Skill Dispersion and Trade Flows

Web Appendix

Matilde Bombardini, Giovanni Gallipoli and Germán Pupato

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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.[1] 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.[2]

In equation (7), vector Z_{ki} includes indicators for 4 categories of educational attainment,[3] 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 char-

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

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

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

acteristics of all the alternatives. In this case, Dahl (2002) argues that under a specific sufficiency assumption,[4] 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[5] 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 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.[6]

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

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

[5] 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).

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

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 (Regulation $\text{days}_H \times$Regulation days_F), number of legal procedures (Regulation $\text{procedures}_H\times$ Regulation procedures_F) and relative cost as a percentage of GDP per capita (Regulation $\text{costs}_H\times$ Regulation costs_F), for an entrepreneur to start operating a business.

Factor endowments: Physical capital endowment and human capital endowment 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.[7] Physical capital intensity is the total real capital stock divided by value added of the industry in the United States in 1996. Skill intensity 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 US For each industry, Share top code_i 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 US For each industry, firm dispersion_i, 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) Judicial quality_i is based on the "rule of law" measures originally from Kaufmann et al. (2003).

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

Labor law rigidity: From Tang (2008) Labor ridigity_H 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).

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

C Appendix - Robustness of Wage Dispersion Rankings across Countries

The use of US estimates as proxies for within-industry wage dispersion (and skill substitutability) in other countries is warranted if they have access to similar production technologies,[8] 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 US and Canada. We compute the sectoral dispersion of wage residuals in Canada to verify whether the ranking is similar to the one prevailing in the US.[9] 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.[10] 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

[8] 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, 2008), 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).

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

[10] 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).

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 (Regulation days$_H \times$Regulation days$_F$), number of legal procedures (Regulation procedures$_H \times$ Regulation procedures$_F$) and relative cost as a percentage of GDP per capita (Regulation costs$_H \times$ Regulation costs$_F$), for an entrepreneur to start operating a business.[11] We find that these proxies are significant predictors of selection into exporting.

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.[12] 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.

[11] 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.

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

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.[13] 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).[14] Columns (1)-(3) add exporter, importer and industry dummies to our variables of interest; columns (4)-(6) include theoretically consistent exporter and importer-industry dummies, along with a vector of bilateral trade barriers described above.

In all specifications the estimated interaction Wage dispersion$_i\times$ Skill dispersion$_H$ shows a positive effect on exports, significant throughout at the 5% level.[15] 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 Wage dispersion$_i\times$ Skill dispersion$_H$ (where the measure of dispersion is not divided by the average), as well as those of the interaction of average scores and average wages, Wage mean$_i\times$ Skill mean$_H$, and of the other two interactions, Wage dispersion$_i\times$ Skill mean$_H$ and Wage mean$_i\times$ Skill dispersion$_H$. 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 Wage mean$_i\times$ Skill dispersion$_H$ 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 Wage dispersion$_i\times$ Skill mean$_H$ plays a similar role. In general, columns (1)-(3) suggest that the coefficient of Wage dispersion$_i\times$ Skill dispersion$_H$ 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 Wage mean$_i\times$ Skill mean$_H$ 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 with the alternative measure of skill endowment given by average IALS

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

[14] 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.

[15] 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).

scores and find that this interaction has an effect of the same order of magnitude as the standard HO control Skill intensity$_i\times$ Skill endowment$_H$. Therefore it seems that Skill mean$_H$ and Skill endowment$_H$ are equivalent proxies for skill endowment, while Wage mean$_i$ has a different effect on trade flows compared to Skill intensity$_i$. While in general these two measures may be correlated, Wage mean$_i$ differs from Skill intensity$_i$ 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 Skill intensity$_i$ in a three-factor model that includes capital, it is not obvious how to adjust Wage mean$_i$ 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.

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.[16] 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

[16] 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%.

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 $\widehat{c}$.[17] Applying this decomposition to the residual 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.

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[17] 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 of C_b.

