residual skills of the set of workers looking for jobs in each industry will resemble the country's distribution, leading to no sorting along this dimension between workers and firms. Extending the model to account for the observable component of individual skills would result in firms only hiring workers of identical *observable* skills, but there would still be no sorting on residual skills. The model is static and, given labor market frictions, once workers are hired, bargaining between firm and workers determines wages, as described in detail in BGP2 and discussed in Section 4.1.

Random matching on unobservable skills implies that, in equilibrium, the residual skill distribution prevailing in a country is passed on to every industry and firm.[14] Therefore output can be rewritten as a function of the mass of workers employed and a 'productivity' factor $A\left(\lambda, c\right)$ defined as $A\left(\lambda, c\right) = \left(\int a^{\lambda} g(a, c) da\right)^{\frac{1}{\lambda}}$, where $g(a, c)$ is the distribution of skills in country c. The variation of $A\left(\lambda, c\right)$ across countries and industries is the unique determinant of comparative advantage and relative trade flows in the model. Of particular interest for the purpose of the empirical analysis in Section 4 is the case in which a country c', with identical mean but higher dispersion of skills than country c, has a comparative advantage in sectors with lower complementarity (high λ). This requires that, for any $\lambda' > \lambda$,

$$\frac{A\left(\lambda, c'\right)}{A\left(\lambda, c\right)} < \frac{A\left(\lambda', c'\right)}{A\left(\lambda', c\right)}. \tag{3}$$

[14] This is consistent with recent international evidence (see Iranzo et al., 2008, and Lazear and Shaw, 2008) suggesting that most of wage dispersion is in fact within, rather than between, firms.

Inequality (3) simply states that countries with high skill dispersion are relatively more productive in low-complementarity sectors. BGP2 examine (3) analytically and provide sufficient conditions on skill distributions and complementarity that ensure its validity. Here we present a simple numerical exercise to verify the empirical relevance of (3) using score distributions from IALS. $A(\lambda, c)$ is computed by replacing $g(a, c)$ with the empirical IALS distribution for each of the 19 participant countries. Given a grid of 100 λ's in the $[0, 1]$ interval, we calculate the ratio $\frac{A(\lambda,c')}{A(\lambda,c)}$ for every pair of countries (c, c') where c' has higher skill dispersion than c -according to the coefficient of variation of scores. We find that, averaging across pairs, $\frac{A(\lambda,c')}{A(\lambda,c)}$ is increasing in λ for 97% of the grid points. This result implies that if the empirical IALS distributions were used to simulate our model, they would generate a pattern of comparative advantage in which countries with higher skill dispersion export relatively more in industries with low complementarity.

Our theoretical analysis differs from GM's in three dimensions. First, we focus on the set of skills which are not easily observable ex-ante, so that random matching prevails along this dimension. This focus reflects the fact (documented in section 4.2.1) that observable worker characteristics account for a smaller share of total variation in IALS scores within countries, i.e. measured skill dispersion is large among workers with similar 'credentials'. Second, we do not assume the existence of submodular sectors, i.e. sectors which benefit from cross-matching of skills. We posit instead that all sectors benefit from assortative matching -albeit to different degrees-, which makes it easier to link our analysis to the existing trade literature, in which most production functions are supermodular.[15] The role of unobservable skills in the presence of supermodular technologies is only briefly discussed in GM.[16] Third, we provide a framework that is suitable for empirical testing

[15] It is worth stressing that in the presence of observable skills and symmetric super-modular production functions there is no basis for comparative advantage even if countries vary in the degree of skill dispersion. Each sector only employs workers of similar ability. Comparative advantage emerges only in the presence of a sub-modular sector where firms actively seek to match workers of different skill levels.

[16] In fact, we expand on an element introduced by GM: at the end of the paper they "note in passing that, with imperfect matching, trade would take place between two countries with different educational processes even if tasks

as we model multiple countries, multiple sectors and transport costs, smoothing out the otherwise knife-edge predictions of Ricardian-type models.[17]

4 Inspecting the Mechanism: Residual Skills and Substitutability

This section presents evidence in support of the specific mechanism discussed above, linking residual skill dispersion to trade flows. First, we discuss the estimation framework. Section 4.2 describes the data and Section 4.3 reports baseline results. Section 4.4 discusses identification and presents robustness checks.

4.1 Estimation Framework

To test whether skill dispersion matters for trade flows through the specific channel of skill substitutability, we build on specification (1) and interact $SkillDisp_H$, a measure of skill dispersion in country H, with $Substit_i$, a measure of skill substitutability in industry i:

$$\log X_{HFi} = \beta Substit_i \times SkillDisp_H + \gamma d_{HF} + \delta_H + \delta_{Fi} + \varepsilon_{HFi}. \tag{4}$$

The variable of interest is $Substit_i \times SkillDisp_H$ and estimation of its coefficient β allows us to test the prediction that, everything else equal, a country with a more dispersed skill distribution, exports relatively more in sectors with high substitutability of workers' skills. To see why, assume that equation (4) correctly specifies a model for the conditional expectation of $\log X_{HFi}$, so that $E\left[\varepsilon_{HFi} | Substit_i \times SkillDisp_H, d_{HF}, \delta_H, \delta_{Fi}\right] = 0$. Then, for any two countries H and G exporting

were complementary in all production activities" , i.e. all production functions were super-modular, which is the case we consider.

[17] Our and GM's models are not the only ones studying theoretical links between skill distributions and trade, although comparative advantage emerges as a result of substantially different mechanisms. Ohnsorge and Trefler (2007), Grossman (2004), Bougheas and Riezman (2007) and Costinot and Vogel (2010) are prominent examples of this literature.

to F, and any two industries i and j, equation (4) implies:

$$E\left[\log\left(\frac{X_{HFi}}{X_{GFi}}\right)-\log\left(\frac{X_{HFj}}{X_{GFj}}\right)\right]=\beta\Delta_{ij}Substit\times\Delta_{HG}SkillDisp \tag{5}$$

where $\Delta_{HG}SkillDisp \equiv SkillDisp_H - SkillDisp_G$ and $\Delta_{ij}Substit$ is similarly defined. Our theoretical framework implies that $\beta > 0$. As in other studies of comparative advantage, our approach does not aim at explaining the overall volume, but rather the pattern of trade, i.e. differences in the composition of trade flows across countries. This initial specification is extended in Section 4.4 to account for alternative sources of comparative advantage that may be correlated with skill dispersion.

A difficulty in implementing a test of our hypothesis comes from the fact that the elasticity of substitution of individuals' skills at the industry level, $Substit_i$, is not directly observable and we are not aware of any estimates of the elasticity of substitution across finely disaggregated skills. We take two different approaches to proxying for the elasticity of substitution of workers skills, $Substit_i$. The first is based on a theoretically-founded link between complementarity and residual wage dispersion. In the second approach we use proxies for complementarity available from occupation-level microdata.

Skill substitutability: residual wage dispersion rankings What follows is a heuristic explanation of the link between complementarity and (residual) wage dispersion.[18] Consistent with empirical evidence, e.g. Altonji and Pierret (2001), suggesting that firms learn only gradually about worker skills, we posit that part of unobservable skills are revealed after hiring. Due to frictions, we assume wages are determined by multilateral bargaining within the firm. At the bargaining stage each worker receives a wage that corresponds to her average marginal product (the Shapley value),

[18] A complete derivation is available in BGP2.

therefore workers of higher skills receive higher wages. To the extent that each sector inherits the country-specific distribution of residual skills, the variation in the distribution of residual wages only reflects technological differences across sectors. Therefore wage dispersion is driven by the degree of skill complementarity. For example, in a sector with high complementarity and a stronger need for a homogeneous labor force, high skill workers have lower marginal product, relative to high substitutability sectors, because their skills are far from the average. In general, sectors with low complementarity (high substitutability) will exhibit more dispersed wage distributions. We cannot rely on our theory to structurally recover actual values of skill substitutability ($Substit_i$), but we can use its unambiguous prediction of a monotonic relationship between skill substitutability and residual wage dispersion to identify a ranking.

Skill substitutability: O*NET rankings In our second approach we construct proxies for complementarity using occupation-level data from O*NET. As described in Section 4.2.2, this database rates industries in three dimensions which are closely associated to skill complementarity: i) *Teamwork*: team production can naturally be thought of as a particular type of O-Ring production process (Kremer, 1993), in which the quality of final output critically depends on the successful completion of a given number of complementary tasks. (ii) *Impact on co-worker output:* a closely related way of characterizing complementarity is to quantify the extent to which a worker's actions impact the performance of co-workers; a higher impact implies a higher degree of complementarity. (iii) *Communication/Contact*: communication and contact intensity are linked to the importance of coordinating tasks to achieve, for example, a given level of output quality; if co-workers have no need for communication or contact with each other, they are likely to have independent contributions to the final outcome. As for wage dispersion, and because we do not know the exact mapping between the O*NET variables and skill substitutability, we simply rely on O*NET to identify a ranking of industries in terms of skill substitutability.[19]

4.2 Data

A detailed data description can be found in the Appendix. Here we discuss the measurement of two key explanatory variables in the empirical analysis, skill dispersion at the country level and skill substitutability at the industry level.

4.2.1 Residual Skill Dispersion

We use test scores from the 1994-1998 International Adult Literacy Survey (IALS) to approximate the skill distribution within a country. Collaborators in this household survey administered a common test of work-related literacy skills to a large sample of adults between the ages of 16 and 65 in 19 countries. The IALS focuses on literacy skills that are needed for everyday tasks (e.g. working out a tip, calculating interest on a loan and extracting information), across three different dimensions of literacy: *quantitative*, *prose* and *document* literacy. We combine the results of these three tests into a single average score for each individual, measured on a scale from 0 to 500. The skill distribution is proxied by the distribution of log-scores of individuals participating in the labor market and living in the same country.

