Published as: "Skill Classification Does Matter: Estimating the Relationship Between Trade Flows and Wage Inequality." Forbes, Kristin J. *Journal of International Trade and Economic Development* Vol. 10, No. 2 (2001): 175-209. DOI: 10.1080/09638190110039046

Skill Classification Does Matter: Estimating the Relationship Between Trade Flows and Wage Inequality

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First version: April 1998
This version: August 2000

JEL Classification: F1
Keywords: Trade, wages, inequality, skill

Abstract: Empirical work must pay careful attention to how it measures the relative skill abundance of countries and the relative skill intensity embodied in trade flows. This paper compiles a new data set, using income levels, average education, manufacturing wages, and an index of these three variables, to classify countries and trade flows as relatively high skill or low skill. Then, in order to show the importance of skill classification, it uses a reduced-form fixed-effects model to estimate the relationship between trade flows and wage inequality. This specification not only controls for any time-invariant omitted variables, but also permits the inclusion of a large number of diverse countries. When more accurate skill rankings are utilized, results suggest that in high-skill abundant countries, increased trade with lower-skill countries is correlated with an increase in wage inequality. This relationship is significant and highly robust and is driven by the negative relationship between trade and low-skill wages (instead of a positive relationship between trade and high-skill wages.) Results, however, are highly dependent on the skill classification utilized.

* Special thanks to Jaume Ventura, an anonymous referee at JITED, and participants in the MIT International Economics seminar for helpful comments and criticism. Further thanks to Martin Rama for use of his wage data.

I. Introduction

Two empirical facts are indisputable. First, trade flows between developed and developing countries have increased since 1970. Second, the demand for low-skilled labor in developed countries has decreased since the end of the 1970's. The popular press rarely questions the link between these two trends, arguing that increased trade is largely responsible for rising inequality in the U.S. and higher unemployment in Europe. Economists, however, are much less certain. Theoretical work, originating with the Heckscher-Ohlin and Stolper-Samuelson theories (referred to as HOS in the remainder of this paper), explains why increased trade between a relatively high-skill abundant and low-skill abundant country would raise wage inequality in the high-skill country and lower it in the low-skill country. More recent theoretical work has offered a number of reasons why this relationship may not hold, and even if it does hold, why the magnitude of any effect may be minor or insignificant. Therefore, the debate on how increased trade has affected wage inequality boils down to an empirical question.

Actually measuring this relationship between trade flows and wage inequality, however, is extremely difficult. Straightforward measures do not exist for many of the variables that form the basis of the HOS theory (and its offshoots), and even if the correct measures do exist for one country, they are rarely consistently measured across countries. One measure that is particularly problematic is the relative skill abundance of various countries. Many economists attempt to measure this variable by using rough proxies for skills--such as the ratio of non-production to production workers. Although most people agree that these proxies are not ideal, they argue that any measurement error is random and therefore should not bias results. For example, in a recent survey of this empirical work, Slaughter writes: "Trade theory is largely silent on this point of how to measure skills. It is generally accepted that the nonproduction-production classification for manufacturing workers suffers more misclassification of skills than a categorization based on education. However, this is [sic] claim is a statement about noisiness of data, not necessarily bias… "[1] Given this difficulty in measuring skill levels, and the belief that any measurement error in existing proxies should not bias estimates, there has been relatively little discussion on how to classify skill abundance across countries.

This paper argues, however, that careful attention must be paid to the definition of skills in the measurement of the effect of trade flows on wage inequality. It shows that reduced-form estimates of this relationship are highly dependent on the skill classification utilized. Section II briefly summarizes key empirical work on this subject and argues that most of this work inaccurately classifies countries and trade flows as high- or low-skill intensive. Section III develops a new data set on trade flows. This data set uses income levels, education, manufacturing wages, and an index of these three variables to classify countries and trade flows as relatively high-skill intensive or low-skill intensive. Section IV then uses this data to measure how changes in trade flows are related to changes in wage inequality within a given country. It utilizes panel estimation in order to control for time-invariant omitted variables. Estimates suggest that when more accurate skill classifications are utilized, increased trade with lower-skill countries is positively related to wage inequality in high-skill countries. This relationship is large, significant, and robust. Next, Section V attempts to decompose this relationship into that with high- and low-skill wages. Results suggest that the positive relationship between trade and wage inequality is driven by a negative relationship between trade and low-skill wages (and not by any relationship with high-skill wages.) Section VI concludes that in each of these tests, the skill definition used to categorize countries and trade flows has a significant impact on coefficient estimates, affecting not only the strengths, but also the signs, of the various relationships between trade flows and wage inequality.

II. Previous Empirical Work and Problems with the Classification of Skills

Economists have utilized an amazing potpourri of methods, samples, and techniques to attempt to measure the impact of increased trade flows on wage inequality.[2] The bulk of this work can be broadly categorized into two approaches: analyses based on changes in goods' prices and changes in factor demands and supplies.

The first approach focuses on the Stolper-Samuelson predictions and papers based on this approach estimate how changes in the relative prices of goods affect relative wages. Results vary from outright rejection of the HOS implications to moderate support. Lawrence and Slaughter (1993) find evidence that the price of low-skill intensive manufacturing goods in the U.S. has actually risen (relative to the price of high-skill intensive goods), thereby rejecting the HOS predictions. Sachs and Shatz (1994) conclude that increased net imports did lower relative prices in low-skill manufacturing goods, and that this exerted some pressure on low-skill wages and employment, but that the aggregate impact was not enough to account for a significant portion of widening inequality. Leamer (1993) finds similar results over some time periods, but reports a large HOS effect during the 1970's and early 1980's. More specifically, he estimates that between 1972 and 1985, trade reduced U.S. average, annual, unskilled wages by $1,000 and raised skilled wages by $6,000—obviously large effects.

The second approach toward testing how increased trade has affected relative wages argues that goods prices are extremely noisy, so papers should focus on changes in factor demands and supplies instead of changes in goods' prices. This "factor-content of trade" approach estimates how changing patterns of trade influence effective factor supplies and demands, and then how changes in factor supplies, demands, and the elasticity of substitution impact relative factor prices. Results obtained using this factor-content approach vary as much as those based on the price-change approach. Borjas, Freeman, and Katz (1997) find that during the 1980's, the labor embodied in trade increased the effective supply of low-skill labor by about 4 to 13 percent, which explains a small (although significant) fraction of this wage decline. Wood (1994, 1995) finds some of the strongest effects of trade on relative wages. He makes several adjustments to the standard analysis, such as using factor requirements of the exporter (instead of the importer), and finds a significant negative correlation between the change in import penetration from developing countries and the change in manufacturing employment. He argues that between one-third and two-thirds of the decreased demand for low-skill workers in developed countries resulted from increased trade with developing nations.

Despite this range of results on the effect of increased trade flows on wage inequality, most economists feel that a consensus has been reached. For example, Lawrence concludes a survey on this topic with the statement: "There is little support for those positions that ascribe a major role to this story [of increased wage inequality] to expanding trade."[3] Rodrik summarizes a literature review with the statement: "… international influences contributed about 20 percent of the rising wage inequality in the 1980s."[4] He admits that although many people consider this contribution unimportant, twenty percent is not a small number. Numerous theoretical and empirical arguments have been proposed to explain why this effect may be so small, and each of these arguments has been countered with equally convincing claims.[5] Therefore, although many economists have come to believe that increased trade flows have had a small impact on wage inequality, the question is still largely unresolved. Moreover, given the ambiguous predictions of the theoretical models, this question must ultimately be answered by further empirical work.

One factor that this empirical work must consider and which has been widely overlooked in the literature is the measurement of skills. According to basic HOS theory, trade flows and countries should be categorized by their relative abundance of skilled and unskilled labor. Yet, accurate statistics on skill abundance only exist for a few countries. As a result, most empirical work uses statistics which should be correlated with skill abundance, such as income per capita or the ratio of nonproduction to production workers in manufacturing. More specifically, one common method of classifying trade flows is by a country's ranking as "high-income" or "low-income" in the World Development Report (WDR). A quick glance at these rankings, however, suggests that income categories, especially when as broad as those utilized by the WDR, are not an accurate indicator of skill levels. For example, in 1990 "High-Income Economies" in the WDR included Saudi Arabia, Kuwait, and the United Arab Emirates—countries that had a high GNP per capita from oil revenues but levels of education lower than most "middle-income" economies. A second common proxy for skill abundance is the ratio of nonproduction (i.e. high-skill) to production (i.e. low-skill) workers. This classification can be a useful indicator of the relative skill intensity embodied in the production of various goods, but it also has a number of problems. For example, "high-skill" jobs such as line-supervisor, product development, and record keeping are classified as production workers, while "low-skill" jobs such as sales delivery, clerical, cafeteria, and construction are classified as nonproduction. Moreover, this classification is only available for manufacturing sectors in most countries, and relative skill intensity could obviously vary across sectors.

