Trade Specialization & the Occupational Wage Distribution: Evidence from OECD Countries[0]

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Abstract

This paper explores the relationship between international trade and inequality through both theoretical and empirical frameworks. I first construct a theoretical model to predict shifts in relative occupational wages following a trade liberalization episode. The model hypothesizes that cross-occupation inequality should increase following skill-intensive trade specialization, yet decrease when specialization occurs in sectors intensive in unskilled labor. Empirical analysis then assesses the strength of this model on a panel of 29 OECD countries between 1990 and 2008. Using occupational wage data, I compare the distributional impacts of trade in six different production sectors varying in technological intensiveness. Fixed-effect regressions specifically target two key inequality measures: the logarithmic wage premium of skilled workers and the wage spread (standard deviation) across all occupations. The wage premium model aligns entirely with theory. Tech specialization holds a positive relationship with the premium, while both labor-intensive sectors show negative relationships as predicted. Across both specifications, labor-intensive trade specialization bears more equalizing effects on the wage distribution than technology-intensive specialization. These conclusions are found robust to tests for reverse causality, functional form bias and specification errors.

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1 Introduction

The developed world has witnessed a striking rise in inequality over the last two decades on both national and global scales. Between 1990 and 2008, the gap in hourly wages between highly skilled and unskilled workers widened almost unanimously in a randomly chosen sample of OECD countries (see Figure 1[1]). International trade is a widely discussed contributor to these growing wage spreads, with greater import competition imposing domestic labor market distortions. However, the true welfare effects of trade liberalization remain in contention. In aggregate production terms, Ricardian theory tells us that trade should create net productivity gains via the laws of comparative advantage. Each nation specializes in its most efficient areas of production; its workers reassemble accordingly. Unfortunately, this story only plays out when laborers fully and efficiently reintegrate into these designated areas of production. With the presence of labor immobility, arising from educational, geographical or other barriers to entry in a particular profession, incomplete integration begets losers of trade and exacerbates inequality. Which argument holds more empirical merit?

The current literature boasts evidence both in favor and against trade as a force in the labor market. Much of the recent research suggests a positive relationship between trade and income inequality (Aradhyula, Rahman & Seenivasan 2007; Cornia 2002). Others claim that recent rises in inequality may have resulted more from global transformations other than trade. Financial globalization and skill-biased technological change top this list (Card and DiNardo 2002; Jaumotte, Lall & Papageorgiou 2013). Many of these studies on both sides of the argument use aggregate inequality measures such as the standard Gini coefficient for analysis (Cornia 2002). Such broad correlations may leave room for ambiguity. For example, a positive relationship found between the Gini coefficient and trade liberalization may simply reflect that exporting firms also enjoy larger volumes of production, benefit from economies of scale, and pass a portion of their gains onto workers via higher wages. The specific types of workers affected by this relationship remain unclear. In this paper, I compare average hourly earnings across different occupations in order to more precisely estimate those aided and harmed by trade.

Among the papers that do use disaggregated skill premium measures (Bernard and Jensen 1995; Klein, Moser & Urban 2010), a gap appears to persist in the literature regarding how the consequences of trade differ across export sectors. Specifically, effects of trade on the skill premium should be expected to vary from one production sector to another. It is important to consider an act of trade liberalization or constriction within the same context as a generalized sector expansion or contraction. The pool of laborers qualified to complete tasks in the newly liberalized export sector should benefit, while those unqualified laborers should suffer as they now face lower relative demand for their skills. In the present research, I therefore decompose trade into six primary sectors of specialization, differing by levels of technological intensiveness used in production. This breakdown serves as a proxy for the skill level of workers required to

[1] All figures and tables in this paper are self-created.

achieve employment in each sector. More tech-intensive sectors are assumed to hire a higher-skilled pool of employees.

The levels of trade specialization in each sector are then analyzed against the occupational wages of 29 OECD countries over the years 1990-2008, using the Occupational Wages around the World (OWW) database. OWW data have taken the form of several indicators in past studies (Freeman and Oostendorp 2000; Corley, Perardel & Popova 2005; Bigsten, Durevall & Munshi 2008), such as the standard deviation of wages and the 90^{th}-10^{th} percentile wage ratio. Skill differentials have been addressed within and across countries, looking at offshoring, intra-occupational inequality and the gender wage gap, among others. This paper supplements past OWW analyses with an emphasis on cross-sector trade specialization.

Hourly wage data for 161 occupations are first broken down into four skill groups according to ISCO-08 skill levels. The base model then examines the impacts of trade specialization on the logarithmic wage premium of high-skilled to low-skilled workers. A second model considers trade impacts on the wage spread (computed by standard deviation) across all occupations. All analyses are conducted through fixed-effect balanced panel data regression methods. Logarithmic wage premium analyses yield results in line with initial hypotheses. Developed nations' increased specialization in tech-heavy export sectors lead to greater wage inequality, while labor-intensive trade specialization reduces inequality. The wage spread model results prove less conclusive, though it does show greater equalization effects from labor-intensive exports than tech-intensive exports as predicted.

Finally, several robustness checks evaluate the strength of the conclusions found. Various frameworks are used to address potential biases, including instrumental variables, alternative control variables and functional form transformation. Data visualizations also reveal an inflection point in wage premium and wage spread trends as net exports in a given sector approach zero. Implications of this pattern are discussed in Section 4.2.3.

While this analysis diverges from the existing literature in its division of export sectors, it does allow for comparison with several country-specific studies. For instance, Dix-Carneiro and Kovak (2014) utilize regional data within Brazil to argue that trade liberalization reduces the skill premium on a region-specific scale. Using Mexican manufacturing wage data, Esquivel and Rodríguez-López (2003) claim that NAFTA negatively impacted Mexico's manufacturing skill premium, though technological growth led to a net increase in the premium. Lastly, Amiti and Cameron (2012) present evidence that tariff reduction in Indonesia, a developing country and net importer of intermediate goods, leads to a reduction in the Indonesian skill premium. All of these papers provide useful foundations to measure against this paper's multinational analysis. Though I focus solely on industrialized OECD countries, the model developed in the next section allows for dynamic trade effects applicable to both developed and developing nations.

The following sections introduce the theoretical and empirical frameworks outlined above. The theoretical model reworks the standard Heckscher-Ohlin structure to incorporate wage analysis in a two-occupation labor market. I then test the resulting hypotheses with empirical OECD data, followed by robustness checks and concluding discussion.

2 Theoretical Framework

Let's begin by constructing a theoretical model for the distributional wage impacts of trade. The basis for this model stems from the Stolper-Samuelson Theorem of standard Heckscher-Ohlin (HO) trade theory. The Heckscher-Ohlin Theorem suggests a natural tendency for a nation to specialize in the production of those goods and services in which it enjoys comparative advantage (Feenstra & Taylor 2010). The Stolper-Samuelson Theorem then predicts that the returns to the factor intensive in the production of that specialized sector will subsequently rise relative to the remaining factors of production. This paper reworks the standard HO model to incorporate occupations and their relative wage shifts following a trade liberalization episode.

Allowing for the simplest explanatory model possible, we may establish the following arrangement of the world economy:

Two Countries	Two Occupations	Two Production Sectors
Home (H)	Software Engineer (E)	Technology (T)
Foreign (F)	Art Designer (D)	Apparel (A)

In this example, one should intuit Engineers as the skilled labor force and Designers as the unskilled labor force. To limit the present discussion to labor market shifts, I assume that the aggregate capital stock and relative shares of that capital allocated to each industry remain fixed in both countries. Only the relative quantities of software engineers and art designers in each industry remain as varying production factors. In the empirical analyses of Section 4, I partially relax this assumption by accounting for movements in capital stock.

An additional set of assumptions restricts Home and Foreign to perfectly competitive economies, such that full employment and zero-profit conditions exist in both countries. First, engineers and designers compose the entire viable labor force ($\bar{\mathrm{L}} = \mathrm{E} + \mathrm{D}$). Second, all labor is distributed between the technology and apparel industries ($E = E_T + E_A$; $D = D_T + D_A$). Next, free labor mobility exists between industries T and A for workers of the same occupation. However, labor immobility exists between occupations E and D, as well as between countries. This immobility can be interpreted as any occupational barriers to entry, such as geographical or educational restrictions. Lastly, both industries face Cobb-Douglas production functions with constant returns to scale, such that technology is highly engineer-intensive and apparel is designer-intensive.

Our setup is now complete to examine the effects of trade. The structure of Equations (1)-(10) is applicable to both Home and Foreign; only the numerical values plugged into each equation will differ between the two.

From the fourth condition, the aggregate values of production in each occupation are determined by the following functions:

$$Y_T = A \cdot E_T^{0.9} D_T^{0.1} \overline{K_T} \tag{1}$$

$$Y_A = A \cdot E_A^{0.1} D_A^{0.9} \overline{K_A} \tag{2}$$

A accounts for any exogenous, country-specific efficiency affecting production levels in each country (e.g. technology available only to workers in Home or Foreign). $\overline{K_T}$ and $\overline{K_A}$ depict the fixed quantities of nonhuman capital allocated to each industry.

Given Equations (1) and (2), partial differentiation yields the respective marginal products of engineer (MPE) and designer (MPD) labor in industries T and A:

$$MPE_T = \frac{dY_T}{dE} = 0.9\, A \left(\frac{D_T}{E_T}\right)^{0.1} \overline{K_T} \tag{3}$$

$$MPD_T = \frac{dY_T}{dD} = 0.1\, A \left(\frac{E_T}{D_T}\right)^{0.9} \overline{K_T} \tag{4}$$

$$MPE_A = \frac{dY_A}{dE} = 0.1\, A \left(\frac{D_A}{E_A}\right)^{0.9} \overline{K_A} \tag{5}$$

$$MPD_A = \frac{dY_A}{dD} = 0.9\, A \left(\frac{E_A}{D_A}\right)^{0.1} \overline{K_A} \tag{6}$$

For both technology and apparel industries, notice that MPE is decreasing in the relative quantity of engineers employed in that industry, while MPD decreases in the relative quantity of designers. Real wages in each sector can be derived from Equations (3)-(6), such that:

$$\frac{w_E}{P_T} = MPE_T \tag{7}$$

$$\frac{w_D}{P_T} = MPD_T \tag{8}$$

$$\frac{w_E}{P_A} = MPE_A \tag{9}$$

$$\frac{w_D}{P_A} = MPD_A \tag{10}$$

The labor mobility assumption permits only occupational wage variation. Earnings remain equal in both industries for each occupation. The autarkic skill premium, $\frac{w_E}{w_D}$, signifies differing returns to each factor of production. In this case, $\frac{w_E}{w_D} > 1$ in both Home and Foreign; engineers comprise the higher-skilled pool of laborers in each country.