To ensure consistency with the theoretical assumption of imperfect skill observability, we construct a measure of residual score dispersion within countries. For an individual k participating in the labor market of country H, we obtain the estimated residual $\widehat{\epsilon_{kH}}$ from the following regression:

$$\log(s_{kH}) = X_{kH}\beta_H + \epsilon_{kH} \tag{6}$$

[19] For both wage dispersion and O*NET, regression results are qualitatively unchanged if we employ the value of the proxies instead of their ranking.

where s_{kH} is the IALS score of k and X_{kH} is a vector of individual demographic information from the IALS questionnaire: education, age, gender, immigrant status and on-the-job training (details in Appendix A.1). The residual $\widehat{\epsilon_{kH}}$ is then used to compute the skill dispersion measures used for the estimation of trade flows. Analyzing the R-squared of these country-by-country regressions, we find that the variation in residual scores $\widehat{\epsilon_{kH}}$ accounts for a minimum of 46% of the observed variation in log-scores in Canada, for a maximum of 83% in Germany and for 70% in Finland, the median country in the sample.

Table 2 ranks 19 countries according to the coefficient of variation (CV) of IALS scores, and also reports their rank by mean, standard deviation (St Dev) and standard deviation of residual IALS (St Dev Res). The table shows how countries at similar stages of development differ substantially in the degree of skill dispersion: the US and the UK display a more dispersed skill distribution than Sweden and Germany.[20]

4.2.2 Substitutability

In this section we describe the construction of the two rankings of skill substitutability at the industry level, based on residual wage dispersion and O*NET indices.

Residual Wage Dispersion We use the 5% Public Use Microdata Sample (PUMS) files of the 2000 Census of Population in the United States to construct industry-specific measures of wage dispersion and identify a ranking of industries with respect to the unobserved elasticity of substitution. An advantage of our approach is that we can match individual wage observations to a detailed industry classification, accounting for the entire manufacturing sector. This procedure results in 63 industries for which both wage dispersion and international trade flows can be computed, at a level

[20] Brown et al. (2007) report similar variation in skill distributions in a comprehensive study using IALS, the 1995, 1999 and 2003 Trends in International Maths and Science Study (TIMSS), the 2000 and 2003 Programme for International Student Assessment (PISA) and the 2001 Progress in International Reading Literacy Study (PIRLS).

of aggregation between the 3 and 4 digit levels of the 1997 North American Industry Classification System (NAICS).

As with IALS scores, we focus on residual wage dispersion. We start by removing variation in wages driven by individual characteristics on which firms can typically condition employment decisions. We also adapt the correction method proposed in Dahl (2002) to address the possibly non-random selection of workers into multiple industries.[21]

For an individual k employed in industry i, we obtain the estimated residual $\widehat{\xi_{ki}}$ from the following regression:

$$\log(w_{ki}) = Z_{ki}\beta_i + \xi_{ki} \tag{7}$$

where w_{ki} is the weekly wage of k and Z_{ki} is a vector of observable characteristics (education, age, gender and race, see Appendix A.2 for details). Note that we run these regressions separately for each industry to allow for differences in the return to observable characteristics across industries.[22]

Several studies have shown that firm size affects wages (Oi and Idson, 1999). This implies that wage dispersion might also reflect variation in the distribution of firm size across different industries. Therefore we purge residual wage dispersion of the effect of firm heterogeneity in order to isolate the degree of complementarity. Since the Census does not provide the size of the establishment at which individual workers are employed, we regress measures of dispersion of $\widehat{\xi_{ki}}$ on the coefficient of variation of firm size within industry i, $FirmDisp_i$. The residuals from this regression are employed to construct $WageDisp_i$, a ranking of industries (in Table 3 we report the top and bottom 5). For example, in terms of the standard deviation of residual wages, the three lowest ranked sectors are railroad, ship building and aerospace. The three highest ranked are apparel accessories, bakeries

[21] In essence, this procedure controls for selection effects using differences in the probability of being observed in a given industry due to exogenous variation, such as the state of birth of two people who are otherwise similar in terms of education, experience, household structure, race and gender. Details are provided in the Appendix.

[22] Regression results are available upon request.

and cut and sew apparel. Although these rankings are constructed using US data, in Appendix C we show that rankings based on Canadian data are highly correlated.

O*NET survey-based measures of complementarity Sponsored by the Employment and Training Administration of the United States Department of Labor, O*NET provides detailed information on job requirements and worker attributes for 965 occupations in the U.S. Information on 277 descriptors including abilities, work styles, work context, interests, experience and training, is annually updated by ongoing surveys of each occupation's worker population and occupational experts.

Our complementarity rankings are based on four selected O*NET (Version 12.0) questions capturing different aspects of skill complementarity: (1) *Teamwork*: How important are interactions that require you to work with or contribute to a work group or team to perform your current job?[23] (2) *Impact*: How do the decisions an employee makes impact the results of co-workers, clients or the company? (3) *Communication*: How important is communicating with supervisors, peers or subordinates to the performance of your current job? (4) *Contact*: How much contact with others (by telephone, face-to-face, or otherwise) is required to perform your current job? Respondents were asked to rate these questions on a scale from 1 to 5. The O*NET database provides average scores for each occupation.

In constructing industry-level proxies of complementarity, O*NET scores were matched to the 2000 Census microdata through a common occupational classification (the Standard Occupational Classification). In this way, as occupational structures vary across industries, we obtain a different distribution of scores for each industry. Using the median score[24] for each industry we generate

[23] An alternative measure of teamwork can be obtained from the Detailed Work Activities (a supplemental file to O*NET). Reported results are qualitatively unchanged when this measure is used.

[24] We employ average scores to break ties based on the medians.

O^*NET_i, a ranking of sectors in terms of substitutability.[25] Industries with higher O^*NET_i exhibit lower skill substitutability. Table 3 reports the ranking in terms of $Contact_i$ for the top and bottom 5 industries as ranked according to residual wage dispersion (other O*NET variables produce similar rankings). The table shows that among the lowest ranked sectors in terms of wage dispersion appear the top ranked sectors in terms of O*NET measures. These are the low substitutability sectors. Similarly, among the highest ranked sectors in terms of $WageDisp_i$ we find the bottom O^*NET_i sectors (those sectors with high substitutability). This reflects the fact that, as shown in Appendix Table A-1, the rankings based on occupational surveys, O^*NET_i, and the rankings based on residual wage dispersion, $WageDisp_i$, are inversely correlated.

4.3 Baseline Results

This section discusses results of the empirical analysis of trade flows using specification (4). We report results employing first wage dispersion rankings and then O*NET rankings. Unless otherwise noted, the method of estimation is OLS. For comparability, all tables report standardized coefficients of the explanatory variables.

4.3.1 Results with Substitutability proxied by Wage Dispersion Rankings

Table 4 reports estimates of the impact of skill dispersion as proxied by the dispersion of residual IALS test scores (defined in Section 4.2.1): we identify this effect through an interaction with residual wage dispersion rankings (defined in Section 4.2.2). The measures of dispersion employed in Table 4 are: the standard deviation in columns (1) and (4), the 95-5 interpercentile range in columns (2) and (5), and the Gini mean difference in columns (3) and (6). Columns (1)-(3) add exporter, importer and industry dummies to our variables of interest; columns (4)-(6) include

[25] The results are robust to reweighting by hours worked and to using mean scores instead of medians as complementarity proxies.

theoretically consistent exporter and importer-industry dummies, along with a vector of bilateral trade barriers described in the Appendix. We find that the interaction of skill substitutability and skill dispersion has a positive and significant effect on exports. Note that the magnitudes of the coefficient are stable across specifications and measures of dispersion. The standardized coefficient of the interaction varies between 1.3% and 1.7% in the six specifications. The quantitative relevance of this channel is discussed in Section 5 alongside that of other sources of comparative advantage.

4.3.2 Results with Substitutability proxied by O*NET rankings

Next, we report estimates of the effect of skill dispersion on trade flows using four alternatives measures of skill complementarity constructed from the O*NET database. Table 5 replicates the structure of columns (4)-(6) of Table 4, in terms of the set of fixed effects included and trade barriers used as controls. The variable of interest is the interaction of $SkillDisp_H$ (measured by the standard deviation of residual scores) and the corresponding O*NET ranking: $Teamwork_i$, $Impact_i$, $Communic_i$ and $Contact_i$. Note that since O*NET rankings are proxying for complementarity, the expected sign of the interaction is negative (i.e. countries with a higher skill dispersion export relatively less in industries with high skill complementarity). This is confirmed in every specification of Table 5 at the 1% significance level. The estimates of the effect of skill dispersion are of similar magnitude to the ones generated using the wage dispersion rankings.[26] Since we find consistent results across all four correlated survey-based measures of complementarity, and in order to provide a concise robustness analysis section, we create an O*NET ranking based on the four rankings above. Column 5 of Table 5 reports similar results using this *Aggregate* O^*NET_i ranking.[27]

[26] In unreported regressions we check that these results are qualitatively unchanged if (i) skill dispersion is measured as either the 95-5 interpercentile range or the Gini mean difference of residual scores; (ii) importer-industry fixed effects are replaced by importer and industry fixed effects; (iii) trade barriers are not included in the estimation.

[27] *Aggregate* O^*NET_i is a ranking variable based on the median and average of the four O^*NET_i rankings (as we did for each individual O^*NET ranking, the average is employed to break ties in rankings based on the median).

4.4 Identification and Robustness

In this section we discuss some issues related to the identification of the effects quantified in Tables 4 and 5. Table 6 below reports results with both wage dispersion (columns 1, 3, and 5) and aggregate O*NET rankings (columns 2, 4 and 6), although we only include coefficient estimates using the standard deviation of residual skills. Results are unchanged if we employ the 95-5 and Gini skill dispersion measures.