The measurement of skills has received little attention for a number of reasons. First, there is little consensus on how to accurately measure skills, even in the human capital literature. A measure of skills should capture basic education and training, as well as learning from co-workers and the ability to adapt to changes or emergencies. These traits are obviously difficult to capture in any one statistic. Second, most preferred statistics on skills are not consistently measured across countries, and even fewer are available across countries as well as across time (which is necessary for panel estimation to control for omitted-variable bias.) Third, although most work on trade and inequality admits that skills are measured with error, most economists believe that this error is random so that it should not bias results.

This lack of attention to the measurement of skills, however, can have a significant impact on estimates of how increased trade flows have affected wage inequality. To show the importance of carefully defining skills, this paper uses several alternative measures of skill abundance. It not only classifies countries and trade flows by income rankings, but also by educational attainment, manufacturing wages, and an index of these three variables.[6] Educational attainment is the most obvious and widely available measure of skills. Not only should education capture years spent in the formal acquisition of skills, but if school is largely a screening device, then education should also capture innate ability. One problem with educational attainment as a measure of skills is that it does not control for school quality. Manufacturing wages should provide a complementary measure of skills since wages should capture skills such as training, learning-by-doing, and learning from co-workers. The disadvantage with wages as a measure of skills is that it assumes perfectly competitive labor markets and does not control for other factors influencing wages. The final measure of skills utilized in this paper, the index, combines statistics on income, education, and wages and is discussed in more detail below.

III. The Model and the Data

To show the importance of more accurately measuring skills, this paper will estimate the effect of increased trade flows on wage inequality throughout the world. The majority of the empirical work on trade and wages has focused on this relationship within the U.S. [7] This focus is not surprising given that increased inequality is more of a concern in the U.S. than in other developed nations, and especially given that even in the data-intensive U.S., it is difficult to obtain information on all of the requisite variables. Extending this analysis to more than one country is extremely difficult, because even if data on wages, production technologies, and skill levels does exist, it is rarely comparable across countries. This paper, however, will take a different approach than traditionally followed in this literature. Instead of using de-aggregated data to estimate the impact of one type of trade flow on workers in one country, it will use a more general framework and panel estimation to simultaneously estimate a number of relationships between trade flows and wage inequality. In other words, it will attempt to estimate how various trade flows impact low-skill wages, high-skill wages, and wage inequality in both high-skill abundant and low-skill abundant countries. A disadvantage of this approach is a loss of specificity in the data available for the analysis. A major advantage is the ability to compare results across countries and thereby develop a more complete picture of how increased trade is related to wage inequality around the world. Another major advantage of this approach is that it allows the use of panel estimation to control for omitted-variable bias.

More specifically, the reduced-form model on which I focus is:

$$\begin{aligned} INEQ_{it} &= \frac{WGHISK_{it}}{WGLOSK_{it}} \\ &= \alpha_i + \beta_1 TRHISK_{it} + \beta_2 TRLOSK_{it} + \beta_3 TRSIMIL_{it} + \beta_4 CAP_{it} \\ &\quad + \beta_5 SKILL_{it} + \beta_6 SKILL_{it}^2 + \beta_7 RIGID_{it} + \eta_t + \varepsilon_{it} \end{aligned} \qquad (1)$$

Where *i* represents each country and *t* represents each time period; $INEQ_{it}$ is inequality for country *i* at time *t*; $WGHISK_{it}$ and $WGLOSK_{it}$ are wages for high-skill and low-skill workers, respectively; α_i is the country-specific effect; $TRHISK_{it}$ is total trade with relatively higher-skill countries in a low-skill abundant country *i; $TRLOSK_{it}$* is total trade with relatively lower-skill countries in a high-skill country *i*; $TRSIMIL_{it}$ is trade with countries of similar skill abundance (i.e. trade other than that counted in $TRHISK_{it}$ and $TRLOSK_{it}$); CAP_{it} is the capital stock; $SKILL_{it}$ is a measure of relative skills; $RIGID_{it}$ is a measure of labor market rigidities; η_t are period dummy variables; and ε_{it} is a randomly distributed error term for country *i* during period *t*.

This model is clearly a simplification of the relationship between trade and wage inequality. It focuses on volumes of trade instead of prices, due to the difficulty in obtaining accurate measures of prices across countries and time. It does not decompose exports and imports into their embodied skills (as suggested by the factor-content approach), since it is impossible to attain this level of detail for a large sample of countries across periods. Instead, this model assumes that aggregate exports from a given country embody, on average, the relative skill abundance of that country as a whole.[8] Variables not captured in the model could simultaneously impact both trade flows and wage inequality. For all of these reasons, this model is not a direct test of the HOS theory, or of any specific theory of how trade flows affect wage inequality. Instead, it attempts to measure how changes in trade flows between different types of countries are related to changes in relative wages. Although a gross simplification, this model does allow a simple comparison of how different skill classifications affect estimates of the relationship between trade and wage inequality.

The variables included in this model are fairly straightforward and theoretical work suggests why these variables ought to be controlled for in tests of the relationship between trade flows and wage inequality. The sensitivity analysis also shows that results are highly robust to changes in model specification. $TRSIMIL_{it}$ captures the fact that trade with similar countries can affect the elasticity of demand (and therefore wages) for low-skill labor. CAP_{it} controls for changes in the capital stock, since capital is a complement to high-skill labor and a substitute for low-skill labor. $SKILL_{it}$ and $SKILL^2_{it}$ adjust for the fact that changes in the relative supplies of skill can affect relative wages and that this impact could be nonlinear. $RIGID_{it}$ corrects for changes in labor-market structures across time, as well as for the manner in which different labor-market structures influence how trade affects relative wages. For example, in flexible labor markets (such as the U.S.) changes in labor demands are quickly absorbed by changes in relative wages. In more rigid labor markets, similar changes in relative labor demands are absorbed by changes in the unemployment rate (which has a higher proportion of low-skill workers). Finally, the period dummies are included to control for any global shocks which might affect wage inequality in any period but are not otherwise captured by the explanatory variables. Appendix A explains, in more detail, the theory linking each of these variables to trade flows and wage inequality.

One final important point about equation (1*)* is that it is a panel model. I use this panel specification to avoid the omitted-variable bias common in most other work estimating the relationship between trade and relative wages.[9] In the standard cross-country approach, if any variable affects relative wages and is correlated with trade but is not otherwise controlled for in the analysis, then estimates of the effect of trade on wages will be biased and inconsistent. Some variables that could potentially cause this problem are: institutions, preferences, measurement techniques, or skill-biased technological change. There are two methods of adjusting for this omitted-variable bias. One is to control for each of these country-specific variables. This is clearly not feasible—especially for a large number of very different countries. The other method is to utilize panel estimation to calculate a constant term or "fixed effect" for each country. This technique controls for country-specific differences that remain constant across time (although it does not correct for any differences that change across periods). This has not been done yet (to my knowledge) in any analysis of the impact of trade on relative wages.

Before estimating this reduced-form model, it is necessary to describe the data used to measure each of these variables. Some of the statistics, such as the capital stock, are fairly straightforward and are taken directly from standard data sets. Others, such as trade flows with relatively low-skill abundant countries, are more complicated, and must be calculated using a combination of data sources. The remainder of this section discusses the statistics used to measure each of these variables in order of increasing complexity. It closes with a description of several different methods of classifying countries and trade flows by relative-skill abundance.

The statistic used to measure the capital stock (CAP_{it}) is the most straightforward. I utilize the ratio of real domestic investment (private plus public) to real GDP as reported in Barro and Lee (1997). My measure of labor market rigidity ($RIGID_{it}$) is only slightly less straightforward. Since there are no internationally comparable measures of labor market structures across countries over time, I simply utilize the unemployment rate reported in the *Statistical Yearbook* published by the United Nations.

Finding data on relative wages is more difficult. While it is possible to obtain data on manufacturing wages or non-agricultural wages for a number of countries, there are no statistics on relatively high- and low-skill wages that are comparable across countries and periods. Therefore, I utilize a narrower definition of high- and low-skill wages. As a proxy for high-skill wages ($WGHISK_{it}$), I average gross annual income for engineers and for skilled industrial workers, and as a proxy for low-skill wages ($WGLOSK_{it}$), I use gross annual income for unskilled or semi-skilled laborers. Wage inequality, or the relative return to skills, is calculated as the ratio of these two wages. The annual incomes used to calculate these statistics are reported by the Union Bank of Switzerland in *Prices and Earnings Around the Globe* for about fifty countries.