Let's consider the case of Home under trade. For this scenario, assume Home has a comparative advantage in technology goods. It is relatively abundant in engineers and enjoys a lower relative autarky price of producing goods in the engineer-intensive sector (technology) than does Foreign $\left(\frac{P_T^H}{P_A^H} < \frac{P_T^F}{P_A^F}\right)$. When Home and Foreign open up to trade, comparative advantage will motivate Home to specialize in the technology sector. The relative price of technological goods in Home will then rise as it reaches equilibrium with Foreign's higher autarkic relative price. The resulting equilibrium world relative price of technology goods will reside between the two autarky ratios: $\frac{P_T^H}{P_A^H} < \frac{P_T^W}{P_A^W} < \frac{P_T^F}{P_A^F}$.

The relative demand for Engineers at Home will also increase. Given higher prices of technology goods, Home firms will seek to employ more of the factor intensive in tech production to expand industry T and maximize revenues. This augmented demand for Engineers will then reduce the ratio of Engineers to Designers in both industries ($\downarrow \frac{E_A}{D_A}$; $\downarrow \frac{E_T}{D_T}$) and increase the relative wage of Engineers ($\uparrow \frac{W_E}{W_D}$).

Figure 2 illustrates the mechanism by which this these shifts occur. This graph relates occupational wages to the relative number of workers employed in each occupation. Consistent with Equations (3)-(10), downward-sloping labor demand curves reflect the negative relationship between occupational wages and the relative abundance of that occupation in each industry. Following an increase in the price of technological goods after opening to trade, Home's relative demand for engineers over designers shifts rightward from curve D_1 to D_2. The shifted demand curve must stay between curves $\frac{E_T}{D_T}$ and $\frac{E_A}{D_A}$. In this two-occupation, two-sector model, the aggregate relative demand function can essentially be interpreted as an average of these two curves, weighted by the relative demand for each sector's goods. As Home firms capitalize on the increased relative price of technological goods, overall demand will shift toward the engineer intensity of sector T in order to augment tech production. $\frac{E_T}{D_T}$ remains parallel and to the right of $\frac{E_A}{D_A}$. Neither curve shifts, due to unchanging relative proportions of engineers and designers needed for production in sectors T and A.

Given a fixed relative supply of engineers and designers in the short run (once again from the assumption of labor immobility), the labor market equilibrium moves upward from point A to point B. The proportion of engineers to designers then decreases in both the technology and apparel sectors, while the relative wage of engineers to designers increases from $\frac{w_{E,1}}{w_{D,1}}$ to $\frac{w_{E,2}}{w_{D,2}}$.

We can also comprehend the relative rise in Engineer wages directly from Equations (3)-(10). As the factor intensity of engineers falls relative to designers in each sector, the following chain reactions occur:

$$\downarrow \frac{E_i}{D_i} \quad \Rightarrow \quad \uparrow x_{E,i}\, A \left(\frac{\boldsymbol{D_i}}{\boldsymbol{E_i}}\right)^{y_{E,i}} \overline{K_i} \quad \Rightarrow \quad \uparrow MPE_i \quad \Rightarrow \quad \uparrow \frac{w_E}{P_i}$$

$$\downarrow \frac{E_i}{D_i} \quad \Rightarrow \quad \downarrow x_{D,i}\, A \left(\frac{\boldsymbol{E_i}}{\boldsymbol{D_i}}\right)^{y_{D,i}} \overline{K_i} \quad \Rightarrow \quad \downarrow MPD_i \quad \Rightarrow \quad \downarrow \frac{w_D}{P_i}$$

where x and y reference the coefficient and exponent of each marginal product equation in sector i, respectively. The combination of these two wage shifts yields an increase in the wage premium of software engineers relative to art designers, $\frac{w_E}{w_D}$, following a specialization in technology-related exports[2].

What happens in the Foreign labor market? Given that Foreign has a comparative advantage in apparel $\left(\frac{P_A^F}{P_T^F} < \frac{P_A^H}{P_T^H}\right)$, exactly the opposite shifts will occur in its relative demand for engineers and designers. Trade liberalization will induce a Foreign specialization in the apparel industry, raising relative demand for designers, the intensive factor of apparel production. The ratio of designers to engineers will fall in both industries, MPD will rise and MPE will fall. Hence, the relative wage of designers rises and the skill premium *decreases* in Foreign following trade liberalization.

What I have shown here is that trade should raise the occupational skill premium in nations with a comparative advantage in skill-intensive production; it should lower the premium in countries abundant in unskilled labor. The empirical analyses in the following sections will examine the validity of these conclusions in the context of OECD countries over the years 1990-2008. Regression analysis compares distributional wage impacts of specialization in technology-intensive exports versus labor-intensive exports. Just as in the theoretical example, I assume that trade specialization in a particular sector signifies a nation's comparative advantage (low autarkic relative price) in that area. Higher exports should therefore increase the relative price of goods in that sector as equilibrium is reached with the higher world price. In accordance with the Stolper-Samuelson Theorem, I hypothesize that this higher relative price will stimulate demand for workers in the occupations intensive in that production sector, ultimately benefiting those laborers relative to other workers.

3 Methodology & Model Specifications

The following models evaluate the hypotheses of Section 2 with OECD balanced panel data. This section presents the fixed-effect regression methods used to investigate trade impacts on the wages of workers across 161 occupations using Occupational Wages around the World data[3]. Rather than detailing the effects of liberalization on each individual profession, occupations are categorized according to skill level, utilizing the ILO's ISCO-08 skill level

[2] The wage shifts in this example require an increase only in the *relative* price of technology goods. The following cases are all equally viable within the scope of the model: (i) $\Delta P_T > \Delta P_A > 0$; (ii) $\Delta P_T > \Delta P_A = 0$; (iii) $\Delta P_T > 0 > \Delta P_A$; (iv) $\Delta P_T = 0 > \Delta P_A$; and (v) $0 > \Delta P_T > \Delta P_A$.

[3] This paper analyzes solely occupational wages, straying from industry wage analysis studied in the past (Bernard and Jensen 1995). One fundamental reason for this choice is a phenomenon known as "interindustry wage differentials" (Thaler 1989). Thaler discusses the reality that wage differentials among industries often endure over time, establishing wage premia in entire industries over others. While some have attributed such differences to industry-specific marginal products or desirability of work environments, Thaler argues for greater depth in research and data accumulation in order to truly analyze the pattern. This paper avoids these confounding industry wage gaps by narrowing the discussion to occupational earnings.

allocations. I assign each occupation to one of four ISCO skill levels through a discretionary skill-matching assessment. The occupations assigned to each skill group are displayed in Table 7.

The first principal specification is introduced below in Equation (11):

$$P_{ct} = \boldsymbol{x}'_{ct}\boldsymbol{\beta} + \boldsymbol{z}'_{ct}\boldsymbol{\gamma} + \nu_t + \varepsilon_{ct} \tag{11}$$

Dependent variable P_{ct} takes the logarithmic wage premium between high-skilled and low-skilled workers as the dependent variable of interest. The variable is computed by differencing logarithmic average hourly wages for ISCO Skill-4 and Skill-1 workers by country and year. Economically, it can be interpreted as the difference between the percentage growth of Skill-4 wages and Skill-1 wages following a shift in trade specialization. Analysis using the nominal, linear-scale wage premium is excluded, due to the inflationary and PPP-adjustment issues associated with comparing current values of USD across time. The logarithmic premium evades measurement error and produces a sounder model.

As introduced in Section 1, volumes of net exports as a percentage of GDP are computed for six production sectors as the key independent variables. An array of control variables then seeks to minimize omitted variable bias and ensure consistent coefficient estimates. Finally, additional fixed effects account for time-specific wage trends. They are captured by a set of yearly dummy variables for all years analyzed. Country-specific effects are accounted for implicitly within fixed-effect regressions on the panel data, which group data according to each country-occupation combination.

Values of *t* reflect yearly increments; all data are accumulated annually. $\boldsymbol{x_{ct}}$ signifies the vector of net exports as a proportion of GDP, $\frac{Exports-Imports}{GDP}$, for six trade sectors in each country *c* in year *t*. Vector $\boldsymbol{\beta}$ contains all corresponding coefficients of interest. Export sectors include high-technology manufacturing, medium-high technology manufacturing, medium-low technology manufacturing, low-technology manufacturing, agriculture and mining. As evidenced by the breakdown of manufacturing, the prime distinction among sectors is the level of technology used in their production. Mining and agriculture are traditionally known as labor-intensive areas of production; manufacturing is technology-intensive. From the theoretical model, trade specialization in tech-heavy sectors should augment demand for skilled laborers capable of working with the required technology. As skilled wages rise relative to the unskilled labor force, a country's wage premium should increase and demonstrate rising national inequality.

$\boldsymbol{z_{ct}}$ presents a vector of control variables for each country-year combination. All corresponding coefficients are collected in vector $\boldsymbol{\gamma}$. ν_t and ε_{ct} capture time fixed effects and observational error terms, respectively.

Vector $\boldsymbol{z_{ct}}$ is comprised of macroindicators largely accumulated from the outstanding literature on trade and inequality. I discuss only their methodological value in this section.

Detailed descriptions and data sources for these variables can be found at the back of the appendix.

The first is educational attainment. This control is perhaps the most theoretically significant, given that this research directly examines the returns to workers of different skill levels. Heckscher-Ohlin theory suggests that both supply-side and demand-side components intervene in a nation's distribution of wages (Katz & Murphy 1992). In regard to the former, a greater supply of high-skilled workers in an otherwise unchanging economy should lower a country's skill premium as the relative rarity and value of unskilled labor rises. The analysis of Teulings and van Rens (2008) reinforces this conclusion with their findings that greater educational attainment and enrollment rates yield lower levels of national income inequality. If unaccounted for, this interaction effect of labor supply and demand may bias the desired estimators. Its inclusion attempts to isolate the demand-side distributional effects of trade specialization.

The next three indicators include unemployment rates[4], trade openness and technological development as discussed in Woo, Bova, Kinda and Zhang (2013). While the authors target the Gini coefficient in their analysis of inequality, the relevance of these controls in the context of wage inequality proves just as convincing. The aggregate trade openness measure removes any potential bias arising from trade impacts in industries excluded from the six key export sectors. The fact that these six sectors do not include all industries also negates the risk of multicollinearity upon inclusion of this control. Technological development controls for a widely discussed contributing source of rising inequality in the developed world: skill-biased technological change (Krugman (1995); Wood (1994); Freeman (1995); Bekman, Bound & Machin (1998)). Though a broad indicator, multi-factor productivity places a valuable check on the relative distributional effects of trade and technology[5].