4.4.1 The Extensive Margin of Trade: Selection

Tables 4 and 5 report estimation results which do not take into account the fact that a substantial fraction of bilateral trade flows are zero and that trade flows reflect both an intensive margin (the amount exported by each firm) and an extensive margin (the number of firms exporting, possibly zero). The estimation of (4) requires excluding observations for countries which do not trade in specific industries. These amount to 66.5% of the sample. As discussed in Helpman et al. (2008), selection of trading partners induces a negative correlation between observed and unobserved trade barriers (d_{HF} and u_{HF}) that might bias OLS estimates in (4), including β. In order to correct for selection bias, we implement the two-step estimation procedure proposed by Helpman et al. (2008) (details in Appendix). Table 6 reports second stage results obtained using the selection correction. Columns 1 and 2 document the robustness of the skill dispersion effect.

4.4.2 Omitted Determinants of Comparative Advantage

A second potential source of bias is due to the omission of other determinants of comparative advantage, possibly correlated to our variable of interest. Columns 3 and 4 of Table 6 show that the estimated effect of the interaction of substitutability ranking and residual skill dispersion is robust to a number of controls for other potential determinants of comparative advantage. We introduce controls for standard Heckscher-Ohlin sources of comparative advantage: the interaction of factor endowment of a country (in particular human capital, $SkillEndow_H$ and physical capital, $KEndow_H$) and factor intensity of the sector (human capital $SkillIntens_i$ and physical capital, $KIntens_i$), in the spirit of Romalis (2004). Since 95% confidence intervals overlap, the impact on trade flows of our interaction of interest is quantitatively similar to the Heckscher-Ohlin effects of the human and physical capital interactions, $SkillIntens_i \times SkillEndow_H$ and $KIntens_i \times KEndow_H$. We also control for institutional characteristics of exporters. In particular, we interact $Diff_i$ (a measure of sector i contract intensity) with $JudicQual_H$ (a measure of judicial quality) as in Nunn (2007) and our skill substitutability proxies with $LaborRigid_H$, a measure of labor law rigidity in country H, from Tang (2008). Including these alternative controls does not substantially affect the magnitude of our variable of interest and indicates that institutional quality has an impact on trade flows that is quantitatively similar to that of skill dispersion. We also introduce the share of individual wages that are top-coded within an industry, $TopCode_i$, interacted with skill dispersion, $SkillDisp_H$, to show that our result is not driven by the fact that some sectors rely on 'superstars' (those sectors that have a high share of top-coded wages).[28]

Finally, we expand our analysis by including a measure of observable skill dispersion. Although not a formal test of GM's theory,[29] columns 5 and 6 add an interaction of skill substitutability with the coefficient of variation of the predicted component of skills as estimated in (6). The coefficient on our interaction of interest is unchanged, while the effect of observable skill dispersion is broadly

[28] For briefness we include all controls at once. The working paper version reports estimates with controls included one at a time.

[29] A difficulty in testing GM is that it is unclear how their predictions can be extrapolated in order to carry out a multi-country and multi-sector empirical analysis of the impact of skill dispersion on trade flows. Moreover, our substitutability proxies only identify a *ranking* of industries according to the degree of skill substitutability, but not whether any given sector's technology is submodular or supermodular in skills. When skills are observable, GM find that skill dispersion has an ambiguous effect on the pattern of trade across industries that are ranked in terms of skill substitutability. For example, in a two-country two-sector setting, skill dispersion will not generate comparative advantage if both production technologies have different degrees of supermodularity in skills. Conversely, trade will emerge if one of the sectors has a submodular production function. As a result, the same ranking can yield different trade patterns.

in line with the intuition suggested by the GM model, although not always statistically significant.

4.4.3 Reverse Causality

Wage dispersion rankings and skill dispersion might be partly influenced by the pattern of international trade, potentially resulting in reverse causality.[30] The orthogonality condition needed for consistent estimation of β in equation (4) is:

$$E\left(WageDisp_s \times SkillDisp_c \times \varepsilon_{HFi}\right) = 0 \quad \forall s, c \tag{8}$$

By the Law of Iterated Expectations, a sufficient condition to obtain identification is:

$$E\left(WageDisp_s \times \varepsilon_{HFi} | SkillDisp_c\right) = 0 \quad \forall s, c \tag{9}$$

which requires that, for every exporter in our sample, within-industry wage dispersion be uncorrelated with unobserved determinants of trade. For example, a violation of (9) would arise if ε_{HFi} contained the unobserved share of exporting firms in a given sector in H and the proportion of exporters varied across industries and importers. In a model with heterogeneous firms, Helpman et al. (2010) show that within-industry wage dispersion is a function of the proportion of firms exporting in the industry since, on average, exporters pay higher wages than non-exporters.[31] However, as shown in Helpman et al. (2008), the correction for self-selection into the export market discussed in Section 4.4.1 effectively removes this potential bias.

Furthermore, since we measure wage dispersion at the industry level using U.S. data, we can check the robustness of our estimates by removing the U.S. from our set of exporters. To the extent

[30] It is less obvious how international trade may affect the survey based rankings O^*NET_i.

[31] Exporters do pay higher wages. See, for example, Bernard et al. (1995) and Bernard and Jensen (1997).

that the U.S. wage structure is not significantly affected by bilateral trade flows between other countries, this procedure substantially decreases the likelihood of feedback effects running from trade flows to wage dispersion. This procedure yields a coefficient on our interaction of interest of 0.035 (with standard error 0.01), effectively unchanged when compared to the specification in column 3 of table 6.

An alternative sufficient condition that guarantees (8), $E\left(SkillDisp_c \times \varepsilon_{HFi} | WageDisp_s\right) = 0$ for all s, c is discussed in Appendix E.

5 Magnitudes

Although regression coefficients are standardized and therefore readily comparable, in this section we interpret their magnitude in terms of trade flows. For ease of comparison with other control variables we focus on the full specification in column 3 of Table 6 and take 0.032 as the estimated effect of the interaction of country skill dispersion and industry substitutability measures. Consider two countries, the UK and Canada, and two industries, ‘computers’ and ‘plastics’. These countries and industries are chosen because residual skill dispersion in the UK is (approximately) one standard deviation higher than in Canada and the residual wage dispersion rank in computers is one standard deviation higher than in plastics. Since the standard deviation of log exports is 2.204 (Table A-5), the expected ratio of relative exports of computers in the UK and Canada, i.e. $E\left[\frac{X_{UK,F}(computers)}{X_{UK,F}(plastics)} / \frac{X_{CAN,F}(computers)}{X_{CAN,F}(plastics)}\right]$, is given by $e^{0.032 \times 2.204}$. This implies that, all else constant, skill dispersion induces exports of computers (relative to plastics) in the UK to be 7.3% higher than in Canada. To put this result in perspective, the estimates from column 3 of Table 6 imply that similar exercises yield a figure of 7.5% due to cross-country differences in human capital abundance (the Heckscher-Ohlin channel) and 4.7% due to institutional quality as in Nunn (2007).

One could also adopt the standard 'Rajan-Zingales' (Rajan and Zingales, 1998) approach of comparing industries and countries at the 25th and 75th percentiles of their respective distributions. Implementing this exercise for the skill dispersion channel requires similar calculations as before, except that now we consider the countries at the 25th and 75th percentiles of the skill dispersion distribution and the industries at the 25th and 75th percentiles of the residual wage dispersion rankings. As a result, the relative exports of the 75th percentile country in the 75th percentile sector are 24.5% higher due to the skill dispersion channel, 10.9% due to the skill endowment channel and 11.9% due to the institutional quality channel.

6 Conclusions

Relative differences in aggregate factor endowments are central to the classical theory of international trade. In this paper we push this idea further and argue that the entire distribution of a factor, and not just its aggregate endowment, can help rationalize observed trade flows. The analysis presents evidence that skill dispersion in the labor force has a quantitatively comparable effect to skill abundance in shaping comparative advantage. In particular we explore the prediction, developed in BGP2, that if (i) workers and firms randomly match along the unobservable component of skills, and (ii) industries vary in the degree to 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.

The empirical finding that countries with higher residual skill dispersion specialize in low complementarity sectors is robust to alternative measures of skill substitutability and skill dispersion, as well as to controls for alternative sources of comparative advantage. Importantly, the magnitude of the effect of skill dispersion is comparable to that of the aggregate skill endowment and institutional quality.

Finally, we notice that the analysis in the paper has implications for the impact of trade on residual wage inequality, which are beyond the scope of this study. Our results, taken at face value, imply that a more disperse skill distribution might have an indirect effect on a country's earnings distribution, as higher skill dispersion induces specialization in sectors that generate high residual wage dispersion.