Information on the relative supply of high- and low-skill workers is available for only a few countries, while data on educational attainment is widely available and relatively comparable across countries. Some studies therefore suggest combining the data on educational attainment with observations on skill abundance to posit a relationship between these two variables and interpolate the relative supply of skilled workers for any other countries. [10] This procedure is very imprecise, however, since the interpolation generally uses three points to draw two lines, and even these three points are of dubious accuracy and comparability. Moreover, the interpolation is completely unrealistic for developing countries, on which there is no reliable data on relative skill abundance. Therefore, as a proxy for the relative supply of skilled labor, I simply use average years of total education in the population aged over 15, as reported in Barro and Lee (1996). I also include average years of total education squared in order to capture any non-linear relationship between the supply of skills and wage inequality.

A major complication with this global approach to measuring the relationship between trade and wages is how to categorize trade flows. While it is a fairly simple procedure to divide U.S. trade into that with similar or less-skilled countries, it is a much more difficult accounting exercise to sort out individual trade flows between each country in the world. Further complicating this formidable task is that over time the relative skill rankings of many countries have changed significantly. For example, in the late 1960's the East Asian tigers exported low-skill-intensive goods, while recently they export more "middle-skill" goods, and countries such as China and India, which exported very little in the 1960's, are quickly replacing them as exporters of low-skill goods. Even relative rankings with the U.S. can change quickly. Just twenty years ago, Japan had wages one-third of those in the U.S. and trade with Japan could have been categorized as with a "low-skill" nation. This is clearly not the case today. On a more positive note, the International Monetary Fund has compiled a data set *The Direction of Trade* which includes data on trade flows between every country in the world annually since about 1950. Using this data, I label each country in each year as high-skill abundant or low-skill abundant. Next, I consider the flow of trade between each country and each of its partners and categorize each trade flow as with a relatively more-skilled or less-skilled country. Finally, I aggregate these flows for each country, calculating the total amount of trade each country carried out with relatively higher- and lower-skill partners in each year.

While this procedure is mostly an elaborate accounting exercise, the greatest difficulty arose in how to define countries' skills, not only in terms of their absolute ranking as high- or low-skill, but also in terms of their relative rankings for each of the trade flows. As mentioned in Section II, many empirical studies address this problem by using income rankings as reported in the *World Development Report*. As also discussed, these rankings are highly problematic. Therefore, I use this statistic as well as education, wages, and an index of these three variables to categorize the skill abundance and skill intensity of countries and trade flows. [11] Although this further complicates the already laborious accounting of trade flows and countries, it does show how different skill definitions affect estimates of the relationship between trade and wage inequality.

The first categorization procedure repeats the technique used in previous work on this topic—classifying countries according to their income rankings in the *World Development Report*. The World Bank labels each country as high income, middle income, or low income in each year. To define absolute skill levels, I follow the standard procedure and consider high-income countries as high-skill abundant, and middle- and low-income countries as low-skill abundant. To define relative skill levels, I classify trade with a country in a higher-income group as trade with a relatively high-skill nation, and trade with a lower-income group as with a relatively low-skill nation. Note that exports from a middle-income country to a low-income country would be considered trade from a higher-skill to a lower-skill nation, even though both are considered low skill in absolute terms.

Instead of focusing on income levels, the second categorization method uses average years of total education in the population aged over fifteen as a proxy for skills.[12] In absolute terms, a country is considered high skill if its average education level is greater than the mean plus one-quarter of a standard deviation (for the entire sample.) A country is considered low skill if its average education level is less than the mean minus one-quarter of a standard deviation.[13] In relative terms, trade flows are classified as trade with a higher-skill country if the partner's average education is more than 25 percent greater than in the originating country, and trade is classified as with a lower-skill country if the partner's average education is less than 25 percent lower than in the originating country.

The third categorization method utilizes average wages in the manufacturing sector as a proxy for skills.[14] In absolute terms, a country is considered high skill if its average wage is greater than the mean wage plus one-quarter of a standard deviation (for the sample). A country is considered low skill if its average wage is lower than the mean wage less one-quarter of a standard deviation. In relative terms, trade flows are classified as trade with a higher-skill country if the partner's average wage is more than 25 percent greater than in the originating country, and trade is classified as with a lower-skill country if the partner's average wage is less than 25 percent lower than in the originating country.

Since each of these classification techniques has advantages and disadvantages, I use one final method to categorize countries and trade flows. I construct an index based on each of the three measures used above: income levels; average years of total education; and average manufacturing wages. This index is meant to combine the different aspects of skill that are captured in each of the other measures. More specifically, after classifying each country and trade flow as explained above, I calculate total trade flows for each country as an average of trade flows calculated using each of the three measures (placing equal weight on each measure.) For example, to calculate the index of trade flows between country X and higher-skill countries, I average trade flows between country X and higher-skill countries as classified by income, education, and manufacturing wages.

Once this accounting and aggregation procedure is complete, each of the four classification techniques yields three variables: $TRHISK_{it}$ (total trade with relatively higher-skill countries in a low-skill abundant country *i); $TRLOSK_{it}$* (total trade with relatively lower-skill countries in a high-skill country *i*); and $TRSIMIL_{it}$ (trade with countries of similar skill abundance). Each of these variables is then divided by GDP in the home country. These variables are aggregate trade flows and are not converted into measures of the actual skills embodied in the flows. Although this conversion would be useful on theoretical grounds, it is difficult for two practical reasons. First, the issue of what production technology (that of the importer or exporter) to utilize for such a conversion is highly debated, and as shown by Wood and discussed above, this choice can have a significant impact on results.[15] Second, to the best of my knowledge, the data required to make these calculations is not available. For example, I would need information on the average skill content of exports from each country, and given the difficulty in even finding a measure of skills, this information is simply not available.

After compiling these statistics on trade flows, capital stocks, labor market rigidities, wages, and skills, it is necessary to make one final modification to the data set. In order to use panel estimation and control for any time-invariant omitted variables, I divide the data into five-year periods. I focus on five-year instead of annual data for a number of reasons. First, several critical statistics in the data set (including the Barro-Lee information on educational attainment) are only available at five-year intervals. Second, by aggregating the trade flow data across several years, this should minimize the impact of short-run disturbances and/or business cycle fluctuations. Third, the annual time-series variation in most of the variables tends to be limited. Fourth and finally, the longer time periods should reduce the serial correlation in error terms and any problems with endogeneity.

Due to data availability, it is only possible to estimate four periods: 1980, 1985, 1990, and 1995. Each of the independent variables in equation *(1)* is taken from the five-year period preceding the date of the dependent variable. This lagged timing structure is utilized for two reasons. First, not only could trade affect relative wages, but relative wages might affect export sales and trade patterns. Lagging the right-hand side variables should minimize any feedback effect and potential simultaneity.[16] Second, any impact of trade, the supply of skills, or the capital stock is probably not immediate and may take several years before being fully reflected in relative wages.[17] Measuring each of the independent variables at the earlier date will allow for this lagged adjustment period.

[insert Table 1]

This final data set includes 36 countries, 4 periods and 123 observations. Table 1 reports sources, dates and detailed definitions for each of the variables. Table 2 lists the high-skill abundant and low-skill abundant countries categorized by income levels, average years of total education, and average manufacturing wages. Some countries, such as the U.S. and Germany, are consistently classified as high-skill abundant, and others, such as Brazil and Egypt, are consistently classified as low-skill abundant. Other countries, however, switch between high skill and low skill depending on the year and/or the definition utilized. Some of these shifts are not surprising. For example, Hungary is ranked as high skill according to educational attainment, but low skill according to income or wages. Similarly, Korea is ranked as low skill by income level, high skill by educational attainment, and low skill by wages--but only until 1985. Other switches are more surprising. For example, France is high skill when ranked by income or wages, but not by education. This suggests that even variables such as educational attainment are subject to measurement error. Taken as a whole, this chart shows the difficulty in using any single statistic as an indication of a country's relative skill abundance. Moreover, given the changes in country classification across skill measures, it should not be surprising that estimates of the impact of trade on wages are sensitive to the skill definition utilized.