Remaining control variables are inflation, domestic financial development, financial openness, GDP per capita and gross fixed capital formation. Controlling for inflation avoids any distortions resulting from a comparison of current-year-denominated wages over time. Both financial controls are derived from the model introduced in Jaumotte *et al* (2013). Johansson and Wang (2013) and Demirguc-Kunt and Levine (2009) also address the need to consider of financial development when assessing inequality. GDP per capita draws primarily upon the analysis of Cornia (2002) on differing effects of trade across developed and developing nations. Though all nations in the present analyses are broadly considered developed, his conclusions demonstrate the influence a country's income level may have on resulting trade impacts.

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[4] Krugman (1995) distinguishes between "European" and "American" models in his theoretical presentation of trade impacts. The European model first assumes that relative wages between skilled and unskilled laborers remain constant, so that the impact of increased relative demand of a particular sector falls on sector employment shares. The American model takes the contrarian approach, following the textbook image of changing factor prices and resulting wage inequality. With free-market Keynesian dynamics certainly present in the labor market, the fixed relative wages underlying the European model appear a far cry from reality. The present model is therefore geared toward the American model of trade. I control for the unemployment rate, however, as a consideration of trade impacts on employment patterns in addition to wage patterns.

[5] Also see Jorgenson and Vu (2005) for discussion of IT development's impact on inequality.

Lastly, gross fixed capital formation is also of considerable theoretical importance for this model. In Section 2, the wage implications of trade rely upon a key assumption that the physical capital stock and relative capital intensities between sectors remain fixed. This requirement dramatically simplified the model by eliminating the possibility of capital-induced effects on production levels, and consequently on the skill premium[6]. However, quantities of fixed capital formation are constantly in flux in the real world. Changes in a country's capital stock may therefore distort the observed trade-induced effects on the labor market. This capital formation variable is necessary to control for estimator biases.

A second base model alters the dependent variable from the logarithmic wage premium to the *spread* of all occupational wages by country and year. Equation (12) reflects this wage spread specification:

$$S_{ct} = \boldsymbol{x}'_{ct}\boldsymbol{\beta} + \boldsymbol{z}'_{ct}\boldsymbol{\gamma} + \nu_t + \varepsilon_{ct} \tag{12}$$

This altered dependent variable S_{ct} is computed as the standard deviation of all occupational wages for each country and year. All right-hand side variables follow directly from those in Equation (11). The relevant hypothesis for this model predicts that more tech-intensive export sectors will yield more positive coefficients. In other words, specializing in technological industries should increase the wage spread in the OECD countries studied.

All models presented in this paper take on a set of overarching assumptions. Several overlap with those of the theoretical model. First, all countries analyzed share the same relative preferences for high-tech and low-tech goods and services. Next, free labor mobility exists within a country between occupations only in the absence of educational, geographical or skill-based barriers to entry. In this vein, I assume that workers are bound both to their country and to the occupations within their respective ISCO skill groups during the time period analyzed. The educational attainment control variable also captures violations of this assumption via changes in a country's human capital. Lastly, I assume technology is stochastically determined at the firm level[7].

Various robustness checks are imposed on the initial models and methodologies in Section 4.2.

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[6] Imagine capital stock is not held constant and a large influx of capital arrives at Home. From equations (1) and (2), it can be seen that this additional capital formation will affect each sector's production differently. If factor price insensitivity fails to hold and this new capital is unevenly distributed between sectors, a spike in relative labor demand (due to rising MPL) in the capital-receiving sector will increase the relative wages of the occupation intensive in that sector.

[7] With demonstrated failures of the Stolper-Samuelson Theorem and Heckscher-Ohlin-Vanek sign test (Goldberg & Pavcnik 2007), standard theory has been newly adapted to accommodate the influences of firm heterogeneity on trade impacts (Sampson 2012; Yeaple & Ross 2005). With heterogeneity, Sampson (2012) argues that if technology is non-stochastically determined at the firm level, the impacts of trade on the wage distribution applicable only to exporting sectors, rather than the aggregate population.

4 Results & Robustness Checks

4.1 Baseline Results

Base model regressions seek to quantify the impact of trade specialization on the logarithmic wage premium and wage spread specifications outlined by respective Equations (11) and (12).

Before detailing outcomes of the initial regressions, an important trend across specifications bears mentioning. While the base models disaggregate trade into six aforementioned export sectors, the resulting coefficients fail to show clear distinctions among the four manufacturing sectors. Potential explanations for this pattern are discussed in Section 5. Still, it is important to note that the comparison of greatest interest rests between technology-intensive sectors (high, medium-high, medium-low, and low-technology manufacturing) and labor-intensive sectors (agriculture and mining). To pin down more succinct conclusions, an average of the four manufacturing sectors is included for comparison in the regressions of Section 4.2.1.

4.1.1 Ln Wage Premium

The principal specification of this paper examines changes in the logarithmic wage premium between Skill-4 and Skill-1 workers. The output is shown in Table 1. Columns (1)-(3) differ only in their inclusion or exclusion of control variables and yearly dummies. With the inclusion of both in Column (3), the results indicate a relationship between trade specialization and inequality well aligned with theoretical predictions. Three out of four manufacturing sectors yield positive effects on the wage premium, with high-tech manufacturing specialization displaying an elasticity of $\frac{\%\Delta\ wage\ premium}{\%\Delta\ high-tech\ net\ exports} \approx +1$, statistically significant at all confidence intervals. By contrast, agriculture holds a highly negative and significant estimator of -0.078, reinforcing the prediction that higher proportions of labor-intensive exports reduce the skill premium. The mining coefficient is also negative, but found to be quite small in magnitude and statistically insignificant.

4.1.2 Wage Spread

The second base model reflects the specification described in Equation (12). Illustrated in Table 2, technology-intensive specialization does not reveal a powerful impact on the wage spread in either direction. The four manufacturing coefficients differ greatly in both sign and magnitude, yet average a mere -0.018 (less than 2% of the magnitude of the agriculture coefficient). Trade theory does hold up strongly for the two labor-intensive sectors of agriculture and mining, showing highly negative and statistically significant coefficients when controls and year dummies are included. Provided we are most interested in a comparison of tech-intensive and labor-intensive sectors, these results continue to reinforce the predicted higher demand for skilled labor following tech specialization relative to labor-intensive sectors. Tech-intensive sectors consistently show more positive coefficients than agriculture and mining. Nevertheless, this model suffers from the previously mentioned unit bias associated with comparing current nominal US dollar units over time. Only cross-sector comparisons can be reliably gleaned from these conclusions.

Comparative alignment with theoretical predictions across the two base models is outlined in Table 3. To compensate for a lack of clear distinction among the four technological sectors, the average of these four coefficients is listed for each model specification. The logarithmic wage premium model lends a high level of theoretical consistency; coefficient signs for all key independent variables reflect earlier predictions (though the mining coefficient is miniscule). The wage spread model coefficients are all negative. However, F-tests (see page 24) show positive and statistically significant differences between the averaged manufacturing coefficient and agriculture coefficient for both base models. These tests demonstrate the superior equalizing effects of agriculture specialization compared to manufacturing specialization. The robustness check of Section 4.2.1 also presents an altered model where the average of all manufacturing sectors' net exports is first computed and then included in the regressions. Resulting output is consistent with my initial findings.

4.2 Robustness Checks

4.2.1 Average technological specialization measure

The ambiguous results across manufacturing sectors elicited a separate set of regressions on the average of all four. Instead of averaging the coefficients of initial regressions (as in Table 3), an *average tech specialization* variable calculates the average of all four manufacturing sector net exports as a percentage of GDP. This measure replaces the four individual sectors in the regressions illustrated in Table 4.

The logarithmic wage premium model is first tested, yielding relatively consistent outcomes shown in Column (1). The principal difference arises in the reevaluation of the wage spread in Column (2). With controls and year dummies, *average tech specialization* reveals a negative coefficient, significant at all intervals. This final model implies that augmenting tech exports reduces the wage premium, contrasting theoretical predictions. Yet this specification should raise some eyebrows, as it suggests a reduction in the wage spread from specialization in *all* export sectors. Existing research unravels this argument of unanimously equalizing impacts of trade. Mining also holds a much more positive coefficient than manufacturing, though still negative in sign. This alternative specification reveals immediate weaknesses in the wage spread model.

4.2.2 Instrumental Variables Framework

Instrumental variable regression analysis is then implemented to examine the risk of reverse causality bias in the estimates[8]. One-year lagged variables for each of the export sectors are used as instruments for the present values of each corresponding sector. There is no possibility of reverse causality in this case. The current wage distribution cannot influence past net export values, making these instruments entirely exogenous. Clustering standard errors by Group ID is not possible in instrumental variable panel data regressions, in contrast to all previous specifications. Variance is instead given by conventional standard errors for the IV regressions. Full regression output for logarithmic wage premium and wage spread models is presented in Columns (1) and (2) of Table 6. Overall, the coefficients prove largely robust to the IV analysis. The coefficients for all export sectors become more negative, though the relationships among coefficients remain unchanged: $\beta_{agriculture} < \beta_{mining} < \beta_{tech}$, where β_{tech} references the average of manufacturing sector coefficients. All but one coefficient of interest are significant at the 95%-confidence level.

4.2.3 Altered Functional Form

A set of regressions includes squared terms for all six export sectors to assess the model for functional form bias. Original signs are maintained to avoid producing positive quadratic terms for net importers. The output for logarithmic wage premium and wage spread specifications does not fundamentally differ from initial conclusions. The output for both models can be viewed in Table 5. In the logarithmic wage premium model, the average across the four manufacturing coefficients decreases slightly to +0.047 from an initial +0.06, still in line with theoretical predictions. Agriculture remains negative and statistically significant with a coefficient of -0.05 in the altered regression. The mining sector produces the biggest change, possibly reflecting once more its borderline status between tech-intensive and labor-intensive. The negative mining coefficient of the initial regressions now becomes positive for wage premium and wage spread specifications, with unanimously negative quadratic terms.

This alteration of functional form seeks to address a striking trend in the data visualizations common to wage premium and wage spread models. Across all trade sectors, inequality tends to peak as that sector's net exports approach zero. Wage spread relationships are illustrated with high-tech manufacturing, low-tech manufacturing, agriculture, and mining sectors in respective Figures 3-6[9]. In spite of distinct linear correlations with the wage spread, all

[8] Motivating this robustness check is a paper by Adam, Katsimi & Moutos (2008) looking at the implications of inequality on a country's import demand function. The authors argue that increased inequality has an adverse effect on the import demand of low-income countries and a positive impact on that of high-income countries. This instrumental variable analysis checks for the possibility of changes in a country's trade specialization patterns resulting from inequality.

[9] It is important to view the plots below simply as explanatory aids, and not as conclusive relationships between specialization in each sector and the wage spread. These four graphs exclude all other relevant variables that inevitably impact the correlations shown, as evidenced by the analyses conducted thus far in this paper.

four plots demonstrate powerful trend shifts as nations transform from net importers to net exporters of goods in a particular sector.