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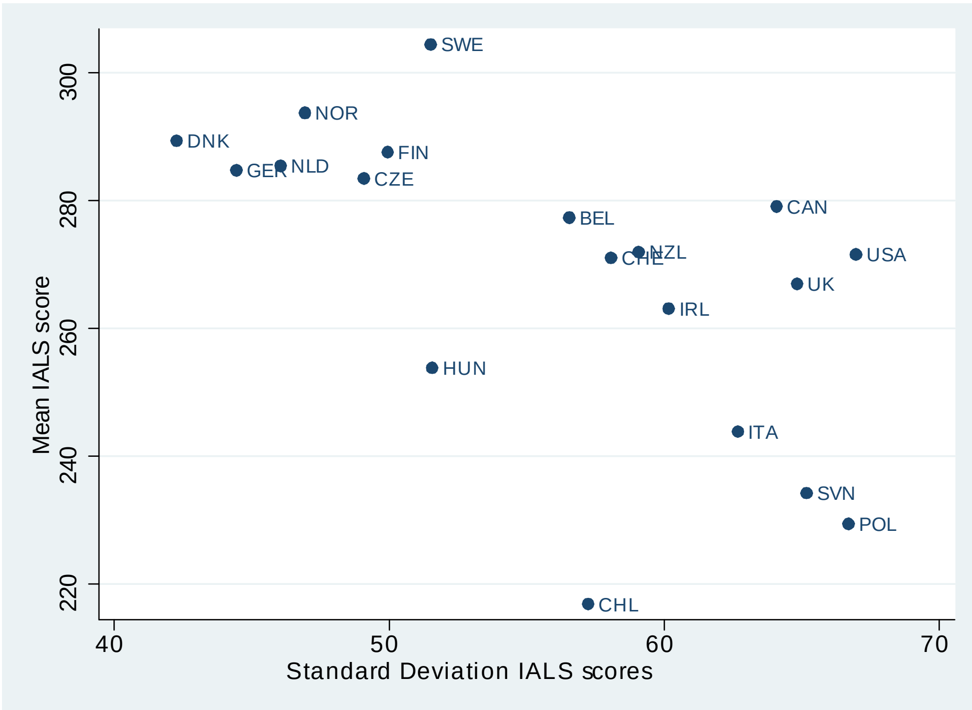

Figure 1: Mean and Dispersion in IALS scores (1994-1998)

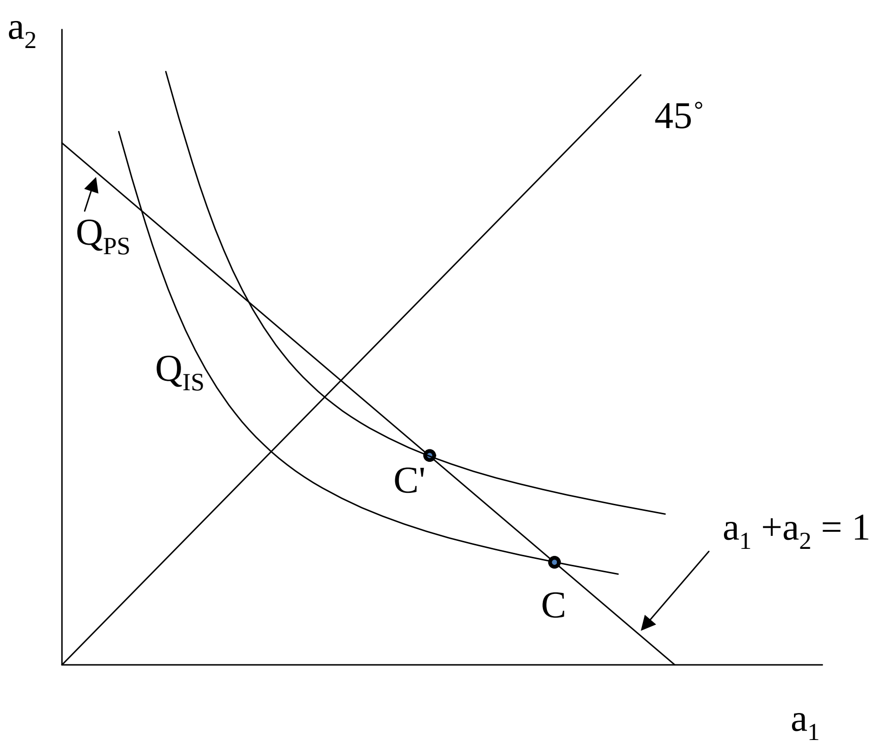

Figure 2: Comparative advantage: two countries and two sectors

Table 1 - Unrestricted effects on relative trade flows: 95% confidence intervals

	(1)	(2)	(3)	(4)
Average log IALS	0.24-0.30	0.25-0.33	0.22-0.27	0.20-0.25
Std Dev log IALS	0.15-0.20	0.24-0.30		
Pop Share 1^{st} quintile IALS		0.20-0.25		
Pop Share 5^{th} quintile IALS		0.42-0.54		
Std Dev Predicted log IALS			0.11-0.15	
Std Dev Residual log IALS			0.11-0.17	0.12-0.16

This table reports 95% confidence intervals for the mean difference of the 62 coefficients associated with interactions of standardized features of an exporter's log IALS score distribution (first column) and a full set industry dummies from an OLS regression of equation 1. Standard errors are calculated using the Delta method.

Table 2 - IALS log-scores

CV Rank	Exporter	*Mean* Rank		*St Dev* Rank		*St Dev Res* Rank	
1	Denmark	3	5.671	1	0.150	1	0.128
2	Germany	6	5.654	2	0.162	4	0.147
3	Netherlands	4	5.666	3	0.167	2	0.136
4	Norway	2	5.684	4	0.171	3	0.145
5	Finland	5	5.666	5	0.181	5	0.151
6	Sweden	1	5.717	6	0.184	6	0.153
7	Czech Republic	7	5.636	7	0.190	7	0.168
8	Hungary	15	5.546	8	0.204	8	0.176
9	Belgium	8	5.632	9	0.221	10	0.187
10	New Zealand	10	5.597	10	0.240	13	0.211
11	United Kingdom	11	5.595	11	0.262	17	0.234
12	Ireland	14	5.569	12	0.266	12	0.209
13	Switzerland	13	5.573	13	0.269	9	0.186
14	Canada	9	5.628	14	0.274	11	0.187
15	Italy	16	5.499	15	0.285	15	0.224
16	United States	12	5.587	16	0.289	14	0.215
17	Chile	19	5.355	17	0.302	16	0.224
18	Slovenia	17	5.446	18	0.314	18	0.246
19	Poland	18	5.415	19	0.333	19	0.284

Table 3 - Substitutability Rankings	$WageDisp_i$ $St\ Dev\ Res$ Rank	O^*NET_i $Contact_i$ Rank
Lowest $Substit_i$		
Railroad rolling stock	1	60
Ship and boat building	2	40
Aircraft, aerospace products and parts	3	28
Engines, turbines, and power trans. equipment	4	42
Nonferrous metals, exc. aluminum	5	59
Highest $Substit_i$		
Leather tanning and products, except footwear	59	21
Seafood and other miscellaneous foods, n.e.c.	60	31
Apparel accessories and other apparel	61	2
Bakeries	62	32
Cut and sew apparel	63	1

Table 4 - Residual Wage Dispersion Rankings and Residual Score Dispersion

Measure of Dispersion	(1) St Dev	(2) 95-5 IPR	(3) Gini MD	(4) St Dev	(5) 95-5 IPR	(6) Gini MD
$WageDisp_i \times SkillDisp_H$	0.017**	0.015**	0.016**	0.016**	0.013**	0.014**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Trade Barriers	No	No	No	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Importer-Industry FE	No	No	No	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124	58124
R-squared	0.54	0.54	0.54	0.70	0.69	0.70

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications).

Table 5 - O*NET Rankings and Residual Score Dispersion (St Dev)

Measure of Complementarity	(1) $O^*NET_i =$ $Teamwork_i$	(2) $O^*NET_i =$ $Impact_i$	(3) $O^*NET_i =$ $Communic_i$	(4) $O^*NET_i =$ $Contact_i$	(5) $Aggregate$ O^*NET_i
$O^*NET_i \times$ $SkillDisp_H$	-0.029**	-0.027**	-0.028**	-0.023**	-0.032**
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)
Trade Barriers	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes
Imp-Ind FE	Yes	Yes	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124
R-squared	0.70	0.70	0.70	0.70	0.70

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications).

Table 6 - Robustness						
	(1)	(2)	(3)	(4)	(5)	(6)
	HMR Selection		Controls		Predicted Skills	
$Substit_i =$	$WageDisp_i$	O^*NET_i	$WageDisp_i$	O^*NET_i	$WageDisp_i$	O^*NET_i
$Substit_i \times SkillDisp_H$	0.016**	-0.033**	0.032**	-0.066**	0.035**	-0.050**
	(0.004)	(0.010)	(0.009)	(0.012)	(0.009)	(0.011)
$Substit_i \times PredSkillDisp_H$					-0.004	-0.019*
					(0.004)	(0.008)
$KIntens_i \times KEndow_H$			0.029**	0.030**	0.029**	0.030**
			(0.008)	(0.008)	(0.008)	(0.008)
$SkillIntens_i \times SkillEndow_H$			0.033**	0.018**	0.033**	0.023**
			(0.006)	(0.006)	(0.006)	(0.006)
$Diff_i \times JudicQual_H$			$0.021^\dagger$	$0.020^\dagger$	$0.021^\dagger$	0.018
			(0.011)	(0.012)	(0.011)	(0.011)
$Substit_i \times LaborRigid_H$			0.008*	-0.036**	0.007*	-0.034**
			(0.004)	(0.006)	(0.004)	(0.006)
$TopCode_i \times SkillDisp_H$			-0.006	0.029**	-0.006	0.029**
			(0.007)	(0.005)	(0.007)	(0.005)
Trade Barriers	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52455	52455	41301	41301	41301	41301
R-squared	0.69	0.70	0.73	0.73	0.73	0.73

The dependent variable is the natural logarithm of exports from country H to country F in industry i. All columns employ the standard deviation of IALS log-scores as a measure of skill dispersion. As proxy for skill substitutability: columns 1, 3 and 5 employ a ranking based on the standard deviation of residual wages; columns 2, 4 and 6 employ *Aggregate* O^*NET_i ranking. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications). The regression includes an unreported polynomial in the probability to export, obtained from the first stage.

Appendices not for publication

A Appendix - Main variables

A.1 Measuring Skill Dispersion

The IALS microdata used for this paper was compiled by Statistics Canada using the original data sets collected between 1994 and 1998 in each of the participating countries. Tuijnman (2000) describes the three dimensions of literacy used to approximate skills. *Prose literacy* represents the knowledge and skills needed to understand and use information from texts including editorials, news stories, brochures and instruction manuals. *Document literacy* represents the knowledge and skills required to locate and use information contained in various formats, including job applications, payroll forms, transportation schedules, maps, tables and charts. *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 cheque book, figuring out a tip, completing an order form or determining the amount of interest on a loan from an advertisement.