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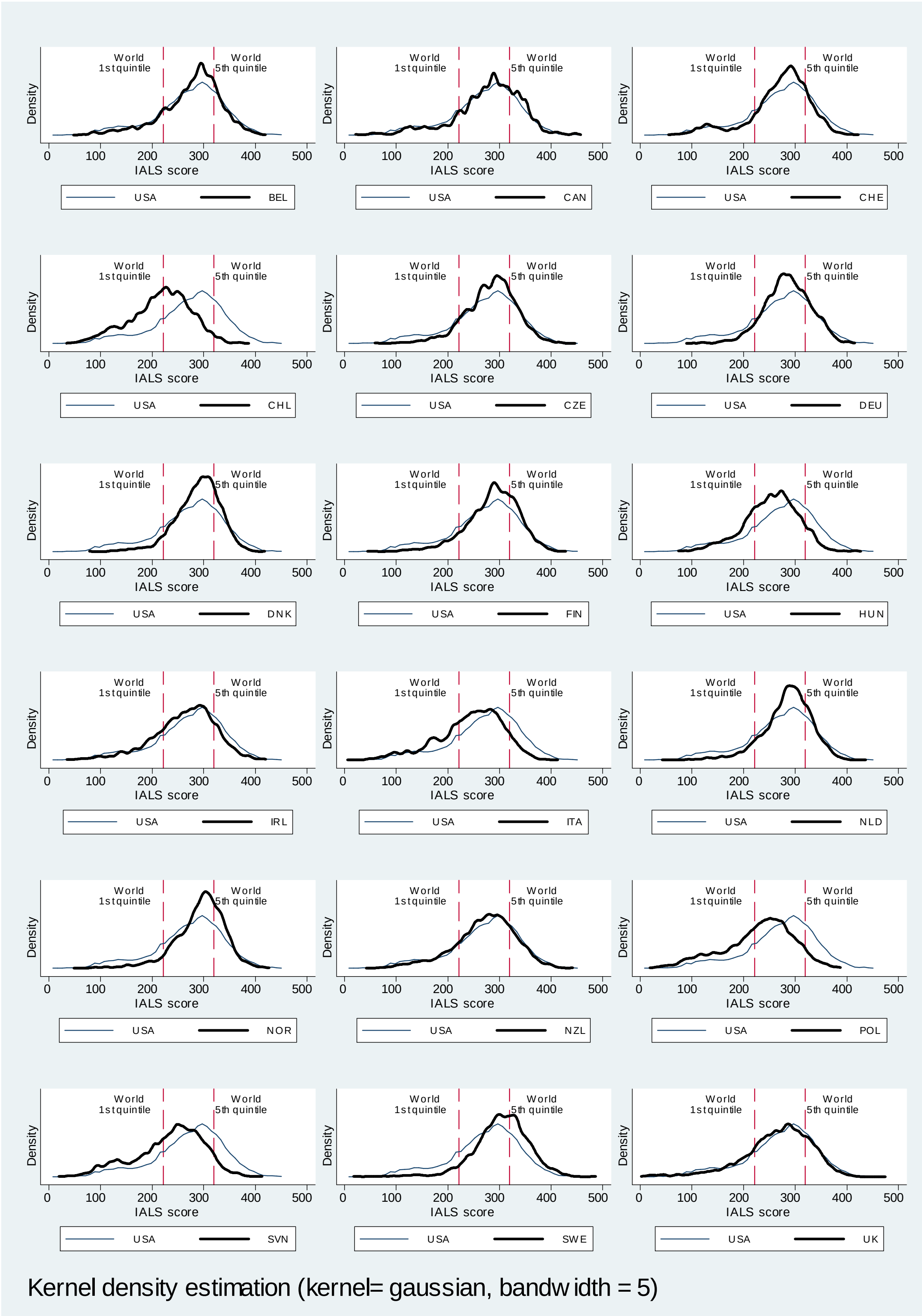

Figure A-1: IALS score distributions (1994-1998)

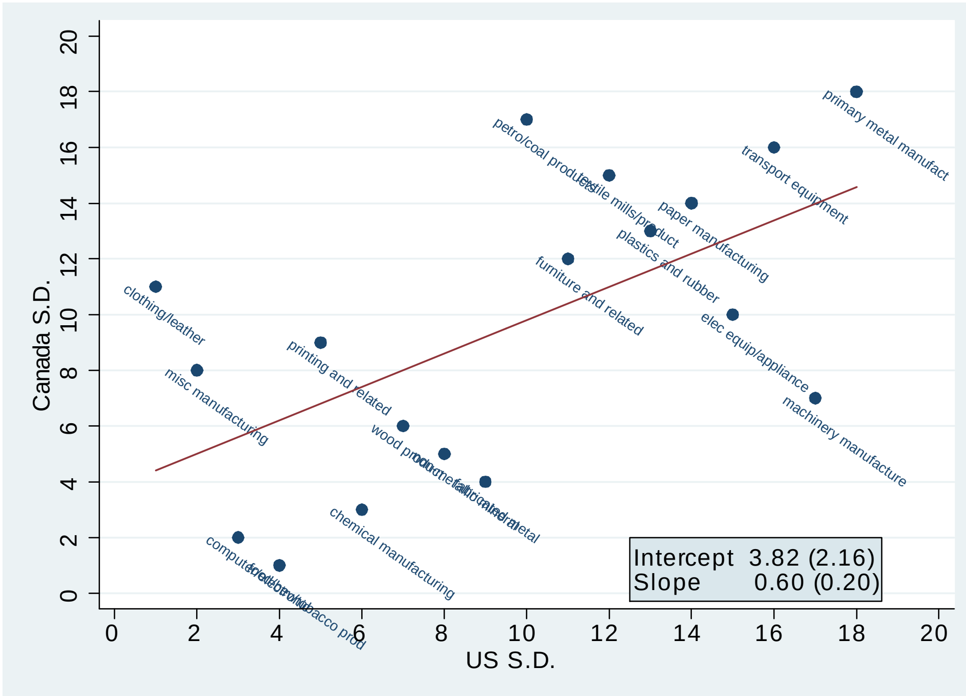

Figure A-2: Industry Rankings in terms of Standard Deviation of Residual Wages

Table A-1 - Correlations of Wage dispersion$_i$ and O*NET$_i$

	Wage dispersion$_i$		O*NET$_i$			
	$\frac{\text{Standard deviation}}{\text{Mean}}$	Residual standard deviation	Contact$_i$	Communic$_i$	Impact$_i$	Teamwork$_i$
$\frac{\text{Standard deviation}}{\text{Mean}}$	1					
Residual standard deviation	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