[insert Table 2]

IV. Estimation Results: Relationships Between Trade Flows and Wage Inequality

Now that the data set and trade variables have been constructed, it is possible to estimate the reduced-form model predicting wage inequality (equation 1) and test if the classification of skills affects estimates. Results obtained using fixed effects and random effects are reported in Table 3. A Hausman specification test rejects random-effects in each of the four cases (at any standard level of significance), so in the discussion that follows, I focus on the fixed-effects estimates.[18]

[insert Table 3]

Although many of the estimated coefficients are not significant, most signs agree with standard economic theory. Focusing first on the non-trade variables, higher levels of capital have a positive (and often significant at the 10 percent level) relationship with wage inequality. This supports the assumption that capital is a complement to high-skill labor and a substitute for low-skill labor. The negative (although insignificant) coefficients on labor-market rigidity supports the theory that in more rigid labor markets, demand shocks will be absorbed more by changes in unemployment and have less of an impact on wage inequality. Given the minimal amount of variation in this variable within most countries, this insignificance is not surprising. Two coefficients that are consistently highly significant are those on the skill variables. The relationship between skills and wage inequality appears to be concave, with a positive coefficient on skills and a negative coefficient on skills squared. This could support the theory discussed in Appendix A: that an initial increase in the supply of skilled labor leads to the adoption of higher-skill intensive technologies, thereby increasing the returns to skills and resultant wage inequality. It could also suggest initial, strong positive externalities between high-skill workers.

Turning next to the trade variables, these coefficient estimates are highly dependent on the skill categorization utilized. In high-skill abundant countries, increased trade with lower-skill countries has a positive relationship with wage inequality. This relationship is highly significant when skill abundance is ranked according to education, wages, or the index, but is not significant when ranked by income. In low-skill abundant countries, increased trade with higher-skill countries has a negative relationship with wage inequality when countries are ranked by income, wages, or the index, but a positive relationship when countries are ranked by education. None of these is significant except that based on wages (which is highly significant.) Trade between similar countries has a positive relationship with inequality (as expected) when countries are classified by income, education, or the index, but this coefficient is only significant under the income classification.

Therefore, the key result of Table 3 is that when skill rankings of countries and trade flows are classified by more accurate measures than using broad income groups, trade with relatively lower-skill countries has a significant positive relationship with wage inequality in high-skill countries. Using the estimate based on the index, if a high-skill country increases trade with relatively lower-skill countries (as a fraction of GDP) by 0.10, this is correlated with an increase of 1.2 in the wage-inequality ratio over the next five years. To put these numbers in a more meaningful context, a difference of 0.10 in the ratio of trade with lower-skill countries (to GDP), is approximately the difference in this ratio between Germany and Spain in 1990. A difference in the wage-inequality ratio of 1.2 is approximately the difference in this ratio between Italy and Sweden in the same year.[19]

Since these results are central to this paper, I do a fairly detailed sensitivity analysis to see if coefficient estimates are robust to changes in variable definitions and model specification. First, since the skill categorization of trade flows based on education and wages uses somewhat random divisions (trade is considered to be relatively more or less skill abundant if skills differ by 25 percent or greater), I reclassify trade flows using a 10 or 50 percent division for these rankings. Next, I try several different definitions of wage inequality[20] and the supply of skills.[21] Finally, to test for the effect of model specification, I drop one variable at a time and add a number of other variables that could have an impact on wage inequality.[22] I also include a time trend, exclude the period dummies, and test if the relationship between trade and wages changes over time. A sample of these results is reported in Table 4. In each of these robustness tests, trade with lower-skill countries continues to have a positive relationship with wage inequality when countries and trade flows are categorized according to education, wages or the index. This relationship is highly significant in almost all cases.[23] In fact, coefficient estimates of TRLOSK are fairly stable.

[insert Table 4]

All of these estimates have one potentially significant problem: endogeneity. The estimated coefficients show a set of relationships between trade and relative wages, but they do not indicate the direction of causality. For example, as explained above, increased trade with low-skill countries might increase inequality in a high-skill country. On the other hand, if wage inequality increased in the high-skill country, its comparative advantage would deteriorate (since the relative cost of producing high-skill intensive goods would increase). This would reduce trade flows with the low-skill abundant country, partially counteracting the impact of trade on relative wages. Not controlling for this simultaneity could downward bias estimates of the impact of trade on relative wages. As discussed above, in an attempt to minimize this problem and isolate the impact of trade flows on wage inequality, I lag each of the explanatory variables by one period. This does not fully correct for endogeneity, however, if errors are correlated across periods.

An alternate technique for addressing this endogeneity problem is to instrument for trade flows. This is difficult due to the lack of good instruments that are available across countries, especially since these instruments must vary within each country across periods in order to use them in this fixed-effects framework. One proxy for trade flows, and especially how these flows have changed since 1970, is trade barriers. So many barriers to trade are non-quantifiable, however, that they are extremely difficult to measure, and of the few data sets that do try to measure them, none cover enough years for panel estimation. Moreover, even if sufficient data on trade barriers did exist, this would capture only part of the impetus behind increased trade flows in the past two decades. Lower transport costs, such as the "container revolution," may have had as substantial an impact on trade flows as the reduction in tariffs and quotas. Potentially even more important than either of these changes is the shift in many developing countries toward outward-orientation instead of import-substitution (such as in Latin America.) This sort of policy shift is obviously difficult to capture in any consistent cross-country measure.

Due to all of these problems, I use three variables to instrument for trade flows with relatively lower-skill and higher-skill countries: total trade to GDP; total population; and GDP. I use total trade to GDP as a measure of openness. Since this is the *de facto* amount traded by each country, it should reflect changes in tariffs, non-tariff barriers, transport costs, and even government policy towards outward orientation. I use total population and GDP to control for country size and the size of the domestic market, since theoretical and empirical work on trade has shown that larger countries and markets tend to have lower levels of trade. (I can not use country size because it does not vary across periods.) Using these three instruments for TRHISK and TRLOSK, I reestimate equation *(1)* using fixed effects. Results are reported in Table 5.

[insert Table 5]

Many of the results in Table 5 are similar to those obtained without the instruments for trade flows, although standard errors are higher (as expected with the use of instrumental variables.) Focusing first on the non-trade variables, the coefficients on capital continue to be positive and insignificant. The coefficients on skill levels also continue to be positive (and sometimes significant) and those on skills squared continue to be negative. The coefficients on labor-market rigidities continue to be highly insignificant.

Turning next to the coefficients on the trade variables, these estimates strengthen the results reported above. No matter which skill categorization is utilized, increased trade with lower-skill countries has a positive effect on wage inequality in high-skill countries. This relationship is highly significant when skills are ranked according to education or wages, but is not significant when ranked by income or the index. In each of the four cases, the point estimate of the coefficient on TRLOSK increases from that in Table 3, as predicted if endogeneity between TRLOSK and wage inequality generates a downward bias in equation (1). Point estimates of the coefficient on TRHISK also increase, although each of these estimates is highly insignificant. Trade between similar countries also has an insignificant impact on wage inequality. The estimated signs on TRHISK and TRSIMIL continue to fluctuate based on which skill categorization is utilized.

Since these results are central to this paper, I repeat the sensitivity analysis performed above to see if coefficient estimates are robust to changes in the sample, variable definitions and model specification. I test for the effect of utilizing different divisions to classify trade flows, redefining several key variables, and varying model specification. Table 6 reports a sample of these results, focusing on estimates when countries and trade flows are classified according to education.[24] Many of the coefficient estimates are fairly stable, although standard errors are so high that most coefficients are not significant. Better instruments than total trade to GDP, population, and GDP would undoubtedly improve estimates. Despite this problem, the coefficient on TRLOSK remains positive in each test and is significant (at the 5 percent level and usually at the 1 percent level) in about three-quarters of the cases. The median estimate suggests that if a high-skill country increases trade with lower-skill countries (as a share of GDP) by 0.10, its wage-inequality ratio will increase by 2.3 over the next five years. This is clearly a significant impact.

[insert Table 6]

To summarize, estimated coefficients on the trade variables suggest several key points. First, when skill rankings of countries and trade flows are classified by more accurate measures than broad income groups, trade with relatively lower-skill countries has a significant positive relationship with wage inequality. Second, trade with relatively higher-skill countries has no significant relationship with wage inequality. This could result from the fact that the representation of low-skill countries is fairly limited in this paper. Third, trade with similar countries does not appear to have a significant relationship with inequality, suggesting that any elasticity effect is small. Fourth although it is difficult to isolate the direct impact of trade flows on wage inequality, estimates based on education and wage classifications suggest that, within a given high-skill country, an increase in trade with lower-skill countries will generate a significant increase in wage inequality. Finally, the definition of skill used to categorize countries and trade flows has a significant impact on coefficient estimates, affecting not only the strengths, but also the signs of the various relationships between trade flows and wage inequality.

V. Estimation Results: Relationships Between Trade and High-Skill or Low-Skill Wages

The previous section estimated how increased trade is related to (or affects) wage inequality. Focusing on this ratio of high-skill to low-skill wages as the left-hand-side variable, however, could overlook important information on exactly how trade flows are related to inequality. Does any increase in inequality result mainly from a fall in low-skill wages? Or from a rise in high-skill wages? Or could both high-skill and low-skill wages tend to rise or fall simultaneously, so that there is little impact of trade on relative wages but a substantial impact on absolute wage levels?