We employ the logarithm of scores (in conjunction with the log of wages) because the standard deviation of the logarithm of a random variable is scale invariant. When extracting residual scores in equation (6), using log-scores on the left-hand side is consistent with the common practice of obtaining residual wages from a regression of log-wages, as in equation (7). The results of the empirical analysis are qualitatively similar if we use levels instead of logs.

Only individuals participating in the labor market are included in the estimation of equations (1) and (7). These individuals were either: (i) employed or unemployed at some time in the 12 months previous to the survey or (ii) not searching for a job due to skill upgrading (school or work programs) or a temporary disability.

The right-hand side vector X_{kH} in equation (6) includes a number of observable individual characteristics. Education is among them: we include indicators for 7 levels of educational attainment as defined by the International Standard Classification of Education (ISCED). The levels considered in IALS are: ISCED 0 Education preceding the first level; ISCED 1 Education at the first level; ISCED 2 Education at the second level, first stage; ISCED 3 Education at the second level, second stage; ISCED 5 Education at the third level, first stage (leads to an award not equivalent to a first university degree); ISCED 6 Education at the third level, first stage (leads to a first university degree or equivalent; ISCED 7 Education at the third level, second stage (leads to a postgraduate university degree or equivalent); ISCED 9 Education not definable by level. The vector X_{kH} also includes 5 age intervals 16-25, 26-35, 36-45, 46-55 and 56-65, gender, immigrant status and participation in adult education or training programs 12 months prior to the survey date. The latter filters out the effect of skill upgrading on individual residual scores. As explained in Section 4.4, this is an important issue for the identification of the effect of skill dispersion on trade flows as (unobserved) trade shocks might have an impact on aggregate skill dispersion by changing incentives for skill upgrading at the individual level. Residual scores $\widehat{\epsilon_{kH}}$ are constructed as $\widehat{\epsilon_{kH}} = \log(s_{kH}) - X_{kH}\widehat{\beta_H}$, where $\widehat{\beta_H}$ is estimated by OLS.

As a result of focusing on log-scores, the scale of measurement of IALS scores does not affect the standard deviation of $\widehat{\epsilon_{kH}}$ or $\log(s_{kH})$. Also note that, since X_{kH} in (6) contains a constant, the distribution of $\widehat{\epsilon_{kH}}$ has the same (zero) mean in each country. For this reason, we do not normalize the standard deviation (or any inter-percentile range) by the mean in order to make cross-country comparisons of residual scores dispersion.

A.2 Measuring Wage Dispersion

Wage inequality measures are computed from a sample of full-time manufacturing workers, 16-65 years old, not living in group quarters, reporting positive wages and industry affiliation.[32] Following Dahl (2002), individuals were considered as 'full-time employed' if in 1999 they: (i) were not enrolled full time in school, (ii) worked for pay for at least ten weeks, and (iii) earned an annual salary of at least 2,000 dollars. We focus on the log of weekly wages, calculated by dividing wage and salary income by annual weeks worked. We use weekly wages as opposed to hourly wages, because it requires fewer assumptions to calculate it. In the 2000 Census, hours worked are reported as 'usual hours'. Using this variable to convert weekly wages into hourly wages would almost certainly result in the introduction of a source of measurement error. Incomes for top-coded values are imputed by multiplying the top code value ($175,000) by 1.5.[33]

In equation (7), vector Z_{ki} includes indicators for 4 categories of educational attainment,[34] a quartic polynomial in age, race and gender dummies (plus their interaction), Hispanic and immigrant dummies (plus their interaction) and state of residence dummies. Residual wages are constructed as $\widehat{\xi_{ki}} = \log(w_{ki}) - Z_{ki}\widehat{\beta}_i$, where $\widehat{\beta}_i$ is estimated by OLS.

Correcting for self-selection into industries is important in estimating equation (7), as the assumption that workers do not selectively search for jobs according to comparative advantage or unobservable tastes is relevant for our theoretical framework. In the presence of self-selection the distribution of residual wages in any given industry would reflect not only the degree of skill substitutability in production but also skill composition. For this reason, we use a selection estimator proposed by Dahl (2002). In equation (7), correcting for self-selection is complicated by the fact that individuals could choose to search for a job in any of the 63 industries of the manufacturing sector, potentially making the error mean, i.e. $E(\xi_{ki}|k \textit{ is observed in } i)$, a function of the characteristics of all the alternatives. In this case, Dahl (2002) argues that under a specific sufficiency assumption,[35] the error mean is only a function of the probability that a person born in the same state as k would make the choice that k actually made (i.e. selecting into industry i), which can be estimated. The sufficiency assumption can be relaxed by including functions of additional selection probabilities; for this reason, Z_{ki} includes a cubic polynomial in the estimated first-best selection probability and in the highest predicted probability for k. Identification in this approach is based on the exclusion of state of birth by industry of employment interactions from equation (7).

To estimate selection probabilities, we group individuals into cells defined by state of birth[36] and a vector of discrete characteristics: 4 categories of education attainment, 4 age intervals (16-30, 31-40, 41-50, 51-65), race, gender and 2 binary indicators of family status (family/non-family household and presence of own child 18 or younger in the household). As in Dahl (2002), for every

[32] Manufacturing employment excludes workers in private non-profit and government organizations.

[33] Since top codes vary by state, we follow Beaudry et al. (2007) and impose a common top-code value of $175,000.

[34] These are: (i) High school dropout, (ii) high school graduate, (iii) some college but no degree, (iv) college degree or higher.

[35] See Dahl (2002), page 2378.

[36] As in Beaudry et al. (2007), we keep immigrants in the analysis by dividing the rest of the world into 14 regions (or 'states' of birth).

individual k, we estimate his selection probability into each industry j using the proportion of individuals within k's cell that are observed working in j, denoted by $\widehat{p_{kj}}$. Individual k's estimated first-best selection probability is $\widehat{p_{ki}}$ and k's highest predicted probability is given by $\widehat{p_{kj_*}}$, where j_* is such that $\widehat{p_{kj_*}} = \max\{\widehat{p_{kj}}\} \; \forall j$.

For the empirical analysis, the Census industry classification was matched to NAICS. It was not possible to match the trade data to Census codes directly, since the former is originally coded according to the Standard International Trade Classification (SITC rev.2). However, it is possible to use NAICS as a bridge between the two classifications. We construct a one-to-one mapping between the Census classification and NAICS by re-coding two or more 4 digit NAICS codes into a single industry (which does not necessarily match a 3 digit level). This re-coding also involves cases where two Census codes map perfectly into two NAICS codes -although originally there was no one-to-one matching between them. Importantly, the resulting mapping (available upon request) exhausts all manufacturing sectors in NAICS. Finally, the trade data was matched to wage inequality data using a concordance between SITC rev. 2 and NAICS, available through the NBER online database.

B Appendix - Additional Data

In this Appendix we provide a description of additional data sources used in the empirical analysis. Descriptive statistics for each variable can be found in Table A-5.

Bilateral export volumes at the industry level: From Feenstra et al. (2005), for the year 2000. Sector-level bilateral exports data are categorized at the 4-digit SITC (4-digit rev. 2) level. The mapping from SITC to NAICS required the concordance available at the NBER website.[37]

Bilateral trade barriers: From Helpman et al. (2008). This is a set of exporter-importer specific geographical, cultural and institutional variables. 1) *Distance*, the distance (in km.) between importer's and exporter's capitals (in logs). 2) *Land border*, a binary variable that equals one if and only if importer and exporter are neighbors that meet a common physical boundary. 3) *Island*, the number of countries in the pair that are islands. 4) *Landlocked*, the number of countries in the pair that have no coastline or direct access to sea. 5) *Colonial ties*, a binary variable that equals one if and only if the importing country ever colonized the exporting country or vice versa. 6) *Legal system*, a binary variable that equals one if and only if the importing and exporting countries share the same legal origin. 7) *Common Language*, a binary variable that equals one if and only if the exporting importing countries share a common language. 8) *Religion*, computed as (% Protestants in exporter × % Protestants in importer)+(% Catholics in exporter × % Catholics in importer)+(% Muslims in exporter × % Muslims in importer). 9) *FTA*, a binary variable that equals one if exporting and importing countries belong to a common regional trade agreement, and zero otherwise. 10) *GATT/WTO*, the number of countries in the pair that belong to the GATT/WTO.

Start-up regulation costs: From Helpman et al. (2008). We use exporter-importer interactions of three proxies of regulation costs: the number of days ($RegDays_H \times RegDays_F$), number of legal procedures ($RegProc_H \times RegProc_F$) and relative cost as a percentage of GDP per capita

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

($RegProc_H \times RegProc_F$), for an entrepreneur to start operating a business.

Factor endowments: Physical capital endowment, $KEndow$, and human capital endowment, $SkillEndow$, are taken from Antweiler and Trefler (2002). A country's stock of physical capital is the log of the average capital stock per worker. The stock of human capital is the natural log of the ratio of workers that completed high school to those that did not. The measures used are from 1992, the closest year of which data are available. There are no data on factor endowments for four countries in our sample: Switzerland, Czech Republic, Hungary and Poland.

Factor intensities: From Nunn (2007). Coded as 1997 I-O industries, the mapping to NAICS required a concordance available from the Bureau of Economic Analysis.[38] Physical capital intensity, $KIntens$, is the total real capital stock divided by value added of the industry in the United States in 1996. Skill intensity, $SkillIntens$, is the ratio of non-production worker wages to total wages at the industry level in the United States in 1996. There are no data on factor intensities for two industries: 'Furniture and related products manufacturing' and 'Sawmills and wood preservation'.