Measure of Dispersion	(1) $\frac{\text{St Dev}}{\text{Mean}}$	(2) $\frac{\text{95-5 IPR}}{\text{Mean}}$	(3) Gini RMD	(4) $\frac{\text{St Dev}}{\text{Mean}}$	(5) $\frac{\text{95-5 IPR}}{\text{Mean}}$	(6) Gini RMD
Wage dispersion$_i \times$ Skill dispersion$_H$	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	0.70	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-3 - Non-Normalized Interactions

Measure of Dispersion	(1) St Dev	(2) 95-5 IPR	(3) Gini MD	(4) St Dev	(5) St Dev
Wage dispersion$_i$	0.024**	0.013*	0.022**	0.029**	0.024**
$\times$ Skill dispersion$_H$	(0.006)	(0.006)	(0.008)	(0.004)	(0.006)
Wage mean$_i \times$	0.145**	0.157**	0.164**		0.134**
Skill mean$_H$	(0.007)	(0.007)	(0.009)		(0.008)
Wage mean$_i \times$	0.075**	0.090**	0.093**		0.078**
Skill dispersion$_H$	(0.007)	(0.006)	(0.008)		(0.007)
Wage dispersion$_i \times$	0.023**	0.011	0.025**		0.012
Skill mean$_H$	(0.008)	(0.008)	(0.009)		(0.008)
Skill intensity$_i \times$				0.065**	0.026**
Skill mean$_H$				(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						
	HMR		Controls		Predicted Skills	
Substitutability$_i$	Wage dispersion$_i$	O*NET$_i$	Wage dispersion$_i$	O*NET$_i$	Wage dispersion$_i$	O*NET$_i$
	(1)	(2)	(3)	(4)	(5)	(6)
Substitutability$_i\times$ Residual	0.004**	-0.017**	0.017**	-0.027**	0.016**	-0.02**
skill dispersion$_H$	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)	(0.003)
Substitutability$_i\times$ Predicted					0.0016	-0.008**
skill dispersion$_H$					(0.0013)	(0.002)
Regulation costs$_H\times$	0.008**	0.008**	0.001	0.001	0.001	0.001
Regulation costs$_F$	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Regulation days$_H\times$	0.007*	0.007*	0.009	0.009	0.009	0.009
Regulation days$_F$	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Regulation procedures$_H\times$	0.008**	0.008**	0.021**	0.021**	0.021**	0.021**
Regulation procedures$_F$	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Capital intensity$_i\times$ Capital			0.005**	0.005**	0.004**	0.005**
endowment$_H$			(0.001)	(0.001)	(0.001)	(0.001)
Skill intensity$_i\times$			-0.006**	-0.01**	-0.006**	-0.008**
Skill endowment$_H$			(0.001)	(0.002)	(0.001)	(0.002)
Differentiated$_i\times$			0.022**	0.023**	0.022**	0.023**
Judicial quality$_H$			(0.002)	(0.002)	(0.002)	(0.002)
Substitutability$_i\times$			0.001	-0.008**	0.001	-0.007**
Labor rigidity$_H$			(0.001)	(0.002)	(0.001)	(0.002)
Share top code$_i\times$			-0.014**	0.007**	-0.014**	0.007**
Skill dispersion$_H$			(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
Regulation procedures$_F$	112	9.679	3.491	2	19
Regulation days$_F$	112	49.402	38.593	2	203
Regulation costs$_F$	112	90.065	165.785	0	1268.4
Regulation procedures$_H$	19	5.947	2.818	2	10
Regulation days$_H$	19	23.842	16.433	3	61
Regulation costs$_H$	19	7.874	7.190	0	22.9
Skill endowment$_H$	14	-3.435	0.402	-4.522	-2.957
Judicial quality$_H$	18	0.832	0.115	0.615	0.972
Labor rigidity$_H$	19	0.473	0.155	0.205	0.667
Capital endowment$_H$	14	-0.530	0.662	-1.377	0.925
Skill intensity$_i$	61	0.381	0.116	0.166	0.757
Capital intensity$_i$	61	0.859	0.464	0.235	2.535
Differentiated$_i$	62	0.496	0.221	0.036	0.929
Share top code$_i$	63	0.009	0.005	0.004	0.030