In an attempt to isolate these various relationships, I repeat the analysis of Section IV, but replace the dependent variable in equation *(1)* (previously wage inequality) with either the logarithm of high-skill or low-skill wages. Results based on fixed effects are reported in Table 7. Most coefficient estimates are insignificant and R^2's are low, suggesting (not surprisingly) that a wide variety of factors not captured by this simple model drive changes in wages within each country. Despite this lack of explanatory power, several results do merit comment. In columns 1-4, where the dependent variable is high-skill wages, two of the coefficients on TRLOSK are negative and significant (at the 5 percent level.) This implies that in high-skill countries, increased trade with lower-skill nations may be correlated with a reduction in high-skill wages. This is the opposite relationship than that predicted by the HOS theory. When skills are classified according to income or wages, however, this negative relationship disappears.

[insert Table 7]

A more robust relationship between trade and wages appears in columns 5-8, where the dependent variable is low-skill wages. When skill rankings of countries and trade flows are classified by any measure except income, an increase in trade with relatively low-skill countries is correlated with a decrease in low-skill wages. These results support the HOS predictions. Moreover, this relationship could be substantial. Taking the median of the three estimates (which is based on education classifications), if a high-skill country increases trade (as a share of GDP) with relatively low-skill countries by 0.10, this is correlated with a 34 percent decrease in low-skill wages over the next five years. Given the magnitude of this relationship, I repeat the sensitivity tests used above. Table 8 reports a sample of these results, focusing on estimates when countries and trade flows are classified by education. Results are highly robust, with the coefficient on TRLOSK always positive and significant at the 5 percent level, and almost always significant at the 1 percent level.

[insert Table 8]

To summarize, columns 1-4 of Table 7 suggest a small, borderline significant, negative relationship between trade with lower-skill countries and high-skill wages. Columns 5-9 suggest a large, highly robust, negative relationship between trade with lower-skill countries and low-skill wages. Combining these results provides evidence on the impetus behind the positive effect of increased trade with low-skill countries on wage inequality, as found in Section IV. This positive effect appears to be driven by changes in the denominator (low-skill wages.) Any change in the numerator (high-skill wages) appears to be very small or even counteract the change in low-skill wages. Therefore, the greatest impact of increased trade with low-skill countries on wage inequality appears to be a negative effect on low-skill wages, with little positive effect on high-skill wages (as predicted by the HOS theory.) This suggests that in wealthy countries, the concerns of low-skill workers may be justified. Increased trade with developing countries may have generated a significant decline in their relative wages.

One potential problem with these estimates of the relationship between trade flows and high- and low-skill wages is endogeneity. As discussed above, not only could trade flows affect wages, but a change in either wage could affect comparative advantage and the resultant trade flows. In order to correct for this problem, I follow the procedure outlined in Section IV and instrument for trade flows with total trade to GDP, total population, and GDP. Results are disappointing. No matter which skill classification is utilized, all of the trade variables (and in fact, almost all of the variables) are insignificant. Table 9 presents a sensitivity analysis for the impact of trade flows on low-skill wages when countries and trade flows are classified according to education. In each specification, increased trade with lower-skill countries has a negative impact on low-skill wages, although in most cases this effect is not significant. This series of regressions attempting to estimate the impact of various trade flows on high- and low-skill wages supports two of the previous conclusions: the importance of obtaining better instruments for trade flows and the difficulty in capturing any within-country wage changes in this simple, reduced-form model.

[insert Table 9]

VI. Summary

Basic trade theory predicts that increased trade between a high-skill and low-skill country should increase wage inequality in the high-skill country and decrease inequality in the low-skill country. These relationships, however, are extremely difficult to test empirically. Straightforward measures do not exist for many of the key variables which form the basis of the HOS theory, and even if the correct measures do exist for one country, they are not consistently measured across countries. One measure which is particularly problematic is skill abundance. Many economists address this problem by using rough proxies for skills--such as the ratio of nonproduction to production workers. Although most people agree that these proxies are not ideal, they argue that any measurement error is random and therefore should not bias results.

This paper argues, however, that careful attention must be paid to the definition of skills. To show the importance of skill definition, this paper compiles a new data set on trade patterns, using income levels, average education, manufacturing wages, and an index of these three variables, to classify countries and trade flows as relatively high-skill intensive or low-skill intensive. Then, using a reduced-form model, it estimates several different relationships between trade and relative wages. In each case, this paper utilizes panel estimation in order to control for any time-invariant omitted-variable bias. When skills are classified by more accurate measures than broad income groups, trade with lower-skill countries has a significant positive relationship with wage inequality in high-skill countries. This relationship is large and highly robust and is driven by the negative relationship between trade and low-skill wages (instead of a positive relationship between trade and high-skill wages.) This negative relationship between trade and low-skill wages is also large and highly robust.

One potential problem with these estimates is endogeneity between trade flows and wages. I attempt to correct for this problem by instrumenting for trade flows. Due to the difficulty in finding good instruments in this panel framework, these estimates of the effect of trade flows on wage inequality and high- and low-skill wages are not as robust as those without instruments. They do, however, show that when skill abundance is ranked according to education or wages, increased trade with lower-skill countries has a positive effect on wage inequality in high-skill countries.

Endogeneity and a lack of good instruments are not the only potential problems with this paper. The measure of wage inequality (the ratio of average wages of engineers and skilled industrial workers to average wages of unskilled building laborers) may not accurately capture changes in aggregate wage inequality within a given country. Sample size and period coverage is limited, and low-income countries are underrepresented. This could explain the fairly weak estimates of the impact of trade on low-skill countries. Finally, the reduced-form approach of this paper does not allow a careful investigation of the specific channels through which trade flows affect wage inequality.

Despite these problems, this paper does make several important contributions. It emphasizes the importance of using panel estimation in order to control for any time-invariant omitted-variable bias. Most important, it shows the need to more accurately classify the relative skill abundance and skill intensity of countries and trade flows. When skill rankings are based on income levels, as frequently done in this literature, the impact of trade flows on wages and wage inequality is significantly different than that based on more accurate measures. When these more accurate skill rankings are utilized, estimates suggest that in high-skill abundant countries, increased trade with lower-skill countries may have generated a significant increase in inequality and decrease in low-skill wages.

Appendix A

This appendix explains the theory justifying the inclusion of each of the explanatory variables in this paper's central model. The reduced-form model is:

$$\begin{aligned} INEQ_{it} &= \frac{WGHISK_{it}}{WGLOSK_{it}} \\ &= \alpha_i + \beta_1 TRHISK_{it} + \beta_2 TRLOSK_{it} + \beta_3 TRSIMIL_{it} + \beta_4 CAP_{it} \qquad (1) \\ &\quad + \beta_5 SKILL_{it} + \beta_6 SKILL_{it}^2 + \beta_7 RIGID_{it} + \eta_t + \varepsilon_{it} \end{aligned}$$

Where *i* represents each country and *t* represents each time period; $INEQ_{it}$ is inequality for country *i* at time *t*; $WGHISK_{it}$ and $WGLOSK_{it}$ are wages for high-skill and low-skill workers, respectively; α_i is the country-specific effect; $TRHISK_{it}$ is total trade with relatively higher-skill countries in a low-skill abundant country *i; $TRLOSK_{it}$* is total trade with relatively lower-skill countries in a high-skill country *i*; $TRSIMIL_{it}$ is trade with countries of similar skill-abundance (i.e. trade other than that counted in $TRHISK_{it}$ and $TRLOSK_{it}$); CAP_{it} is the capital stock; $SKILL_{it}$ is a measure of relative skills; $RIGID_{it}$ is a measure of labor market rigidities; η_t are period dummy variables; and ε_{it} is a randomly distributed error term for country *i* during period *t*.

$TRSIMIL_{it}$ is included in this model in order to control for trade between similar countries (i.e. between two high-skill or two low-skill countries). Granted, according to the HOS theory, there would be minimal trade between countries with similar factor endowments. This is obviously not the case in the real world, however, where a majority of trade is between countries of comparable income levels. Moreover, trade between countries with the same relative skill abundance could affect relative wages by changing the elasticity of demand for labor, and especially for unskilled labor.[25] To use a concrete example, consider the impact of NAFTA on low-skill labor in the U.S. According to the standard HOS analysis, the U.S. would import low-skill intensive goods from Mexico and export high-skill intensive goods, which would decrease the demand for low-skill workers and lower their relative wage in the U.S. This is shown in Figure 1 as an inward shift of the demand curve for low-skill labor from A to B. At the same time, the increased effective supply of labor in the U.S. would increase the elasticity of demand for low-skill workers (because firms have less power to raise wages and stay in business). This is represented in the figure by a flattening of the demand curve from A to C. The total impact of trade with Mexico on low-skill wages in the U.S. would be the combination of these two effects, shown as the new demand curve D and wage W'.