Proportion of top-coded wages: From the 2000 Census of Population in the U.S. For each industry, $TopCode$ is calculated as the proportion of workers earning a wage exceeding the top code value of $175,000.

Firm size dispersion: From the 1997 Census of manufacturing in the U.S. For each industry, we calculate $FirmDisp$, the coefficient of variation in the average shipments per establishment across bins defined by employment size. The employment bins defined in the Census are: 1-4, 5-9, 10-19, 20-49, 50-99, 100-249, 250-499, 500-999, 1000-2499 and 2500 employees or more.

Quality of the judicial system: From Nunn (2007) $JudicQual$ is based on the "rule of law" measures originally from Kaufmann et al. (2003).

Contract intensity: Based on Nunn (2007), $Diff_i$ is the proportion of intermediate inputs that is neither sold on an organized exchange nor reference priced.

Labor law rigidity: From Tang (2008) $LaborRigid$ is an index that summarizes firing and employment contract adjustment costs combined with measures of the power of labor unions. These measures are originally from Botero et al. (2004).

C Appendix - Robustness of Wage Dispersion Rankings across Countries

The use of U.S. estimates as proxies for within-industry wage dispersion (and skill substitutability) in other countries is warranted if they have access to similar production technologies,[39] which implies that the elasticity of substitution in any given industry will be similar across countries. It is not easy to verify whether the ranking of industries based on wage dispersion is in fact similar within each country, due to the scarcity of publicly available microdata with comparable sector classification. However, we do perform this exercise for the U.S. and Canada. We compute the

[38] http://www.bea.gov/industry/xls/1997import_matrix.xls

[39] The assumption that industry-specific characteristics computed for the United States also apply to industries in other countries is not an unusual one in the recent empirical trade literature on comparative advantage. Examples include the measurement of financial vulnerability (Manova, 2008b), the importance of relationship-specific investment (Nunn, 2007), firm-specific skill intensity (Tang, 2008) and the variance of firm-specific shocks (Cuñat and Melitz, 2010).

sectoral dispersion of wage residuals in Canada to verify whether the ranking is similar to the one prevailing in the US.[40] To maximize comparability, we are careful to control for the same set of observable characteristics of workers in both countries when computing the residuals, use similar sampling criteria and the same industry classification. Figure A-2 shows industry rankings in terms of the standard deviation of the wage residuals in the two countries. The positive slope of the fitted line is significant at the 1% level. Clearly, the sectoral ranking of residual dispersion in the US is strongly correlated to the one observed in Canada. Sectors like computers and clothing exhibit higher dispersion in both countries, compared to sectors like machinery and paper manufacturing.

D Appendix - Selection correction

This section describes the two-step selection correction employed in the estimation of columns 1 and 2 of Table 6. In the first step we account for the discrete export decision using a linear probability model and obtain the predicted probabilities of observing positive exports, $\widehat{\varphi_{HFi}}$; in the second stage, equation (4) is estimated including a flexible polynomial of degree four in $\widehat{\varphi_{HFi}}$ to control for selection bias.[41] For identification not to rely on the non-linearity of $\widehat{\varphi_{HFi}}$, it is necessary to identify a source of variation which affects the discrete choice of engaging in exports without changing the intensity of trade flows. Helpman et al. (2008) argue that cross-country variation in start-up regulation costs likely relates to the decision to export, and it has no bearing on the intensive margin. The economic rationale lies in the fact that start-up costs in the exporting country, as well as in the importing one, affect fixed rather than variable costs of trade. Different forces can be at work and the nature and strength of this effect may depend on characteristics of both exporting and importing countries. For example, HMR find that start-up regulation costs are an effective predictor of the extensive export decision and that the interaction between home and foreign regulation costs has a negative gradient on the likelihood to export. On the other hand, De Groot et al. (2004) show that *differences* in institutional factors, including differences in regulation and red tape, have large effects on trade flows; their work unveils an alternative channel through which regulation can affect trade, and stresses the importance of 'similarity' in institutional frameworks.

An analysis of the first-stage bilateral export decisions (see Table A-4) uncovers strong effects of regulation costs. We use exporter-importer interactions of three proxies of regulation costs: the number of days ($RegDays_H \times RegDays_F$), number of legal procedures ($RegProc_H \times RegProc_F$) and relative cost, as a percentage of GDP per capita ($RegProc_H \times RegProc_F$), for an entrepreneur to start operating a business.[42] We find that these proxies are significant predictors of selection into exporting.

[40] We use the Canadian Labor Force Survey data for May 2000. Details of this exercise are available upon request.

[41] We favor using a linear probability model in the first stage since its two most common alternatives, probit and logit models, suffer different problems in the current application. The probit model with fixed effects yields inconsistent estimates. In turn, estimating a fixed effects logit becomes computationally very costly due to the large number of fixed effects required in equation (4).

[42] To test the overidentifying restrictions we performed a Hausman test comparing second stage estimates using all three instruments to the corresponding estimates using only a subset of them. We tested all possible combinations of exclusion restrictions and in no case could we reject the null hypothesis that they are valid and, therefore, estimates with different restrictions only differ as a result of sampling error.

E Appendix - Additional Discussion of Identification

An alternative sufficient condition that guarantees (8), and therefore identification of β, is

$$E\left(SkillDisp_c \times \varepsilon_{HFi} | WageDisp_s\right) = 0 \quad \forall s, c$$

which means that, for every sector, skill dispersion in every exporting country is uncorrelated with the error term ε_{HFi}. This condition is satisfied if unobserved exporting opportunities captured in ε_{HFi} are not significantly related to the dispersion, and overall distribution, of residual skills in a country. There are several reasons to believe that this is plausible. First, the unobserved exporting opportunities ε_{HFi} must occur at levels other than exporter or importer-industry, which are already captured by our set of dummies. Moreover, since our skill dispersion measures pre-date trade flows by several years, the link between ε_{HFi} and $SkillDisp_c$ introduces bias only if: (i) ε_{HFi} is a highly persistent shock to exporting opportunities which is not captured by our dummies and also affects the long-term, residual skill distribution, and (ii) the skill distribution reacts very quickly in response to export shocks. In this respect Glaeser et al. (2004) show that the education system is a slow-changing characteristic of a country. However, skill dispersion is not only the product of the formal education system, but may change after school through on-the-job training. A number of papers have established the relatively limited impact of on-the-job training on the overall level of human capital.[43] Nevertheless, we explicitly account for the possibility that re-training is triggered by exporting opportunities through the inclusion, in the derivation of residual skills, of a control for whether a worker was re-trained in the previous year.

F Appendix - Additional results with raw wage rankings and raw scores

The goal of this section is to explore whether the relationship between skill dispersion and trade flows reported in Section 4 of the paper can also be observed when analyzing the raw variation in scores and wages.[44] It is important to remark that the specifications explored here are not founded on theory. In particular they should not be interpreted as a test of the mechanism described in Section 3. However they are useful in setting the stage for the analysis of Section 4. Table A-2 reports estimates of the impact of skill dispersion as proxied by the dispersion of (raw) test scores: we identify this effect through an interaction with a (raw) wage dispersion ranking. We show results based on three alternative measures of dispersion: the 95-5 interpercentile range divided by the average in column (1), the Gini relative mean difference (i.e. twice the Gini coefficient) in column (2) and the coefficient of variation in column (3).[45] Columns (1)-(3) add exporter, importer and industry dummies to our variables of interest; columns (4)-(6) include theoretically consistent

[43] See discussion in Carneiro and Heckman (2003) and Adda et al. (2006).

[44] Raw measures are not purged of the effect of observable characteristics.

[45] We note that all three measures have a common structure in that the numerator is a measure of dispersion (the 95-5 interpercentile range, the standard deviation and the Gini mean difference) while the denominator is the average of the variable. Since we are using the logarithm of variables, the reason why we employ measures of dispersion divided by the average is not for rescaling, but rather to parsimoniously control for the effect that the interaction of the averages might have on trade flows.

exporter and importer-industry dummies, along with a vector of bilateral trade barriers described above.

In all specifications the estimated interaction $WageDisp_i \times SkillDisp_H$ shows a positive effect on exports, significant throughout at the 5% level.[46] Columns (1)-(3) of Table A-3 reproduce the structure of columns (4)-(6) of Table A-2 in terms of controls, but they separately report the effect of the interaction $WageDisp_i \times SkillDisp_H$ (where the measure of dispersion is not divided by the average), as well as those of the interaction of average scores and average wages, $WageMean_i \times SkillMean_H$, and of the other two interactions, $WageDisp_i \times SkillMean_H$ and $WageMean_i \times SkillDisp_H$. The interaction of the averages is expected to capture standard factor proportions effects: on average, countries with more skilled workers specialize in sectors that employ skilled workers and have higher average wages. The interaction $WageMean_i \times SkillDisp_H$ is a flexible way to control for possible bias, due to differences in sectoral average wages, in the estimated effect of our interaction of interest. The interaction $WageDisp_i \times SkillMean_H$ plays a similar role. In general, columns (1)-(3) suggest that the coefficient of $WageDisp_i \times SkillDisp_H$ is robust to the inclusion of all interactions: all estimates are similar to the ones in Table A-2 and significant at the 5% level. We note that the magnitudes of the impact of our variable of interest are similar in Tables A-2 and A-3 to the ones in Table 4 through 6, indicating a substantial degree of robustness in our results. The interaction $WageMean_i \times SkillMean_H$ has a strong and positive impact on trade flows. This is not, for reasons of comparability, our preferred control for HO effects, but we further investigate what may be driving its large effect. We therefore interact the standard measure of skill intensity employed in Table 6, $SkillIntens_i$ with the alternative measure of skill endowment given by average IALS scores, $SkillMean_H$ and find that this interaction has an effect of the same order of magnitude as the standard HO control $SkillIntens_i \times SkillEndow_H$. Therefore it seems that $SkillMean_H$ and $SkillEndow_H$ are equivalent proxies for skill endowment, while $WageMean_i$ has a different effect on trade flows compared to $SkillIntens_i$. While in general these two measures may be correlated, $WageMean_i$ differs from $SkillIntens_i$ in that it depends crucially on the absolute level of wages in sector i, which may depend on, for example, industry-specific productivity and not just the ratio of skilled and unskilled workers. Furthermore, while it is immediate how to define $SkillIntens_i$ in a three-factor model that includes capital, it is not obvious how to adjust $WageMean_i$ in that case.