Standard trade theory offers no comprehensive basis for this transfer of trade gains in the labor market. It is possible that these observed quadratic relationships simply indicate high levels of wage inequality in countries with low general trade openness. However, aggregate trade openness coefficient is negative and statistically significant in the wage spread model. The data suggest this is not a sufficient explanation.

Departing from purely Keynesian forces, this pattern may also tap into policy implications associated with trade liberalization. In the case of high-technology manufacturing, it would be reasonable for an advanced nation to implement a wage equalization policy upon expanding its specialization in high-tech production. This policy would shift the wage spread downward as a way to compensate the losers of trade (unskilled laborers). However, the same trend appears in labor-intensive agriculture and mining industries, specialization in which should naturally reduce the wage spread without need for compensation. A focused study of this phenomenon, ideally with a larger sample size, is necessary to explain these trends and would provide an interesting addition to the literature.

4.2.4 Alternative Control Variables

The strength of the financial openness and educational attainment indicators are also tested via substitution of alternative measurements. FDI net inflow and secondary education variables allow for the greatest number of observations during the years of interest. They have been widely regarded as viable proxies for their respective measures (Quinn, Schindler & Toyoda 2011). Still, a more comprehensive financial openness indicator from the Jaumotte *et al* (2013) dataset is substituted to assess the validity of the FDI indicator via any significant variation in results. An alternative educational attainment variable is also obtained from the Jaumotte dataset, denoting the proportion of higher education attainment within the population aged 15+ in place of secondary education enrollment. It is possible that higher education provides a better threshold for attainment of high-skilled occupations than does secondary education. However, trivial differences are found for all coefficients of interest. Logarithmic wage premium and wage spread results with these variable adjustments can be found in Columns (3) and (4) of Table 6, respectively.

4.2.5 Gini Coefficient Extension

The present research places emphasis on the distributional wage impacts of trade and finds alignment between theoretical predictions and OECD data. As a final robustness check, I extend this analysis to aggregate inequality for comparison. The standard Gini coefficient is applied as a dependent variable against the same six export sectors, control variables and dummies. The results (see Column (5) of Table 6) my conclusions echo those of the current literature: Heckscher-Ohlin theory bears little predictive value on the Gini coefficient (Harrison, McLaren & McMillan 2011; Jaumotte *et al* 2013). The resulting estimators are all over the board, with high-tech and low-tech specialization holding negative coefficients (against HO theory), along with agriculture (pro HO theory), while mining has a remarkably positive and statistically significant coefficient of $\frac{\Delta\ Gini\ coefficient}{\%\Delta\ mining\ net\ exports} \approx +1.7$. Alternative methodologies are needed to explain shifts in this aggregated measure.

5 Concluding Remarks

This paper decomposes the correlation between trade and inequality into a set of specific relationships between groups of workers and areas of specialization. I examine inequality through the scope of occupational wages, grouping all workers into one of four occupational skill groups. Their relative wage shifts are measured against specialization in six production sectors of trade. I find OECD evidence that technology-intensive trade specialization contributes much more highly to wage inequality than specialization in labor-intensive sectors.

One large limitation of these findings is the lack of discrimination among technology-intensive sector coefficients. According to the theoretical model constructed, the relationship between trade and wage inequality should become increasingly positive as sector specialization becomes more technology-intensive. Despite observed distinctions between labor-intensive and tech-intensive sector groups, sector coefficients within the tech-intensive group prove unstructured in their impacts on the skill premium. It is for this reason that manufacturing sectors are averaged when presenting the majority of relevant results.

One possible explanation for this trend is the limited sample size. While wage data exists for 29 countries, the country count falls to as low as 17 in certain specifications when implementing a balanced panel with control variables. Perhaps this pattern is specific to countries in the sample, and greater variation would allow for more distinguished trends among manufacturing sectors. Alternatively, the OECD's division of sectors by levels of tech-intensiveness may simply be too limited to reveal tangible differences. The import-export data are derived primarily from 2-digit ISIC industries. Greater industry disaggregation may allow for more telling outcomes.

A second unanticipated result involves the conflicting coefficients between agriculture and mining exports across certain specifications. Logarithmic wage premium analyses reveal a correlation with mining specialization of almost zero, statistically insignificant in base model regressions. Theory predicts a negative correlation between mining and wage inequality, given its association as a labor-intensive sector. In this study, the data designate mining as more of a borderline case between labor-intensive and technology-intensive in the context of wage inequality.

Finally, I would like to reiterate that the logarithmic wage premium model produces more robust results than the wage spread indicator. The coefficients in Column (2) of Table 3 suggest a unanimously negative effect of trade on the occupational wage spread. This relationship is unlikely against the backdrop of past research. However, both wage premium and wage spread models reinforce the relatively equalizing impacts of agriculture specialization compared to tech specialization. Wage spread proves more valuable for determining the distributional effects of one trade sector relative to others than for explicitly correlating trade and inequality.

While my empirical analysis is limited to developed nations, the conclusions drawn should extend to the developing world with equivalent analysis. My theoretical model, in accordance with standard Heckscher-Ohlin trade theory, assumes complete specialization of a country in its comparatively advantaged sectors. However, empirical evidence shows various levels of specialization in multiple sectors for all nations studied. Provided developing countries also show diversity in their export sectors[10], they should experience parallel trends in inequality stemming from tech-intensive versus labor-intensive specialization.

In this sense, a sectorial decomposition of trade may alleviate well-known conflicts associated with testing standard trade theory against low-income nations (Burstein and Vogel 2012). This shift in the current discussion on trade and inequality toward sector-specific relationships has the potential to establish a globally predictive model. Unfortunately, the OECD's STAN bilateral trade flow database currently appears to stand alone as a thorough source for disaggregated import-export information. With improved data collection, an extension of this analysis to the developing world would be a welcome addition.

REFERENCES

Adam, Antonis, Margarita Katsimi, and Thomas Moutos. *Inequality and the Import Demand Function*. Working paper no. 2196. Category 6: Monetary Policy and International Finance. CESIFO, 2008.

Afonso, António, Ludger Schuknecht, and Vito Tanzi. *Income Distribution Determinants and Public Spending Efficiency*. Working paper no. 861. Frankfurt Am Main: European Central Bank, 2008.

Amiti, Mary, and Lisa Cameron. "Trade Liberalization and the Wage Skill Premium: Evidence from Indonesia." Journal of International Economics 87, no. 2 (2012): 277-87. doi:10.1016/j.jinteco.2012.01.009.

Andersson, Thomas. "North-South Trade, Employment, and Inequality: Changing Fortunes in a Skill-Driven World by Adrian Wood." Review of *North-South Trade, Employment, and Inequality: Changing Fortunes in a Skill-Driven World. The Journal of Developing Areas* 30, no. 1 (October 1995): 125-28.

Aradhyula, Satheesh, Tauhidur Rahman, and Kumaran Seenivasan. *Impact of International Trade on Income and Income Inequality*. 2007. AgEcon Search, University of Minnesota.

Atkinson, A. B. *Income Inequality in OECD Countries: Data and Explanations*. Working paper no. 881. Category 10: Empirical and Theoretical Methods. Oxford: CESIFO, 2003.

Autor, David H., David Dorn, and Gordon H. Hanson. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103, no. 6 (2013): 2121-168. doi:10.1257/aer.103.6.2121.

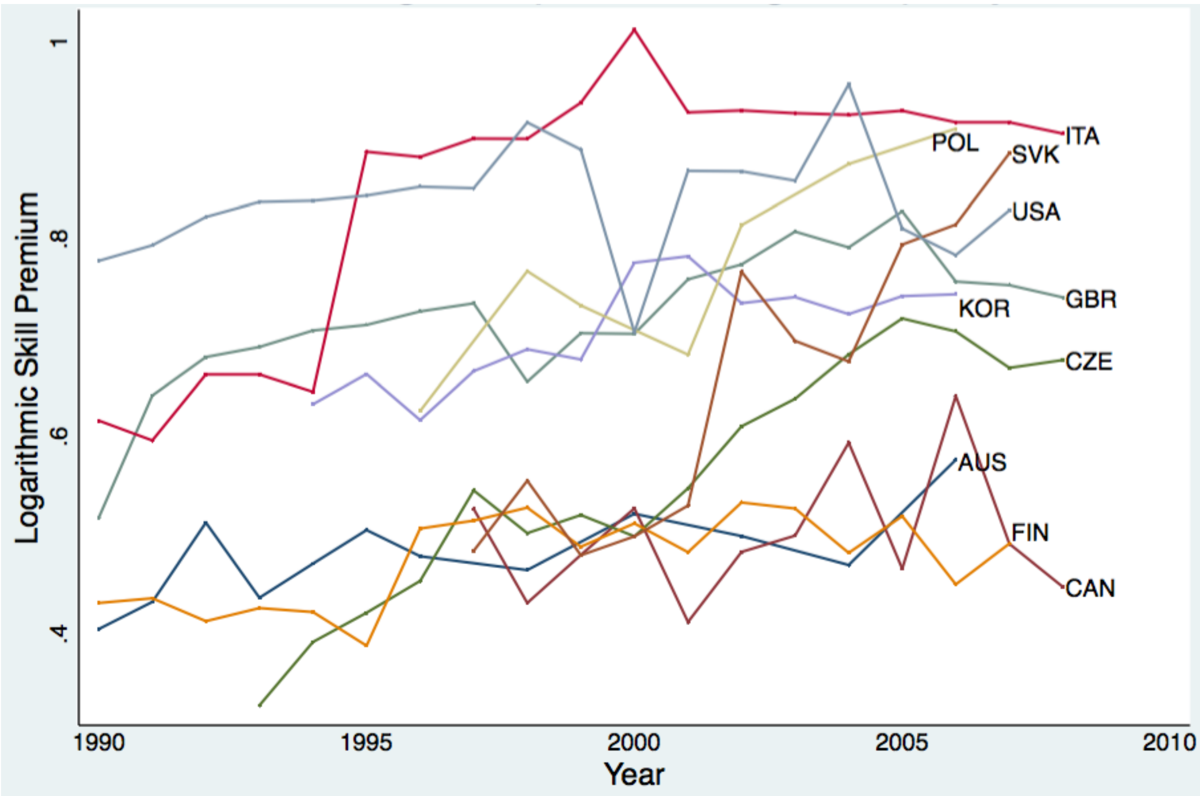
[10] The odds are high that developing nations, in fact, show much less diversity in exports than the nations in this study. Since many of these nations are highly relatively abundant in unskilled labor, they are prone to specialize very little in tech-intensive sectors. In this case, resulting conclusions would be drawn from data skewed toward the unskilled labor force and hold questionable merit.