[insert Figure 1]

This is not, however, the end of the story. Under NAFTA, the U.S. simultaneously increased trade with Canada. Since the relative abundance of skills is similar in Canada and the U.S., this increased trade would not affect the position of the low-skill labor-demand curve. The increased effective supply of low-skill labor would, however, further increase the elasticity of demand for low-skill labor and flatten the labor demand curve. This additional effect implies that after freeing trade with both Mexico and Canada, the demand curve for low-skill labor in the U.S. was actually E instead of D, and the wage was W* instead of W '. Any analysis of the impact of increased trade with Mexico which ignores simultaneous changes in trade with Canada would overestimate the impact on low-skill wages (measuring the impact as the change from W to W* instead of from W to W '.)

Few economists have corrected for (or even mentioned) this effect of increased trade on the elasticity of demand for labor. This is surprising. Not only is there strong empirical evidence that trade integration increases the elasticity of demand for output faced by domestic producers (as seen, for example, in a reduction of price-cost margins), but it is widely accepted that the demand for labor is largely a derived demand that is directly linked to elasticities in the product market. In one of the only attempts to measure these effects, Slaughter estimates that the demand for production labor in U.S. manufacturing has become more elastic over time, but the demand for non-production labor shows no clear trend and “the hypothesis that trade contributed to increased elasticities has mixed support, at best.”[26] While the impact of trade on labor elasticities is therefore far from resolved, any analysis that omits the effect of increased trade between similar countries (when estimating the impact of trade between dissimilar countries) could be biased. This is a valid concern since the volume of trade between developed countries has actually increased more than the volume of trade between developed and developing countries in the past twenty years.

CAP_{it} is included in this basic model to control for the fact that changes in capital levels can affect the relationship between trade and wages. Much theoretical work on trade and wages assumes that either capital is immobile or that relative levels of capital remain constant in each country. Authors usually justify this assumption with the observation that capital and labor shares have remained fairly constant in western economies. Empirical evidence, however, suggests that capital is highly mobile, especially in the past decade, and capital shares in many developing economies have increased significantly. Evidence also suggests that capital is a complement to high-skill labor and a substitute for low-skill labor, so that changes in capital flows could significantly affect the relative return to skills. As a result, not controlling for capital flows could downward bias estimates of the impact of trade on inequality. For example, if a developing country increased trade with a developed country, HOS theory predicts that wages of low-skill workers in the developing country would rise. Since capital is a substitute for low-skill labor, the return to capital would also rise and generate a capital inflow into the developing country. This would, in turn, lower unskilled wages and raise skilled wages, thereby muting the impact of increased trade on relative returns and inequality. The opposite would occur in the developed country, where capital would flow out, mitigating the decline in low-skilled wages and the increase in inequality.

Changes in $SKILL_{it}$ can also affect the relationship between trade and wages. Work based on the factor-content-of-trade approach stresses the importance of controlling for this variable, while most work based on the price-change approach argues that it is not necessary because factor prices are mainly derived from goods' prices. Ignoring changes in the supply of skills, however, could bias estimates of the effect of trade on inequality. For example, according to the HOS theory, increased trade between developed and developing countries would increase high-skill wages in developed countries and lower them in developing countries. But at the same time, educational attainment and the relative abundance of high-skill workers has increased in most of the world. If all else remained constant, this supply change would have reduced the relative wages of high-skill workers in both types of countries, counteracting the Stolper-Samuelson effect in the developed country and augmenting it in the developing country. Therefore, ignoring this supply change would lead us to underestimate the HOS impact of trade on inequality in the developed country and overestimate it in the developing country.

Moreover, this relationship between the supply of skills and wage inequality may not be linear. If most of a country's work force is low skilled, then firms will focus on low-skill intensive production processes. As a small percent of the population becomes high skilled, however, this could lead firms to invest in high-skill intensive technology and actually increase the demand for high-skill workers.[27] If this effect dominates the increased supply of high-skill workers, it would generate an increase in high-skill wages and wage inequality, and if this effect only dominates for certain distributions of skills, then the relationship between the supply of skills and wage inequality may be non-linear. Few studies estimating the relationship between wage inequality and increased trade flows control for this potential non-linearity.

The final variable included in the basic specification of equation (1) is $RIGID_{it}$. Several recent papers argue that labor market structure and changes in this structure are critical determinants of the cross-country relationship between trade and wages.[28] Specifically, countries such as the U.S. and U.K. have reformed and deregulated their labor markets, so that these markets are fairly flexible. As a result, changes in relative labor demands are quickly absorbed by changes in relative wages. Other European countries, however, did not undergo these reforms, so their labor markets are much more rigid. As a result, similar changes in relative labor demands are absorbed by changes in the unemployment rate (which has a higher proportion of low-skill workers) instead of relative wages. Therefore, if trade decreases the relative demand for low-skill workers by the same amount in each of these countries, it would increase wage inequality in the U.S. and U.K., but have little impact on wage inequality in the rest of Europe. An analysis that does not control for these differences in labor market structure would underestimate the impact of trade on the relative demands for high-skill and low-skill labor.

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Table 1
Summary Information

Variable	*Definition*	*Source*	*Years*
CAP	Ratio of real domestic investment (private plus public) to real GDP (averaged over the given years) (SH 5.5)	B&L (1)	1970-75, 1975-80, 1980-85, 1985-90
DUMHISK	Dummy variable; 1 for a high-skill country and 0 otherwise	Calc.	1975, 1980, 1985, 1990
DUMLOSK	Dummy variable; 1 for a low-skill country and 0 otherwise	Calc.	1975, 1980, 1985, 1990
EDUC	Average years of total schooling in the total population aged over 15	B&L (2)	1975, 1980, 1985, 1990
INCOME	Income classification. 1=Low income; 2=Middle income; 3=High income.	WDR	1978, 1980, 1985, 1990
INDEX	Index based on average of INCOME, EDUC and WAGE (see text for further information)	Calc.	1975, 1980, 1985, 1990
INEQ	Ratio of WGHISK to WGLOSK	Calc.	1982, 1985, 1991, 1994
RIGID	Percentage of unemployed in the total population	UN	1975, 1980, 1985, 1990
SKILL	Average years of total schooling in the total population aged over 15	B&L (2)	1975, 1980, 1985, 1990
TRHISK (when divided by INCOME)	DUMLOSK*Avg (trade with higher skilled partners / GDP); higher skilled if $INCOME_p > INCOME_c$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRLOSK (when divided by INCOME)	DUMHISK*Avg (trade with lower skilled partners / GDP); lower skilled if $INCOME_p < INCOME_c$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRHISK (when divided by EDUC)	DUMLOSK*Avg (trade with higher skilled partners / GDP); higher skilled if $(EDUC_p/EDUC_c)>125\%$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRLOSK (when divided by EDUC)	DUMHISK*Avg (trade with lower skilled partners / GDP); lower skilled if $(EDUC_p/EDUC_c)<75\%$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRHISK (when divided by WAGE)	DUMLOSK*Avg (trade with higher skilled partners / GDP); higher skilled if $(WAGE_p/WAGE_c)>125\%$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRLOSK (when divided by WAGE)	DUMHISK*Avg (trade with lower skilled partners / GDP); lower skilled if $(WAGE_p/WAGE_c)<75\%$	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRHISK (when divided by INDEX)	Average of TRHISK when divided by INCOME, EDUC and WAGE	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRLOSK (when divided by INDEX)	Average of TRLOSK when divided by INCOME, EDUC and WAGE	Calc.	1973-75, 1978-80, 1983-85, 1988-90
TRSIMIL	Average trade/GDP with "similar" countries, i.e. trade other than that included in TRHISK or TRLOSK	Calc.	1973-75, 1978-80, 1983-85, 1988-90
WAGE	Annual earnings in manufacturing for all workers, in 1987 $U.S.	Rama	1980, 1985, 1990
WGHISK	Average gross income per year of engineers and skilled industrial workers, in 1987 $US	UBS	1982, 1985, 1991, 1994
WGLOSK	Average gross income per year of unskilled or semi-skilled building laborers, in 1987 $U.S.	UBS	1982, 1985, 1991, 1994

NOTE: Total sample is 36 countries and 4 periods.
SOURCES: B&L (1) is "Data Set for a Panel of 138 Countries" collected in Barro and Lee (1997).
B&L (2) is data set compiled in Barro and Lee (1996). Calc. means calculated for this paper. Rama is data compiled by Martin Rama at the World Bank. UBS is Union Bank of Switzerland, various years. UN is *Statistical Yearbook* published by the United Nations. WDR is the World Bank, *World Development Report* for the given year.