G Appendix - Decomposing cross-country differences in residual skill dispersion

Differences in the dispersion of residual skills between any two countries can be traced back to differences in specific parts of their skill distributions. Identifying the latter is relevant to pinpoint the set of workers which drive comparative advantage through the dispersion channel. This section presents a simple variance decomposition exercise with the purpose of quantifying the contribution of each quintile of the skill distributions to the observed cross-country differences in residual skill dispersion.

[46] In regressions we do not report, we interacted all three measures of dispersion for wages and scores with one another obtaining results qualitatively and quantitatively similar to columns (1)-(6).

The decomposition requires partitioning the support of residual skills into B discrete bins indexed by $b \in \{1,..,B\}$. Using the law of total variance and the fact that residual distributions have zero mean in each country c, the variance of residual skills in country c can be written as $\sigma_c^2 = \sum_b p_{bc} g_{bc}$, where p_{cb} is the share of c's workers' population in bin b and $g_{bc} \equiv \mu_{bc}^2 + \sigma_{bc}^2$ is the sum of the bin-specific squared mean μ_{bc}^2 and variance σ_{bc}^2 in country c. For any pair of countries c and $\widehat{c}$, we can assess the contribution of each bin in explaining the observed difference in skill dispersion, according to the following formula:

$$\sigma_c^2 - \sigma_{\widehat{c}}^2 = \sum_b C_{c\widehat{c}b}$$

where $C_{c\widehat{c}b} \equiv p_{bc} g_{bc} - p_{b\widehat{c}} g_{b\widehat{c}}$. For example take two countries, the US and Denmark, where $\sigma_{USA}^2 - \sigma_{DNK}^2 = 0.0334$ and a partition corresponding to the 5 quintile bins of the pooled, cross-country distribution of residual IALS scores.[47] We report the 5 components of the difference in skill dispersion $C_{USA,DNK,b}$:

	$b=1$	$b=2$	$b=3$	$b=4$	$b=5$
$C_{USA,DNK,b}$	0.0219	-0.0004	-0.0001	-0.0002	0.0122

The contribution of each bin to $\sigma_{USA}^2 - \sigma_{DNK}^2$ depends on bin-specific differences in means, variances or population shares. In this example the first bin, i.e. the difference in the left tail of the distribution, contributes the most to the increase in skill dispersion going from Denmark to the US. In general, if $\sigma_c^2 - \sigma_{\widehat{c}}^2 > 0$, the bin with the largest $C_{c\widehat{c}b}$ (i.e. $\max_b \{C_{c\widehat{c}b}\}$) accounts for the biggest contribution to the observed pattern of skill dispersion across the two given countries. If $\sigma_c^2 - \sigma_{\widehat{c}}^2 < 0$ the bin with the biggest contribution should correspondingly be defined as the one that makes $\sigma_c^2 - \sigma_{\widehat{c}}^2$ 'more negative', i.e. $\min_b \{C_{c\widehat{c}b}\}$. Keeping this in mind, we generalize this method to assess the contribution of each bin to the *mean difference* in skill dispersion across N countries, defined as $MD_N \equiv \frac{1}{N(N-1)} \sum_c \sum_{\widehat{c}} \left|\sigma_c^2 - \sigma_{\widehat{c}}^2\right|$. As in the two-country case, it is necessary to keep track of the sign of $\sigma_c^2 - \sigma_{\widehat{c}}^2$. To do this, define a binary function $\phi(c,\widehat{c}) = 1$ if $\sigma_c^2 - \sigma_{\widehat{c}}^2 \geq 0$ and $\phi(c,\widehat{c}) = -1$ otherwise. MD_N can then be decomposed as $MD_N = \sum_b C_b$, where

$$C_b = \frac{1}{N(N-1)} \sum_c \sum_{\widehat{c}} \phi(c,\widehat{c}) C_{c\widehat{c}b}$$

C_b is the contribution of bin b to the mean difference in skill dispersion across countries, MD_N. Note that C_b is the average of $C_{c\widehat{c}b}$ across all possible country pairs, multiplied by $\phi(c,\widehat{c})$. The adjustment function $\phi(c,\widehat{c})$ keeps track of whether each $C_{c\widehat{c}b}$ is adding to, or reducing, the (absolute value of the) difference in skill dispersion between c and $\widehat{c}$.[48] Applying this decomposition to the residual

[47] More specifically, we pool the residual IALS scores for all 19 countries in the sample, and then we partition the range of the resulting distribution into 5 quintile bins. Of course, for each individual country the share of IALS scores in such bins need not be 20%.

[48] For example, suppose that $C_{c\widehat{c}b} > 0$ and $\sigma_c^2 - \sigma_{\widehat{c}}^2 < 0$ for a given pair $(c,\widehat{c})$. In this case, bin b is actually *decreasing* the difference in skill dispersion between c and $\widehat{c}$. Therefore, it is necessary to multiply $C_{c\widehat{c}b}$ by -1 in the computation

score distributions of the 19 participants in IALS, we can compute the contribution of each quintile, C_b, to the observed mean difference $MD_{19} = 0.0262$:

	$b = 1$	$b = 2$	$b = 3$	$b = 4$	$b = 5$
C_b	0.0196	-0.00021	-0.00005	-0.0001	0.007

The results show that differences in the left tail of the residual distributions are, by a large margin, the driving force behind the mean difference of skill dispersion, with the right tail playing a smaller role. Since differences in skill dispersion translate into trade flows, we can infer that cross-country differences in the left tail of the skill distribution are the largest determinant of trade flows through the particular mechanism identified in this paper.

of C_b.

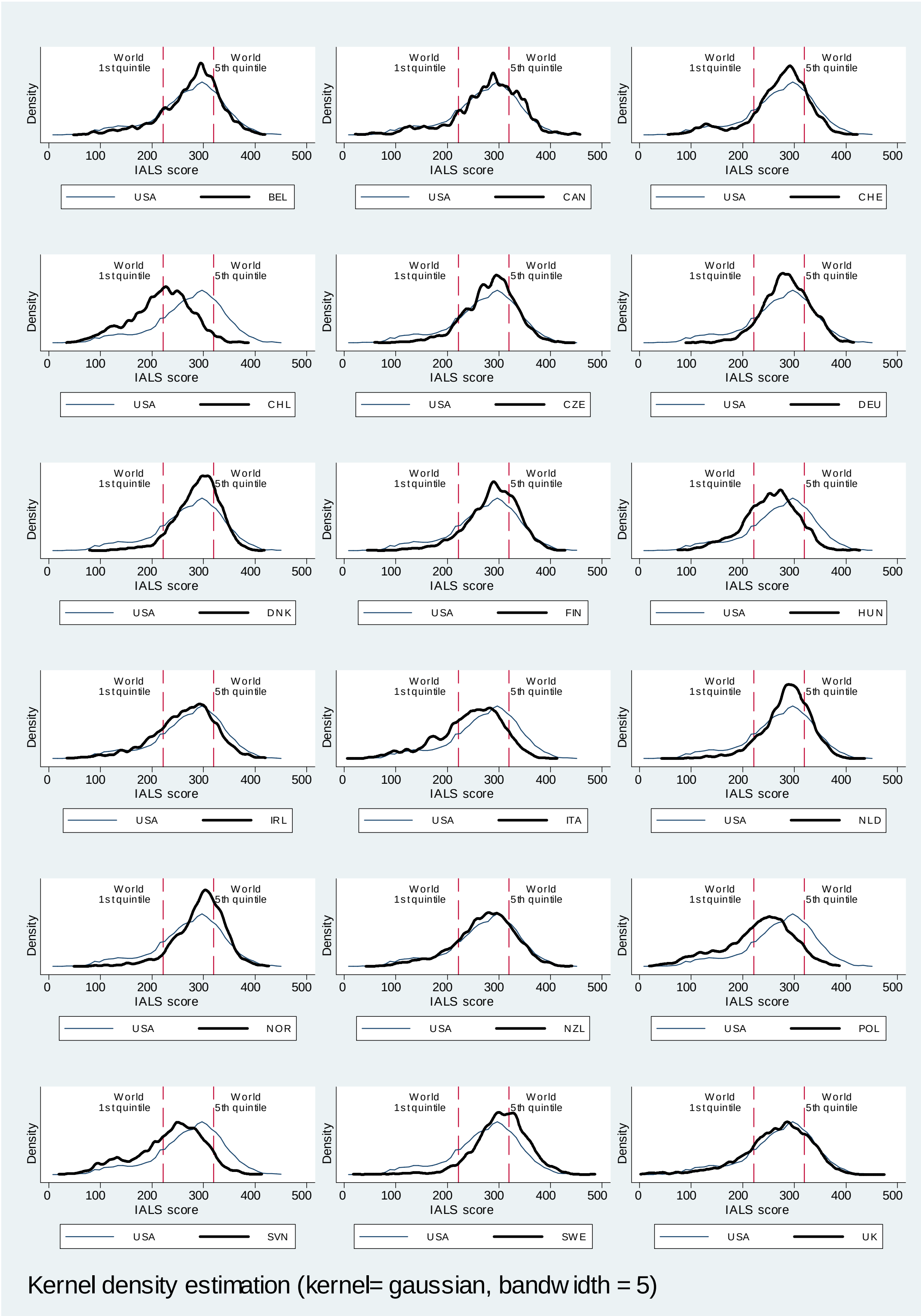

Figure A-1: IALS score distributions (1994-1998)