Beck, T., A. Demirguc-Kunt, and R. Levine. "A New Database on the Structure and Development of the Financial Sector." *The World Bank Economic Review* 14, no. 3 (2000): 597-605. doi:10.1093/wber/14.3.597.
Bekman, E., J. Bound, and S. Machin. "Implications of Skill-Biased Technological Change: International Evidence." *The Quarterly Journal of Economics* 113, no. 4 (1998): 1245-279. doi:10.1162/003355398555892.
Bigsten, Arne, Dick Durevall, and Farzana Munshi. *Offshoring and Occupational Wages: Some Empirical Evidence*. Working paper no. 312. Göteborg: School of Business, Economics and Law, University of Gothenburg, 2008.
Burstein, Ariel, and Jonathan Vogel. *International Trade, Technology, and the Skill Premium*. Technical paper. New York: Columbia University, 2012.
Card, David, and John E. Dinardo. "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles." *Journal of Labor Economics* 20, no. 4 (2002): 733-83. doi:10.1086/342055.
Corley, Marva, Yves Perardel, and Kalina Popova. *Wage Inequality by Gender and Occupation: A Cross-country Analysis*. Publication no. 2005/20. Employment Strategy Papers. International Labour Organization.
Cornia, Giovanni A. *The Impact of Liberalisation and Globalisation on Income Inequality in Developing and Transitional Economies*. Working paper no. 843. Category 5: Fiscal Policy, Macroeconomics and Growth. CESIFO, 2003.
Dix-Carneiro, Rafael, and Brian K. Kovak. *Trade Liberalization and the Skill Premium: A Local Labor Markets Approach*. Technical paper. Pittsburg: Carnegie Mellon University Heinz College, 2014.
Esquivel, Gerardo, and José Antonio Rodríguez-López. "Technology, Trade, and Wage Inequality in Mexico before and after NAFTA." *Journal of Development Economics* 72, no. 2 (2003): 543-65. doi:10.1016/S0304-3878(03)00119-6.
Feldstein, Martin. *The Effects of Outbound Foreign Direct Investment on the Domestic Capital Stock*. Working paper no. 4668. Cambridge, MA: National Bureau of Economic Research, 1994.
Freeman, Richard M., and Remco B. Oostendorp. *Wages Around the World: Pay Across Occupations and Countries*. Working paper no. 8058. Cambridge, MA: National Bureau of Economic Research, 2000.
Harrison, Ann, John McLaren, and Margaret McMillan. "Recent Perspectives on Trade and Inequality." Annual Review of Economics 3, no. 1 (2011): 261-89. doi:10.1146/annurev.economics.102308.124451.
International Labour Office. *International Standard Classification of Occupations: Structure, Group Definitions and Correspondence Tables*. Report. Vol. 1. ISCO-08. Geneva: International Labour Organization, 2012.
Jaumotte, Florence, Subir Lall, and Chris Papageorgiou. "Rising Income Inequality: Technology, or Trade and Financial Globalization?" *IMF Economic Review* 61, no. 2 (2013): 271-309. doi:10.1057/imfer.2013.7.
Johansson, Anders C., and Xun Wang. *Financial Sector Policies, Poverty and Inequality*. Working paper no. 2012-24. Working Paper Series. Stockholm: China Economic Research Center, 2012.
Jorgenson, Dale W., and Khuong Vu. "Information Technology and the World Economy*." *Scandinavian Journal of Economics* 107, no. 4 (2005): 631-50. doi:10.1111/j.1467-9442.2005.00430.x.
Katz, L. F., and K. M. Murphy. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." The Quarterly Journal of Economics 107, no. 1 (1992): 35-78. doi:10.2307/2118323.
Klein, Michael W., Christoph Moser, and Dieter M. Urban. The Contribution of Trade to Wage Inequality: The Role of Skill, Gender, and Nationality. Working paper no. 15985. Cambridge, MA: National Bureau of Economic Research, 2010.
Krugman, Paul. "Growing World Trade: Causes and Consequences." *Brookings Papers on Economic Activity* 1995, no. 1 (1995): 327. doi:10.2307/2534577.

Krugman, Paul. "Trade and Wages, Reconsidered." *Brookings Papers on Economic Activity* 2008, no. 1 (2008): 103-54. doi:10.1353/eca.0.0006.
Lane, Philip R., and Gian Maria Milesi-Ferretti. "The External Wealth of Nations Mark II: Revised and Extended Estimates of Foreign Assets and Liabilities, 1970–2004." *Journal of International Economics* 73, no. 2 (2007): 223-50. doi:10.1016/j.jinteco.2007.02.003.
Oostendorp, Remco H. *The Occupational Wages around the World (OWW) Database: Update for 1983-2008*. Report. May 2012.
Quinn, Dennis, Martin Schindler, and A. Maria Toyoda. "Assessing Measures of Financial Openness and Integration." *IMF Economic Review* 59, no. 3 (2011): 488-522. doi:10.1057/imfer.2011.18.
Sampson, Thomas. *Selection into Trade and Wage Inequality*. Technical paper. Princeton: Princeton University, 2012.
Teulings, Coen, and Thijs Van Rens. "Education, Growth, and Income Inequality." *Review of Economics and Statistics* 90, no. 1 (2008): 89-104. doi:10.1162/rest.90.1.89.
Thaler, Richard H. "Anomalies: Interindustry Wage Differentials." *Journal of Economic Perspectives* 3, no. 2 (1989): 181-93. doi:10.1257/jep.3.2.181.
Wan, Guanghua, Ming Lu, and Zhao Chen. "Globalization And Regional Income Inequality: Empirical Evidence From Within China." *Review of Income and Wealth* 53, no. 1 (2007): 35-59. doi:10.1111/j.1475-4991.2007.00217.x.
Woo, Jaejoon, Elva Bova, Tidiane Kinda, and Y. Sophia Zhang. *Distributional Consequences of Fiscal Consolidation and the Role of Fiscal Policy: What Do the Data Say?* Working paper no. 13/195. International Monetary Fund, Fiscal Affairs Department, 2013.
Yeaple, Stephen Ross. "A Simple Model of Firm Heterogeneity, International Trade, and Wages." *Journal of International Economics* 65, no. 1 (2005): 1-20. doi:10.1016/j.jinteco.2004.01.001.
Zhu, S., N. Yamano and A. Cimper. "Compilation of Bilateral Trade Database by Industry and End-Use Category", OECD Science, Technology and Industry Working Papers, 2011/06, OECD Publishing (2011). doi:http://dx.doi.org/10.1787/5k9h6vx2z07f-en

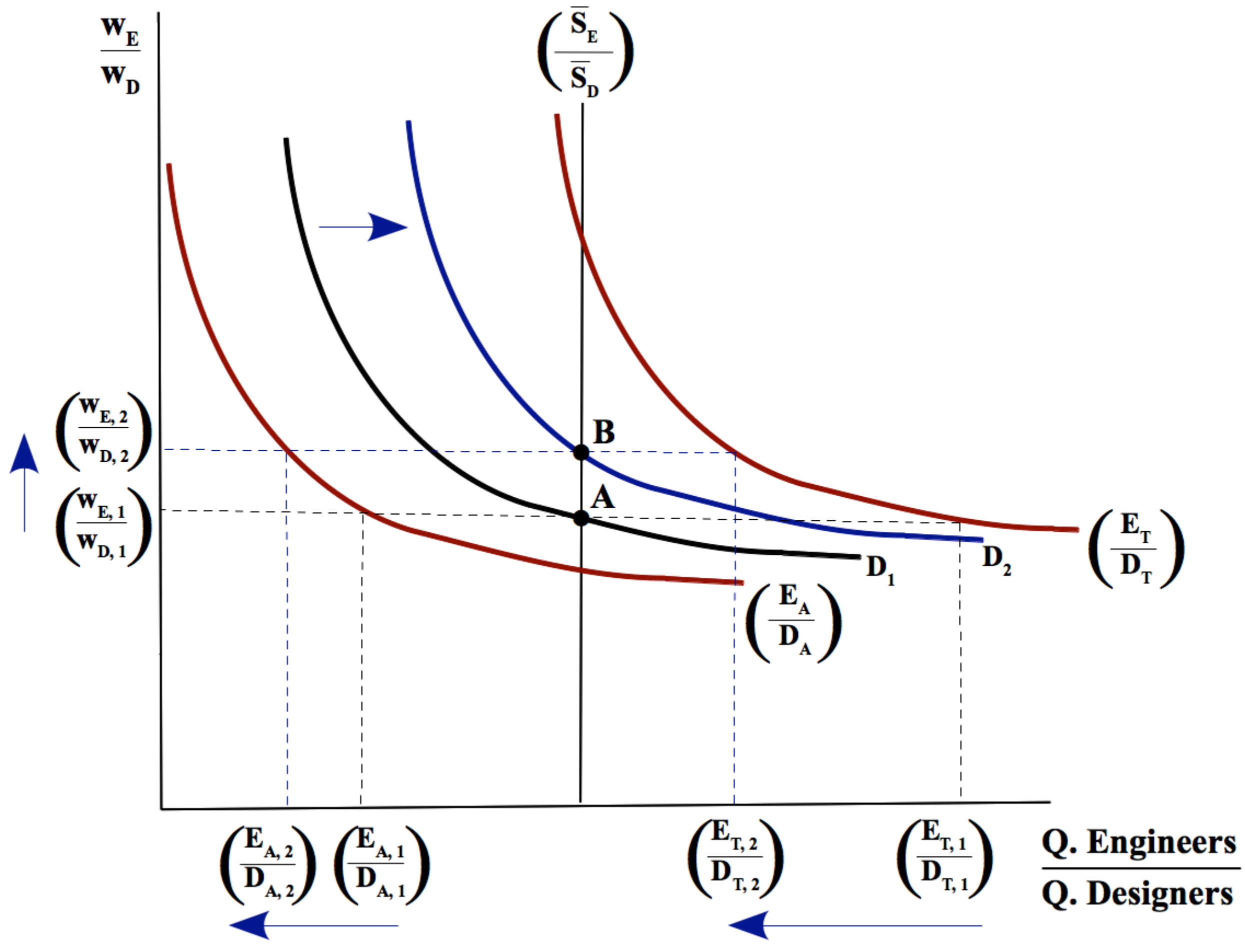
Appendix

Figure 1: Growing Occupational Wage Inequality in OECD Countries



Differences are shown between the logarithmic hourly wages of workers in high-skilled and low-skilled occupations over time for a randomly chosen sample of 10 OECD nations. Wage inequality consistently increases over the 1990-2008 period. Country abbreviations follow standard ISO 3166-1 alpha-3 codes.