Table 2
Country Classifications According to Different Skill Definitions

High-Skill Abundant Countries			*Low-Skill Abundant Countries*		
Divided by Income	***Divided by Education***	***Divided by Wages[a]***	***Divided by Income***	***Divided by Education***	***Divided by Wages[a]***
Australia	Argentina	Australia	Argentina	Bahrain (75, 80, 90)	Argentina
Austria	Australia	Austria	Bahrain (75, 80, 90)	Brazil	Brazil
Canada	Austria (85)	Bahrain (75, 80, 90)	Brazil	Columbia	Egypt
Cyprus (90)	Canada	Canada	Columbia	Egypt	Hungary (90)
Denmark	Cyprus (85, 90)	Columbia	Cyprus (85)	Mexico (75-85)	Korea (75-85)
Finland	Denmark	Denmark	Egypt	Portugal	Mexico (75-85)
France	Finland	Finland	Greece	Singapore (90)	Netherlands (75)
Germany	Germany	France	Hong Kong (75-85)	So. Africa	Panama
Hong Kong (90)	Greece (80-90)	Germany	Hungary (90)	Thailand (75, 80, 90)	Philippines
Ireland	Hong Kong	Greece (90)	Israel (75-85)	Venezuela (75, 85, 90)	Portugal
Israel (90)	Hungary (90)	Hong Kong	Korea		Singapore (75,80)
Italy	Ireland	Ireland	Mexico		South Africa (85)
Japan	Israel	Israel	Panama		Thailand (75, 80, 90)
Netherlands	Japan	Italy	Philippines		
Norway	Korea	Japan	Portugal		
Singapore (90)	Netherlands	Netherlands (80-90)	Singapore (75-85)		
South Africa (75)	Norway	Norway	South Africa (80-90)		
Spain (85, 90)	Panama (90)	Spain (75, 80, 90)	Spain (75, 80)		
Sweden	Sweden	Sweden	Thail. (75, 80, 90)		
Switzerland	Switzerland	Switzerland	Venezuela		
United Kingdom	United Kingdom	United Kingdom			
United States	United States	United States			
		Venezuela (85)			

NOTE: (a) Wages are average manufacturing wages.

Table 3
Regression Results: Relationships Between Trade Flows and Wage Inequality

	Fixed Effects				***Random Effects***			
	Skill defined By INCOME (1)	***Skill defined by EDUC (2)***	***Skill defined By WAGE (3)***	***Skill defined by INDEX (4)***	***Skill defined by INCOME (5)***	***Skill defined by EDUC (6)***	***Skill defined by WAGE (7)***	***Skill defined by INDEX (8)***
TRLOSK	2.59	15.71**	24.43**	11.85**	9.79**	14.23**	11.98**	13.83**
	(3.72)	(2.70)	(3.42)	(4.06)	(2.06)	(2.18)	(2.95)	(2.30)
TRHISK	-1.02	1.53	-11.19**	-1.61	2.95**	-7.81*	1.30	3.78*
	(2.44)	(4.34)	(2.92)	(4.26)	(1.07)	(3.25)	(1.09)	(1.58)
TRSIMIL	2.80**	0.38	-0.63	1.64	-0.88	0.02	-0.53	-0.96
	(1.10)	(1.02)	(0.85)	(1.53)	(0.53)	(0.36)	(0.55)	(0.54)
CAP	8.79	7.53	7.00	13.49*	-2.92	-0.73	-1.89	-0.73
	(4.67)	(4.59)	(5.98)	(6.26)	(3.25)	(3.32)	(4.75)	(4.23)
SKILL	2.53**	1.97*	6.20**	6.08**	0.18	0.19	0.26	-0.06
	(0.87)	(0.82)	(1.58)	(1.68)	(0.52)	(0.55)	(0.84)	(0.70)
$SKILL^2$	-0.11*	-0.13*	-0.34**	-0.32**	-0.03	-0.06	-0.05	-0.03
	(0.06)	(0.05)	(0.11)	(0.12)	(0.04)	(0.04)	(0.06)	(0.05)
RIGID	-0.08	-0.09	-0.03	-0.01	-0.06	-0.04	-0.09	-0.04
	(0.07)	(0.07)	(0.09)	(0.09)	(0.05)	(0.05)	(0.07)	(0.06)
R^2	***0.48***	***0.51***	***0.64***	***0.61***	***0.40***	***0.35***	***0.29***	***0.47***
Counts.	***36***	***36***	***34***	***34***	***36***	***36***	***34***	***34***
Observations	***123***	***123***	***92***	***92***	***123***	***123***	***92***	***92***

NOTES: Dependent Variable is INEQ (High-Skill Wage/Low-Skill Wage). Standard errors in parentheses. Period dummies not reported.
* is significant at the 5 percent level and ** is significant at the 1 percent level.

Table 4
Sensitivity Analysis: Relationships Between Trade Flows and Wage Inequality[a]

	Standard Results (1)	***Gini on LHS (2)***	***10% Educ. Divisions (3)***	***50% Educ. Divisions (4)***	***SKILL is Toted/Prim (5)***	***Drop TRSIMIL (6)***	***Add GDP & GDP^2 (7)***	***Add Avg. Wages (8)***	***No Period Dummies (9)***	***Add Time Trend*[b] (10)**
TRLOSK	11.85**	20.68*	10.05**	19.55	13.99**	14.93**	11.20**	11.62**	10.98**	11.60**
	(4.06)	(10.18)	(1.83)	(13.47)	(4.25)	(2.89)	(4.26)	(4.11)	(3.63)	(3.89)
TRHISK	-1.61	23.58*	0.68	-4.64*	-2.16	1.61	-4.02	-1.95	-2.64	-1.82
	(4.26)	(10.94)	(1.11)	(2.03)	(4.69)	(3.03)	(4.66)	(4.32)	(3.70)	(4.13)
TRSIMIL	1.64	-5.02	0.11	4.41**	0.70		2.16	1.71	1.87	1.68
	(1.53)	(3.67)	(1.09)	(1.29)	(1.60)		(1.58)	(1.54)	(1.44)	(1.50)
CAP	13.49*	-35.50*	9.98*	6.61	17.16*	13.04*	15.69*	13.18*	12.36*	13.15*
	(6.26)	(17.01)	(4.31)	(5.09)	(6.88)	(6.26)	(7.41)	(6.32)	(5.76)	(6.05)
SKILL	6.08**	-3.84	2.42**	1.88*	93.99**	5.70**	5.29**	6.08**	6.12**	6.00**
	(1.68)	(5.37)	(0.78)	(0.92)	(34.66)	(1.65)	(1.80)	(1.69)	(1.60)	(1.63)
$SKILL^2$	-0.32**	0.17	-0.14**	-0.09	-24.85*	-0.30**	-0.25*	-0.32**	-0.32**	-0.32**
	(0.12)	(0.34)	(0.05)	(0.06)	(10.14)	(0.11)	(0.13)	(0.12)	(0.11)	(0.11)
RIGID	-0.01	-0.11	-0.10	-0.13	-0.04	-0.02	-0.05	-0.00	-0.02	-0.02
	(0.09)	(0.21)	(0.07)	(0.08)	(0.10)	(0.09)	(0.10)	(0.00)	(0.07)	(0.07)
							-0.85	-0.00		0.11
							(0.64)	(0.00)		(0.23)
							0.00			
							(0.00)			
Adj. R^2	***0.68***	***0.87***	***0.71***	***0.61***	***0.66***	***0.69***	***0.68***	***0.68***	***0.65***	***0.66***
Countries	***34***	***27***	***36***	***36***	***34***	***34***	***34***	***34***	***34***	***34***
Observations	***92***	***68***	***123***	***123***	***92***	***92***	***92***	***92***	***92***	***92***

NOTES: Dependent Variable is INEQ (High-Skill Wage/Low-Skill Wage). Estimates obtained using fixed effects. Standard errors in parentheses. * is significant at the 5 percent level and ** is significant at the 1 percent level.
(a) All classifications based on INDEX except columns (3) and (4).
(b) Also excludes period dummies.