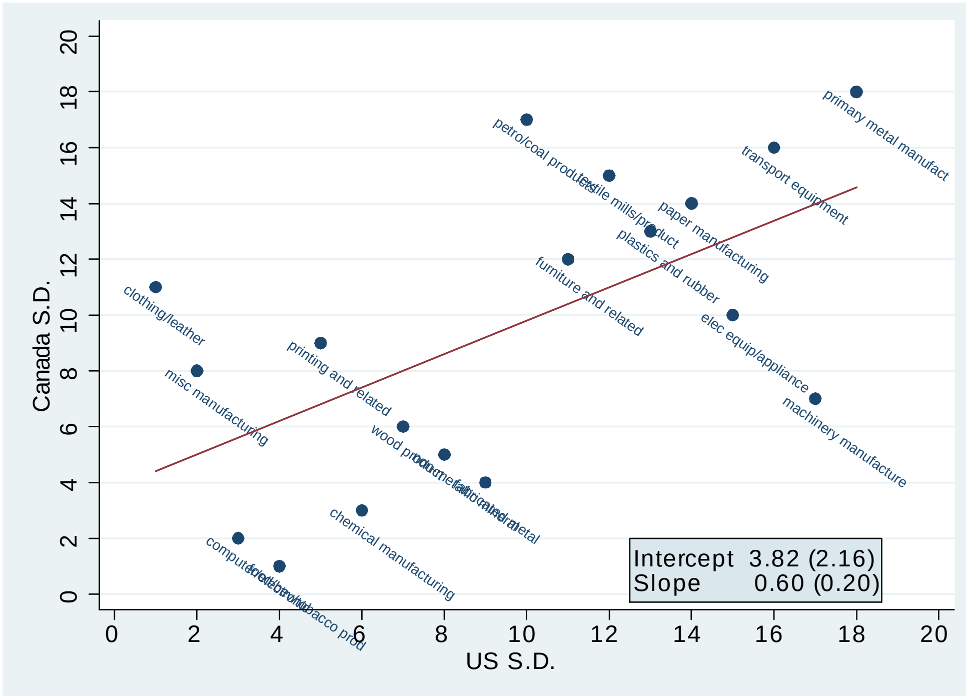

Figure A-2: Industry Rankings in terms of Standard Deviation of Residual Wages

Table A-1 - Correlations of $WageDisp_i$ and O^*NET_i

	$WageDisp_i$		$O * NET_i$			
	$\frac{StDev}{Mean}$	$St\ DevRes$	$Contact_i$	$Communic_i$	$Impact_i$	$Teamwork_i$
$\frac{StDev}{Mean}$	1					
$St\ Dev\ Res$	0.8497	1				
	0.000					
$Contact_i$	-0.2061	-0.1756	1			
	0.1052	*0.1688*				
$Communic_i$	-0.1414	-0.0755	0.5818	1		
	0.2689	*0.5565*	*0.000*			
$Impact_i$	-0.2414	-0.097	0.668	0.7467	1	
	0.0567	*0.4496*	*0.000*	*0.000*		
$Teamwork_i$	-0.1606	-0.1666	0.7943	0.614	0.7254	1
	0.2087	*0.1919*	*0.000*	*0.000*	*0.000*	

p-values in italics

Table A-2 - Normalized Raw Scores and Wage Rankings						
	(1)	(2)	(3)	(4)	(5)	(6)
Measure of Dispersion	$\frac{\text{St Dev}}{\text{Mean}}$	$\frac{\text{95-5 IPR}}{\text{Mean}}$	Gini RMD	$\frac{\text{St Dev}}{\text{Mean}}$	$\frac{\text{95-5 IPR}}{\text{Mean}}$	Gini RMD
$WageDisp_i \times SkillDisp_H$	0.013**	0.009*	0.010*	0.015**	0.010*	0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Trade Barriers	No	No	No	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	Yes	Yes	No	No	No
Industry FE	Yes	Yes	Yes	No	No	No
Importer-Industry FE	No	No	No	Yes	Yes	Yes
Observations	58124	58124	58124	58124	58124	58124
R-squared	0.54	0.54	0.54	0.70	0.69	0.69

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Standard errors clustered by importer-exporter pair in parenthesis.

Table A-3 - Non-Normalized Interactions					
	(1)	(2)	(3)	(4)	(5)
Measure of Dispersion	St Dev	95-5 IPR	Gini MD	St Dev	St Dev
$WageDisp_i \times SkillDisp_H$	0.024**	0.013*	0.022**	0.029**	0.024**
	(0.006)	(0.006)	(0.008)	(0.004)	(0.006)
$WageMean_i \times SkillMean_H$	0.145**	0.157**	0.164**		0.134**
	(0.007)	(0.007)	(0.009)		(0.008)
$WageMean_i \times SkillDisp_H$	0.075**	0.090**	0.093**		0.078**
	(0.007)	(0.006)	(0.008)		(0.007)
$WageDisp_i \times SkillMean_H$	0.023**	0.011	0.025**		0.012
	(0.008)	(0.008)	(0.009)		(0.008)
$SkillIntens_i \times SkillMean_H$				0.065**	0.026**
				(0.005)	(0.007)
Trade Barriers	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes
Importer FE	No	No	No	No	No
Industry FE	No	No	No	No	No
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	58124	58124	58124	56578	56578
R-squared	0.70	0.70	0.70	0.70	0.70

The dependent variable is the natural logarithm of exports from country H to country F in industry i. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Standard errors clustered by importer-exporter pair in parenthesis.

Table A-4 - First Stages of Table 6						
	(1)	(2)	(3)	(4)	(5)	(6)
	HMR		Controls		Predicted Skills	
$Substit_i =$	$WageDisp_i$	O^*NET_i	$WageDisp_i$	O^*NET_i	$WageDisp_i$	O^*NET_i
$Substit_i \times SkillDisp_H$	0.004**	-0.017**	0.017**	-0.027**	0.016**	-0.02**
	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
$Substit_i \times PredSkillDisp_H$					0.0016	-0.008**
					(0.0013)	(0.002)
$RegCosts_H \times RegCosts_F$	0.008**	0.008**	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
$RegDays_H \times RegDays_F$	0.007*	0.007*	0.009	0.009	0.009	0.009
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
$RegProc_H \times RegProc_F$	0.008**	0.008**	0.021**	0.021**	0.021**	0.021**
	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
$KIntens_i \times KEndow_H$			0.005**	0.005**	0.004**	0.005**
			(0.001)	(0.001)	(0.001)	(0.001)
$SkillIntens_i \times SkillEndow_H$			-0.006**	-0.01**	-0.006**	-0.008**
			(0.001)	(0.002)	(0.001)	(0.002)
$Diff_i \times JudicQual_H$			0.022**	0.023**	0.022**	0.023**
			(0.002)	(0.002)	(0.002)	(0.002)
$Substi_i \times LaborRigid_H$			0.001	-0.008**	0.001	-0.007**
			(0.001)	(0.002)	(0.001)	(0.002)
$TopCode_i \times SkillDisp_H$			-0.014**	0.007**	-0.014**	0.007**
			(0.002)	(0.002)	(0.002)	(0.002)
Trade Barriers	Yes	Yes	Yes	Yes	Yes	Yes
Exporter FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132867	132867	94794	94794	94794	94794
R-squared	0.57	0.58	0.59	0.59	0.59	0.59

Columns (1)-(6) report the first stage estimation results corresponding to Columns (1)-(6) of Table 6. The dependent variable is a dummy that is one if exports from country H to country F in industry i are positive and zero otherwise. All columns employ the standard deviation of IALS log-scores as a measure of skill dispersion. As proxy for skill substitutability: columns 1, 3 and 5 employ a ranking based on the standard deviation of residual wages; columns 2, 4 and 6 employ $Aggregate\ O^*NET_i$ ranking. Standardized beta coefficients are reported. †, * and ** indicate the coefficient is significant at the 10%, 5% and 1% levels. Bootstrap standard errors clustered by importer-exporter pair in parenthesis (50 replications). All estimations were performed with a linear probability model.

Table A-5 - Additional Variables

Variable	Obs	Mean	Std. Dev	Min	Max
Exports dummy	173565	0.335	0.472	0	1
Exports volume (X_{HFi})	58124	7.866	2.204	0	17.906
Language	2755	0.193	0.395	0	1
Legal	2755	0.217	0.412	0	1
Religion	2755	0.196	0.257	0	0.973
Land Border	2755	0.019	0.135	0	1
Currency Union	2755	0.002	0.047	0	1
Distance	2755	4.136	0.806	0.882	5.661
FTA	2755	0.017	0.131	0	1
Colonial Ties	2755	0.022	0.146	0	1
Gatt / WTO	2755	1.489	0.578	0	2
Island	2755	0.291	0.494	0	2
Landlock	2755	0.309	0.509	0	2
$RegProc_F$	112	9.679	3.491	2	19
$RegDays_F$	112	49.402	38.593	2	203
$RegCosts_F$	112	90.065	165.785	0	1268.4
$RegProc_H$	19	5.947	2.818	2	10
$RegDays_H$	19	23.842	16.433	3	61
$RegCosts_H$	19	7.874	7.190	0	22.9
$SkillEndow_H$	14	-3.435	0.402	-4.522	-2.957
$JudicQual_H$	18	0.832	0.115	0.615	0.972
$LaborRigid_H$	19	0.473	0.155	0.205	0.667
$KEndow_H$	14	-0.530	0.662	-1.377	0.925
$SkillIntens_i$	61	0.381	0.116	0.166	0.757
$KIntens_i$	61	0.859	0.464	0.235	2.535
$Diff_i$	62	0.496	0.221	0.036	0.929
$TopCode_i$	63	0.009	0.005	0.004	0.030