Figure 2: Shifting Relative Demand in the Two-Occupation Labor Market



Labor immobility across occupations fixes the relative supply of Engineers to $\frac{\bar{S}_E}{\bar{S}_D}$*. Following an increase in the price of technological goods induced by trade liberalization, Home's relative demand for engineers shifts rightward from* D_1 *to* D_2*. This shift then moves the labor-market equilibrium upward from point A to point B. The relative quantities of engineers to designers decrease in both technology and apparel sectors (X-axis movements), while the relative wage of engineers increases from* $\frac{w_{E,1}}{w_{D,1}}$ *to* $\frac{w_{E,2}}{w_{D,2}}$ *(Y-axis movement).*

Figure 3: Wage Spread by High-Tech Manuf. Specialization

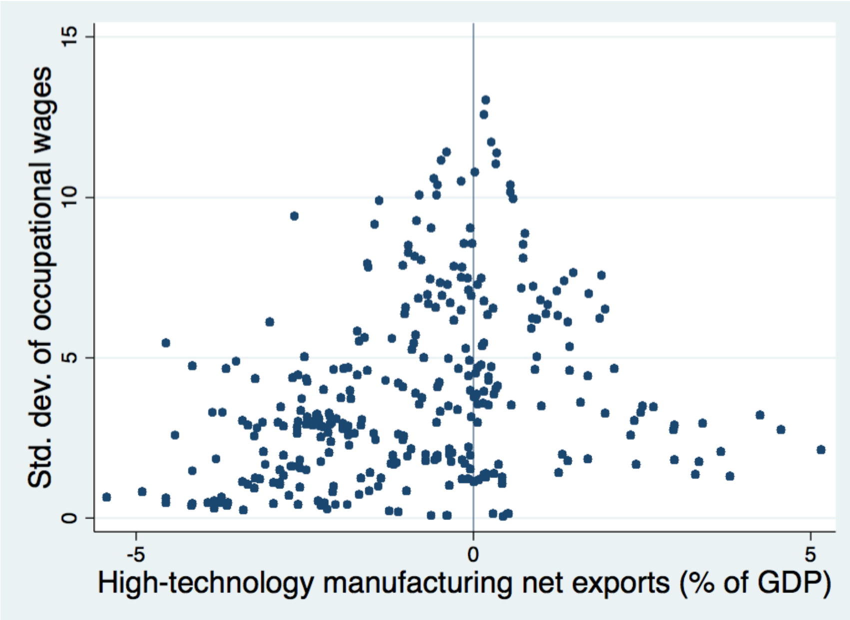


Figure 4: Wage Spread by Low-Tech Manuf. Specialization

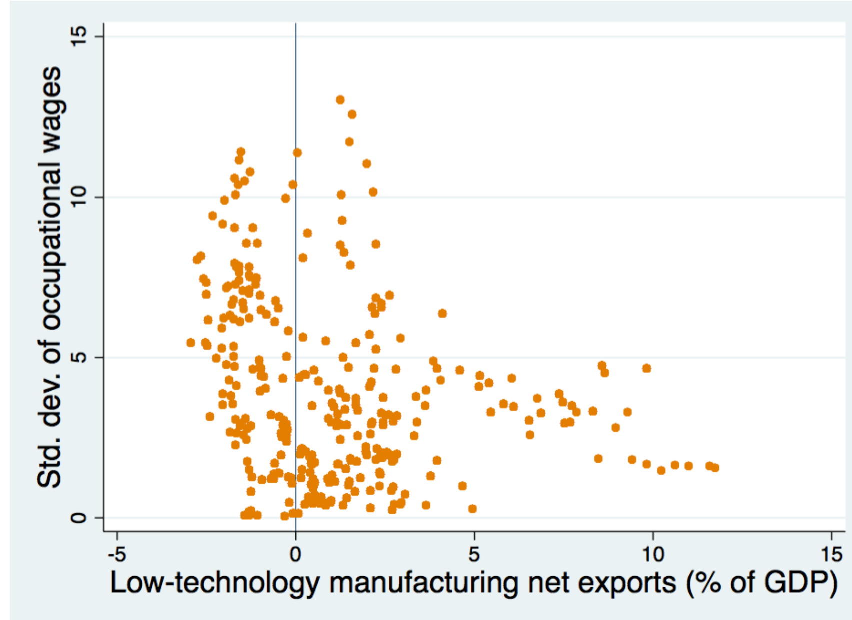


Figure 5: Wage Spread by Agriculture Specialization

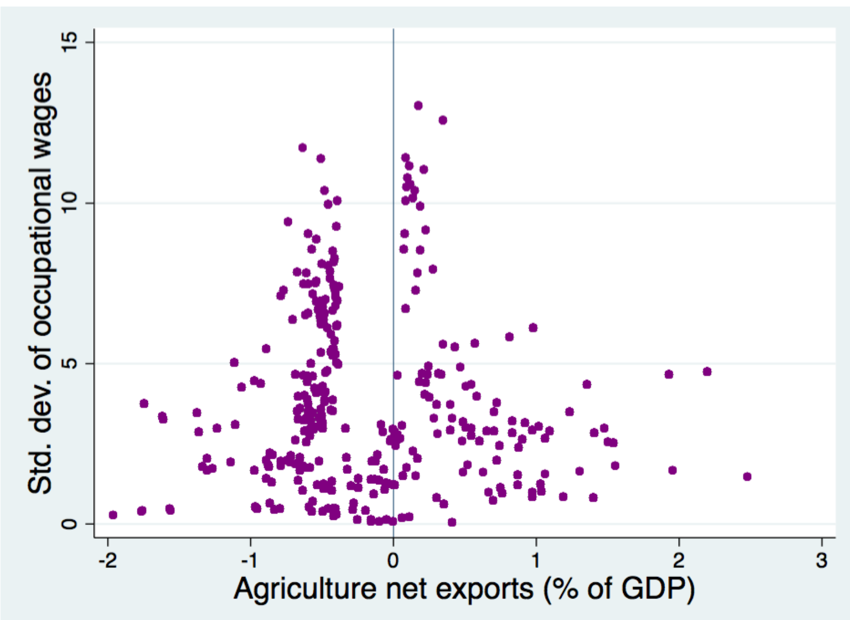
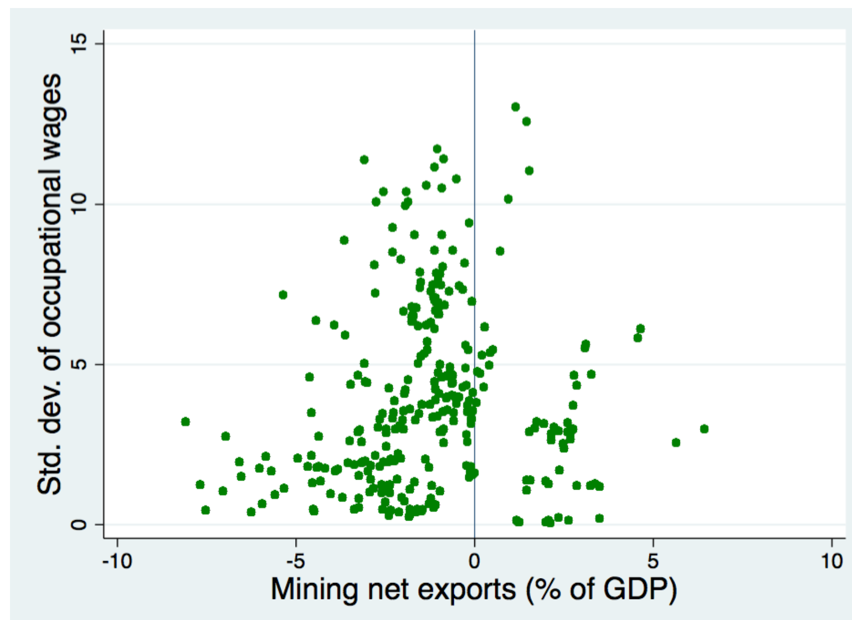


Figure 6: Wage Spread by Mining Specialization



The above figures plot the standard deviation of hourly wages for different levels of specialization in each trade sector.

Table 1: Logarithmic Wage Premium Results

LN WAGE PREMIUM	(1)	(2)	(3)
High-Tech Specialization	0.0341***	0.0108***	0.0116***
	(0.0020)	(0.0016)	(0.0011)
Medium High-Tech Specialization	0.0110***	-0.0127***	-0.0143***
	(0.0009)	(0.0021)	(0.0019)
Medium Low-Tech Specialization	-0.0458***	0.0227***	0.0447***
	(0.0032)	(0.0014)	(0.0016)
Low-Tech Specialization	-0.0036**	0.0184***	0.0241***
	(0.0017)	(0.0013)	(0.0016)
Agriculture Specialization	-0.0267***	-0.0459***	-0.0775***
	(0.0054)	(0.0054)	(0.0057)
Mining Specialization	0.0012	-0.0057***	-0.0003
	(0.0007)	(0.0014)	(0.0019)
GDP Per Capita	-	1.74e-06***	-7.24e-06***
		(1.89e-07)	(4.95e-07)
Inflation	-	-0.0227***	-0.0265***
		(0.0007)	(0.0009)
Unemployment Rate	-	0.0072***	0.0101***
		(0.0007)	(0.0010)
Education	-	7.28e-05***	9.26e-05***
		(1.86e-05)	(2.64e-05)
Financial Openness	-	-0.0016***	0.0006
		(0.0003)	(0.0004)
Trade Openness	-	0.0033***	-1.03e-05
		(0.0003)	(0.0002)
Financial Development	-	0.0125***	0.0211***
		(0.00479)	(0.0059)
Capital Formation	-	0.0199***	0.0303***
		(0.0014)	(0.0017)
Productivity	-	-0.0086***	-0.0053***
		(0.0005)	(0.0005)
Constant	0.757***	-0.0072	0.0208
	(0.0017)	(0.0420)	(0.0395)
Time Dummies	-	-	✓
Observations	30,078	16,454	16,454
R-squared	0.119	0.300	0.387
Number of Group ID	3,241	1,879	1,879

Heteroskedasticity-robust standard errors are given in parentheses for all estimates. SEs are clustered by a *Group ID* variable used to group all observations within a particular country and occupation. Levels of statistical significance are denoted by *** p<0.01, ** p<0.05, * p<0.1. R-squared values listed refer to those within *Group ID* clusters. Differing N across specifications reflect available data for each specification. Observations holding a missing value for any variable in a given specification are omitted from the regression.

Table 2: Wage Spread Results

WAGE SPREAD	(1)	(2)	(3)
High-Tech Specialization	-0.258***	-0.0866***	-0.0442***
	(0.0161)	(0.0124)	(0.0094)
Medium High-Tech Specialization	0.301***	-0.0026	-0.0102
	(0.0104)	(0.0171)	(0.0170)
Medium Low-Tech Specialization	0.171***	-0.0874***	-0.210***
	(0.0179)	(0.0177)	(0.0214)
Low-Tech Specialization	-0.662***	0.225***	0.193***
	(0.0208)	(0.0174)	(0.0201)
Agriculture Specialization	-0.431***	-1.177***	-1.074***
	(0.0655)	(0.0829)	(0.0793)
Mining Specialization	0.0804***	-0.132***	-0.200***
	(0.0299)	(0.0241)	(0.0267)
GDP Per Capita	-	0.0002***	0.0002***
		(2.77e-06)	(7.88e-06)
Inflation	-	-0.102***	-0.0297***
		(0.0094)	(0.0078)
Unemployment Rate	-	0.197***	0.260***
		(0.0090)	(0.0111)
Education	-	0.0018***	0.0015***
		(0.0002)	(0.0003)
Financial Openness	-	-0.0471***	-0.0495***
		(0.0031)	(0.0038)
Trade Openness	-	0.0009	-0.0194***
		(0.0028)	(0.0039)
Financial Development	-	1.052***	0.853***
		(0.0919)	(0.0668)
Capital Formation	-	0.132***	0.111***
		(0.0093)	(0.0120)
Productivity	-	0.0220***	0.0647***
		(0.0050)	(0.0075)
Constant	4.426***	-6.696***	-6.365***
	(0.0456)	(0.363)	(0.443)
Time Dummies	-	-	✓
Observations	30,996	17,028	17,028
R-squared	0.154	0.586	0.617
Number of Group ID	3,307	1,921	1,921

Heteroskedasticity-robust standard errors are given in parentheses for all estimates. SEs are clustered by a *Group ID* variable used to group all observations within a particular country and occupation. Levels of statistical significance are denoted by *** p<0.01, ** p<0.05, * p<0.1. R-squared values listed refer to those within *Group ID* clusters. Differing N across specifications reflect available data for each specification. Observations holding a missing value for any variable in a given specification are omitted from the regression.

Table 3: Theoretical Comparisons by Base Specification

COEFFICIENTS	(1)		(2)	
Dependent Variable	Ln Wage Premium		Wage Spread	
Averaged Manufacturing Coefficient†	+0.0165	✔	-0.0180	✖
Mining Coefficient	-0.0003	✔	-0.2000	✔
Agriculture Coefficient	-0.0775	✔	-1.0744	✔

✔ Consistent with theoretical hypotheses

✖ Inconsistent with theoretical hypotheses

† *Averaged Manufacturing Coefficient* takes the average, unweighted coefficient across High-Tech Manufacturing, Medium High-Tech Manufacturing, Medium Low-Tech Manufacturing, and Low-Tech Manufacturing for each model specification.

F-Tests:

F-tests are run on the difference between the averaged manufacturing and agriculture coefficients across both models. The tests show statistically significant evidence that tech-intensive specialization has less equalizing effects on wages than labor-intensive specialization.

1. Ln Wage Premium:

(1) *Averaged manufacturing – agriculture* = 0
F (1, 1878) = 260.17
→ Probability > F = 0.0000

Hypothesis test for more positive effects of manufacturing on inequality:
H_0: *Averaged manufacturing – agriculture* ≥ 0
P-value = 1.0000

2. Wage Spread:

(1) *Averaged manufacturing – agriculture* = 0
F (1, 1920) = 170.98
→ Probability > F = 0.0000

Hypothesis test for more positive effects of manufacturing on inequality:
H_0: *Averaged manufacturing – agriculture* ≥ 0
P-value = 1.0000

Table 4: Average Technological Premium Regressions

SPECIFICATION VARIABLES	(1)	(2)
Dependent Variable	Ln Wage Premium	Wage Spread
Average Tech Specialization	0.0475***	-0.168***
	(0.0032)	(0.0244)
Agriculture Specialization	-0.0726***	-0.810***
	(0.0060)	(0.0796)
Mining Specialization	0.0049***	-0.0325
	(0.0014)	(0.0208)
GDP Per Capita	-4.68e-06***	0.0002***
	(5.55e-07)	(8.36e-06)
Inflation	-0.0227***	-0.0054
	(0.0010)	(0.0074)
Unemployment Rate	0.012***	0.308***
	(0.0009)	(0.0110)
Education	0.0001***	0.0020***
	(2.90e-05)	(0.0003)
Financial Openness	0.0007	-0.0454***
	(0.0005)	(0.0039)
Trade Openness	0.0001	-0.0095**
	(0.0002)	(0.0038)
Financial Development	0.0177***	0.859***
	(0.0057)	(0.0630)
Capital Formation	0.0297***	0.129***
	(0.0016)	(0.0099)
Productivity	-0.0052***	0.0802***
	(0.0005)	(0.0071)
Constant	-0.0408	-7.176***
	(0.0380)	(0.427)
Time Dummies	✓	✓
Observations	16,454	17,028
R-squared	0.345	0.611
Number of Group ID	1,879	1,921

Heteroskedasticity-robust standard errors are given in parentheses for all estimates. SEs are clustered by a *Group ID* variable used to group all observations within a particular country and occupation. Levels of statistical significance are denoted by *** p<0.01, ** p<0.05, * p<0.1. R-squared values listed refer to those within *Group ID* clusters. Differing N across specifications reflect available data for each specification. Observations holding a missing value for any variable in a given specification are omitted from the regression.

Table 5: Altered Functional Form Results

SPECIFICATION KEY VARIABLES	(1)	(2)
Dependent Variable	Ln Wage Premium	Wage Spread
High-Tech Specialization	0.0005	-0.479***
	(0.0027)	(0.0323)
(High-Tech Specialization) ^{2}	0.0007	0.106***
	(0.0007)	(0.0070)
Medium High-Tech Specialization	-0.0024	-0.268***
	(0.0026)	(0.0234)
(Medium High-Tech Specialization) ^{2}	-0.0047***	0.0207***
	(0.0002)	(0.0023)
Medium Low-Tech Specialization	0.116***	0.265***
	(0.0046)	(0.0589)
(Medium Low-Tech Specialization) ^{2}	-0.0208***	-0.0826***
	(0.0009)	(0.0106)
Low-Tech Specialization	0.0740***	0.557***
	(0.0038)	(0.0398)
(Low-Tech Specialization) ^{2}	-0.0051***	-0.0263***
	(0.0003)	(0.0028)
Agriculture Specialization	-0.0530***	-4.110***
	(0.0196)	(0.325)
(Agriculture Specialization) ^{2}	0.0018	1.853***
	(0.0095)	(0.148)
Mining Specialization	0.0482***	0.282***
	(0.0024)	(0.0487)
(Mining Specialization) ^{2}	-0.0065***	-0.0739***
	(0.0004)	(0.0057)
Constant	-0.0866**	-6.760***
	(0.0433)	(0.415)
Time Dummies	✓	✓
Observations	16,454	17,028
R-squared	0.480	0.637
Number of Group ID	1,879	1,921

Heteroskedasticity-robust standard errors are given in parentheses for all estimates. SEs are clustered by a *Group ID* variable used to group all observations within a particular country and occupation. Levels of statistical significance are denoted by *** p<0.01, ** p<0.05, * p<0.1. R-squared values listed refer to those within *Group ID* clusters. Differing N across specifications reflect available data for each specification. Observations holding a missing value for any variable in a given specification are omitted from the regression.

Table 6: Miscellaneous Robustness Checks

SPECIFICATION DETAILS	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Ln Wage Premium	Wage Spread	Ln Wage Premium	Wage Spread	Gini Coefficient
Bias Addressed	Reverse Causality	Reverse Causality	Spec Error	Spec Error	-
Method	IV Regression	IV Regression	Altered Controls	Altered Controls	Altered Dep. Var.
High-Tech Specialization°	-0.177***	0.235**	0.0214***	-0.0086	-1.411***
	(0.0193)	(0.0990)	(0.0018)	(0.0230)	(0.0209)
Medium High-Tech Specialization°	0.162***	-0.232***	-0.0331***	-0.0741***	0.951***
	(0.0181)	(0.0726)	(0.0040)	(0.0154)	(0.0129)
Medium Low-Tech Specialization°	0.349***	-1.337***	0.0787***	0.514***	1.652***
	(0.0343)	(0.199)	(0.0019)	(0.0300)	(0.0527)
Low-Tech Specialization°	-0.0702***	0.0556	0.0733***	0.426***	-0.348***
	(0.0093)	(0.0519)	(0.0036)	(0.0284)	(0.0174)
Agriculture Specialization°	-0.0752***	-1.681***	-0.0365***	-1.322***	-0.228*
	(0.0243)	(0.184)	(0.0067)	(0.119)	(0.129)
Mining Specialization°	0.157***	-0.604***	0.0192***	-0.136***	1.696***
	(0.0203)	(0.0820)	(0.0032)	(0.0262)	(0.0510)
GDP Per Capita	-9.63e-07	0.00027***	-2.09e-05***	0.0001***	-0.0001***
	(9.49e-07)	(6.03e-06)	(7.81e-07)	(7.59e-06)	(4.55e-06)
Inflation	-0.0523***	0.0870***	-0.0351***	-0.152***	0.861***
	(0.0032)	(0.0232)	(0.0012)	(0.0098)	(0.0173)
Unemployment Rate	0.0498***	0.224***	0.0032**	0.148***	0.179***
	(0.0042)	(0.0173)	(0.0015)	(0.0104)	(0.0153)
Education†	0.0015***	-0.00075	-0.0049**	-0.331***	0.0486***
	(0.0002)	(0.0006)	(0.0023)	(0.0136)	(0.0006)
Financial Openness†	0.0158***	-0.0768***	-0.0005***	-0.0019***	-0.245***
	(0.0016)	(0.0054)	(2.32e-05)	(0.0002)	(0.0043)
Trade Openness	0.0010	0.0059	-0.0030***	-0.0701***	-0.0501***
	(0.0006)	(0.0045)	(0.0006)	(0.0045)	(0.0049)
Financial Development	-0.206***	1.414***	-0.0142*	0.374***	-8.089***
	(0.0267)	(0.115)	(0.00854)	(0.111)	(0.216)
Capital Formation	0.140***	-0.196***	0.0454***	0.345***	1.005***
	(0.0117)	(0.0539)	(0.0024)	(0.0196)	(0.0318)
Productivity	0.0299***	-0.0415**	-0.0071***	0.0598***	0.482***
	(0.0041)	(0.0198)	(0.0006)	(0.0081)	(0.0100)
Constant	-2.800***	-1.443	0.321***	0.911*	8.901***
	(0.290)	(1.196)	(0.0917)	(0.471)	(1.004)
Time Dummies	✓	✓	✓	✓	✓
Observations	14,547	15,121	10,282	10,696	3,948
R-squared	-	0.544	0.455	0.426	0.981
Number of Group ID	1,848	1,890	1,711	1,753	1,407

° Columns (1)-(2) use one-year lagged values for all net export measures. Columns (3)-(5) use present-year values.

† Columns (3)-(4) use different indicators for education and financial openness than Columns (1), (2) and (5), as described in Section 4.2.4.

Heteroskedasticity-robust standard errors are given in parentheses for all estimates. SEs are clustered by a *Group ID* variable used to group all observations within a particular country and occupation. Levels of statistical significance are denoted by *** p<0.01, ** p<0.05, * p<0.1. R-squared values listed refer to those within *Group ID* clusters. Differing N across specifications reflect available data for each specification. Observations holding a missing value for any variable in a given specification are omitted from the regressions.

Table 7: Occupations & Self-Allocated ISCO-08 Skill Levels

#	OCCUPATION DESCRIPTION	ISCO-08 SKILL LEVEL	#	OCCUPATION DESCRIPTION	ISCO-08 SKILL LEVEL
1	Farm supervisor	3	39	Furniture upholsterer	2
2	Field crop farm worker	1	40	Cabinetmaker	2
3	Plantation supervisor	3	41	Wooden furniture finisher	1
4	Plantation worker	1	42	Wood grinder	2
5	Forest supervisor	3	43	Paper-making-machine operator (wet end)	2
6	Forestry worker	1	44	Journalist	3
7	Logger	1	45	Stenographer-typist	3
8	Tree feller and bucker	1	46	Office clerk	3
9	Deep-sea fisherman	2	47	Hand compositor	3
10	Inshore (coastal) maritime fisherman	2	48	Machine compositor	3
11	Coalmining engineer	4	49	Printing pressman	3
12	Miner	2	50	Bookbinder (machine)	2
13	Underground helper, loader	1	51	Labourer	1
14	Petroleum and natural gas engineer	4	52	Chemical engineer	4
15	Petroleum and natural gas extraction technician	2	53	Chemistry technician	3
16	Supervisor or general foreman	2	54	Supervisor or general foreman	3
17	Derrickman	1	55	Mixing- and blending-machine operator	2
18	Miner	2	56	Labourer	1
19	Quarryman	2	57	Mixing- and blending-machine operator	2
20	Butcher	2	58	Packer	1
21	Packer	1	59	Labourer	1
22	Dairy product processor	1	60	Controlman	3
23	Grain miller	1	61	Occupational health nurse	4
24	Baker (ovenman)	2	62	Blast furnaceman (ore smelting)	2
25	Thread and yarn spinner	1	63	Hot-roller (steel)	2
26	Loom fixer, tuner	2	64	Metal melter	2
27	Cloth weaver (machine)	1	65	Labourer	1
28	Labourer	1	66	Metalworking machine setter	2
29	Garment cutter	1	67	Welder	2
30	Sewing-machine operator	2	68	Bench moulder (metal)	2
31	Tanner	2	69	Machinery fitter-assembler	2
32	Leather goods maker	2	70	Labourer	1
33	Clicker cutter (machine)	2	71	Electronics draughtsman	3
34	Laster	2	72	Electronics engineering technician	4
35	Shoe sewer (machine)	2	73	Electronics fitter	2
36	Sawmill sawyer	1	74	Electronic equipment assembler	2
37	Veneer cutter	1	75	Ship plater	2
38	Plywood press operator	2			

#	OCCUPATION DESCRIPTION	ISCO-08 SKILL LEVEL	#	OCCUPATION DESCRIPTION	ISCO-08 SKILL LEVEL
76	Power distribution and transmission engineer	4	113	Long-distance motor truck driver	2
77	Office clerk	2	114	Ship's chief engineer	4
78	Electric power lineman	2	115	Ship's steward (passenger)	2
79	Power-generating machinery operator	2	116	Able seaman	2
80	Labourer	1	117	Dock worker	1
81	Building electrician	2	118	Air transport pilot	4
82	Plumber	2	119	Flight operations officer	3
83	Constructional steel erector	2	120	Airline ground receptionist	2
84	Building painter	1	121	Aircraft cabin attendant	2
85	Bricklayer (construction)	1	122	Aircraft engine mechanic	3
86	Reinforced concreter	1	123	Aircraft loader	1
87	Cement finisher	2	124	Air traffic controller	2
88	Construction carpenter	2	125	Aircraft accident fire-fighter	2
89	Plasterer	1	126	Post office counter clerk	2
90	Labourer	1	127	Postman	2
91	Stenographer-typist	2	128	Telephone switchboard operator	2
92	Stock records clerk	2	129	Accountant	4
93	Salesperson	3	130	Stenographer-typist	3
94	Book-keeper	3	131	Bank teller	2
95	Cash desk cashier	2	132	Book-keeping machine operator	2
96	Salesperson	3	133	Computer programmer	4
97	Hotel receptionist	2	134	Stenographer-typist	3
98	Cook	3	135	Card- and tape-punching-machine operator	2
99	Waiter	2	136	Insurance agent	3
100	Room attendant or chambermaid	1	137	Clerk of works	2
101	Ticket seller (cash desk cashier)	2	138	Computer programmer	4
102	Railway services supervisor	3	140	Stenographer-typist	3
103	Railway passenger train guard	2	141	Card- and tape-punching-machine operator	2
104	Railway vehicle loader	1	142	Office clerk	2
105	Railway engine-driver	2	143	Fire-fighter	2
106	Railway steam-engine fireman	2	144	Refuse collector	1
107	Railway signalman	2	145	Mathematics teacher (third level)	4
108	Road transport services supervisor	3	146	Teacher in languages and literature (third level)	4
109	Bus conductor	2	147	Teacher in languages and literature (second level)	4
110	Automobile mechanic	2	148	Mathematics teacher (second level)	4
111	Motor bus driver	2	149	Technical education teacher (second level)	4
112	Urban motor truck driver	2	150	First-level education teacher	4

#	OCCUPATION DESCRIPTION	ISCO-08 SKILL LEVEL
151	Kindergarten teacher	3
152	General physician	4
153	Dentist (general)	4
154	Professional nurse (general)	4
155	Auxiliary nurse	4
156	Physiotherapist	4
157	Medical X-ray technician	3
158	Ambulance driver	2
159	Automobile mechanic	2
160	Government executive official – central	3
161	Government executive official – regional or provincial	3
162	Government executive official – local authority	3

Note: Data for occupation #139 are missing in the OWW dataset used.

Table 8: Import & Export Production Sectors by ISIC Industries

Import-Export Sector	Revision-3 ISIC Industries Covered
High-Technology Manufacturing	2423, 30, 33, 353
Medium High-Technology Manufacturing	24 (excluding 2423), 29, 31, 34, 352, 359
Medium Low-Technology Manufacturing	23, 25, 26, 27, 28, 351
Low-Technology Manufacturing	15, 16, 17, 19, 20, 11, 22, 36, 37
Agriculture, Hunting, Forestry & Fishing	01, 02, 03, 04, 05
Mining and Quarrying	10, 11, 12, 13, 14

Source: Zhu, Yamano & Cimper (Compilation of Bilateral Trade Database by Industry and End-Use Category 2011, p.15)

Table 9: OECD Countries Included in Empirical Analysis

(1)	Australia	(16)	Korea
(2)	Austria	(17)	Luxembourg
(3)	Belgium	(18)	Mexico
(4)	Canada	(19)	Netherlands
(5)	Chile	(20)	Norway
(6)	Czech Republic	(21)	New Zealand
(7)	Denmark	(22)	Poland
(8)	Estonia	(23)	Portugal
(9)	Finland	(24)	Slovakia
(10)	France	(25)	Slovenia
(11)	Germany	(26)	Sweden
(12)	Hungary	(27)	Turkey
(13)	Israel	(28)	United Kingdom
(14)	Italy	(29)	USA
(15)	Japan		

Variable Descriptions & Data Sources

Wages

The dependent variables of interest rely upon the OWW database within the 1983-2008 ILO October Inquiry, reporting wages for 161 occupations across over 170 countries. Specifically, OWW's *hw4wuus* variable reports hourly occupational wages in current US dollars. All occupational wage data are uniformly weighted, such that each occupational wage is weighted by the inverse of the number of observations received for that particular occupation, country and year (Oostendorp 2012). This weighting system accounts for varying occupational intensities so that the conclusions found in this paper may be accurately extended to countries' aggregate wage distributions. Nevertheless, the absence of explicit occupational employment shares may leave room for estimation bias.

Sectorial Imports & Exports

I accumulate import and export data by sector of production from the STAN Bilateral Trade Flow database within OECD StatExtracts. All values are taken in current US dollars for consistency with wage data. Table 8 (above) lists the Revision-3 ISIC industry codes included in each of the six import-export sectors.

World Development Indicators (World Bank)

(i) Education: Educational attainment measures total enrollment in secondary education as a percentage of the official secondary education age range. Data are sourced from the UNESCO Institute for Statistics.

(ii) Unemployment: Unemployment rates are derived initially from the ILO and take the standard definition of the percentage of the current labor force actively seeking a job but without work.

(iii) GDP per capita: Per-capita income is denoted in current USD, and represents the total gross annual value added of production for a given country divided by its midyear population. Data are acquired from OECD National Accounts databases.

(iv) Inflation: Inflation is measured using annual percentage changes in the Consumer Price Index; it is computed by cost changes for a standard basket of goods via the Laspeyres formula. Inflation data stems from the IMF's International Financial Statistics database.

(v) Trade openness: Data originally source from the OECD National Accounts database. Trade openness calculates the sum of total imports and exports as a percentage of GDP.

(vi) Gross fixed capital formation: Capital formation includes "land improvements (fences, ditches, drains, and so on); plant, machinery and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings; [and] net acquisitions of valuables" (World Bank). Data also come from OECD National Accounts.

(vii) Financial openness: This indicator takes net Foreign Direct Investment (FDI) inflows as a percentage of annual GDP. Data is originally collected from IMF International Financial Statistics and Balance of Payments databases.

Productivity

Technological development is represented using multi-factor productivity level data provided by OECD Statistics, "computed as the difference between the rate of change of output and the rate of change of total inputs" (OECD Statistics).

Additional Education & Financial Variables

A final three control variables source from the public dataset used in Jaumotte *et al* (2013). The latter two are used in the robustness checks of Section 4.2.4.

(i) Domestic financial development: This variable computes the annual ratio of private credit to GDP. Data are taken directly from the Jaumotte dataset, originally sourced from the Financial Structure database presented in Beck, Demirgüç-Kunt, and Levine (2000).

(ii) Higher educational attainment: This measure originally sources from the Barro-Lee (2001) dataset. It calculates the percentage share of the population of ages 15+ with higher education.

(iii) Financial openness: This alternative indicator computes "the sum of total cross-border assets and liabilities over GDP…[including] (for both assets and liabilities) FDI, portfolio equity, debt, financial derivatives, and total reserves minus gold (assets only)" (Jaumotte *et al* 2013).