Table 5
Regression Results: Effect of Trade Flows on Wage Inequality[a]

	Skill defined by INCOME (1)	*Skill defined by EDUC (2)*	*Skill defined By WAGE (3)*	*Skill defined by INDEX (4)*
TRLOSK	5.10	23.26**	37.04*	13.80
	(5.72)	(6.93)	(16.11)	(89.18)
TRHISK	3.13	20.71	-16.64	-16.08
	(7.80)	(26.62)	(30.69)	(119.9)
TRSIMIL	2.75	-1.05	-1.30	4.83
	(2.06)	(1.66)	(1.05)	(29.86)
CAP	8.88	13.51	8.43	13.35
	(5.31)	(9.44)	(11.73)	(13.67)
SKILL	2.45*	1.63	6.99**	7.12
	(0.98)	(1.04)	(2.30)	(7.66)
$SKILL^2$	-0.11	-0.12	-0.42**	-0.37
	(0.06)	(0.08)	(0.14)	(0.29)
RIGID	-0.08	-0.08	0.05	0.03
	(0.09)	(0.09)	(0.13)	(0.23)
Adj. R^2	***0.61***	***0.54***	***0.68***	***0.64***
Countries	***36***	***36***	***34***	***34***
Observations	***119***	***119***	***89***	***89***

NOTES: Dependent Variable is INEQ (High-Skill Wage/Low-Skill Wage). Standard errors in parentheses.
Period dummies not reported. Estimates are fixed effects. * is significant at the 5 percent level and ** at the 1 percent level.
(a) Instruments for TRHISK and TRLOSK are: total trade to GDP, population, and GDP.

Table 6
Sensitivity Analysis: Effect of Trade Flows on Wage Inequality[a]

	Standard Results (1)	*Gini on LHS (2)*	*10% Educ. Divisions (3)*	*50% Educ. Divisions (4)*	*SKILL is Toted/Prim (5)*	*Drop TRSIMIL (6)*	*Add GDP & GDP² (7)*	*Add Avg. Wages (8)*	*No Period Dummies (9)*	*Add Time Trend*[b] *(10)*
TRLOSK	23.26**	4.21	22.71	49.11	24.53**	19.63**	24.25**	23.26**	20.04*	23.47**
	(6.93)	(23.0)	(17.33)	(29.43)	(6.75)	(4.37)	(5.58)	(6.91)	(8.38)	(7.20)
TRHISK	20.71	38.60	6.00	-7.42	16.40	15.37	5.45	20.82	37.97	18.38
	(26.62)	(59.12)	(9.61)	(7.91)	(32.29)	(25.77)	(22.17)	(27.00)	(34.64)	(25.85)
TRSIMIL	-1.05	-0.08	-4.40	5.11	-0.93		-1.33	-1.05	-0.82	-1.75
	(1.66)	(6.53)	(6.56)	(3.29)	(1.49)		(1.40)	(1.66)	(1.93)	(1.68)
CAP	13.51	-37.44	15.65	8.49	14.25	11.87	9.10	13.55	12.88	11.77
	(9.44)	(25.53)	(9.80)	(6.55)	(10.80)	(9.00)	(8.55)	(9.60)	(11.56)	(9.06)
SKILL	1.63	-3.28	2.76*	1.32	28.09	1.77	1.76	1.62	1.59	1.37
	(1.04)	(3.22)	(1.16)	(1.05)	(25.85)	(0.95)	(1.18)	(1.06)	(1.31)	(1.06)
$SKILL^2$	-0.12	0.13	-0.20	-0.07	-9.01	-0.11	-0.14	-0.11	-0.06	-0.11
	(0.08)	(0.21)	(0.10)	(0.07)	(7.14)	(0.07)	(0.08)	(0.08)	(0.10)	(0.08)
RIGID	-0.08	-0.37	-0.10	-0.11	-0.06	-0.08	-0.06	-0.08	-0.12	-0.14
	(0.09)	(0.25)	(0.09)	(0.09)	(0.13)	(0.08)	(0.08)	(0.09)	(0.11)	(0.08)
							0.14	0.00		0.59*
							(0.56)	(0.00)		(0.25)
							0.00			
							(0.00)			
Adj. R^2	***0.54***	***0.80***	***0.53***	***0.54***	***0.56***	***0.63***	***0.62***	***0.54***	***0.28***	***0.54***
Countries	***36***	***27***	***36***	***36***	***34***	***34***	***34***	***34***	***34***	***34***
Observations	***119***	***90***	***119***	***119***	***119***	***119***	***119***	***119***	***119***	***119***

NOTES: Dependent Variable is INEQ (High-Skill Wage/Low-Skill Wage). Estimates obtained using fixed effects.
Standard errors in parentheses. * is significant at the 5 percent level and ** is significant at the 1 percent level. Period dummies not reported.
(a) All classifications based on EDUC divisions. Instruments for TRHISK and TRLOSK are: total trade to GDP, population, and GDP.
(b) Also excludes period dummies.

Table 7
Regression Results: Relationships Between Trade and High- and Low-Skill Wages

	Dependent Variable: High-Skill Wages				*Dependent Variable: Low-Skill Wages*			
	Skill defined By INCOME (1)	***Skill defined By EDUC (2)***	***Skill defined by WAGE (3)***	***Skill defined by INDEX (4)***	***Skill defined By INCOME (5)***	***Skill defined By EDUC (6)***	***Skill defined by WAGE (7)***	***Skill defined By INDEX (8)***
TRLOSK	0.81	-1.37*	0.14	-2.19*	0.51	-3.39**	-3.22**	-3.64**
	(0.93)	(0.66)	(0.99)	(1.08)	(0.98)	(0.67)	(0.98)	(1.10)
TRHISK	0.53	1.04	-1.41	-2.69*	0.84	0.96	0.46	-1.67
	(0.61)	(1.06)	(0.84)	(1.13)	(0.65)	(1.04)	(0.84)	(1.14)
TRSIMIL	0.19	0.88**	0.23	1.01*	-0.21	0.81**	0.42	0.72
	(0.27)	(0.25)	(0.25)	(0.24)	(0.29)	(0.25)	(0.25)	(0.41)
CAP	0.58	0.62	1.35	1.73	-1.47	-1.09	-0.09	-0.90
	(1.16)	(1.12)	(1.72)	(1.67)	(1.23)	(1.13)	(1.74)	(1.68)
SKILL	-0.19	-0.14	0.46	0.63	-0.62**	-0.50*	-0.84	-0.72
	(0.22)	(0.20)	(0.45)	(0.45)	(0.23)	(0.20)	(0.46)	(0.45)
$SKILL^2$	0.01	0.02	-0.01	-0.02	0.04*	0.03**	0.06	0.05
	(0.01)	(0.01)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)
RIGID	0.01	0.00	0.01	0.01	0.02	0.01	0.00	0.00
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Adj. R^2	***0.78***	***0.81***	***0.78***	***0.79***	***0.90***	***0.92***	***0.90***	***0.91***
Countries	***36***	***36***	***34***	***34***	***36***	***36***	***34***	***34***
Observations	***123***	***123***	***92***	***92***	***125***	***125***	***94***	***94***

NOTES: Dependent variables in logs. Estimation technique is fixed effects.
Period dummies not reported. * is significant at the 5 percent level and ** at the 1 percent level.

Table 8
Sensitivity Analysis: Relationship Between Trade Flows and Low-Skill Wages[a]

	Standard Results (1)	*10% Educ. Divisions (2)*	*50% Educ. Divisions (3)*	*SKILL is Toted/Prim (4)*	*Drop TRSIMIL (5)*	*Add GDP & GDP²* *(6)*	*Add Avg. Wages (7)*	*No Period Dummies (8)*	*Add Time Trend*[b] *(9)*
TRLOSK	-3.39**	-2.55**	-7.87*	-3.29**	-2.47**	-3.80**	-3.40**	-2.79**	-3.12**
	(0.67)	(0.41)	(3.25)	(0.67)	(0.64)	(0.66)	(0.66)	(0.66)	(0.68)
TRHISK	0.96	-0.69**	0.08	0.67	0.66	1.71	1.01	0.43	0.52
	(1.04)	(0.26)	(0.49)	(1.08)	(1.09)	(1.00)	(1.03)	(1.07)	(1.06)
TRSIMIL	0.81**	1.09**	0.30	0.71**		0.60*	0.79**	0.53*	0.65**
	(0.25)	(0.26)	(0.31)	(0.26)		(0.25)	(0.25)	(0.25)	(0.25)
CAP	-1.09	-2.24*	-1.67	-1.45	-1.60	-1.22	-0.96	-0.64	-1.20
	(1.13)	(1.04)	(1.24)	(1.19)	(1.18)	(1.09)	(1.12)	(1.12)	(1.15)
SKILL	-0.50*	-0.64**	-0.47*	0.02	-0.53*	-0.44*	-0.53**	-0.65**	-0.59**
	(0.20)	(0.19)	(0.23)	(4.29)	(0.22)	(0.22)	(0.20)	(0.21)	(0.21)
$SKILL^2$	0.04**	0.05**	0.03*	0.30	0.04**	0.04**	0.04**	0.04**	0.04**
	(0.01)	(0.01)	(0.01)	(1.28)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
RIGID	0.01	0.03	0.02	-0.00	0.00	0.03	0.01	0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
						0.30**	0.00		-0.08
						(0.12)	(0.00)		(0.05)
						-0.00**			
						(0.00)			
Adj. R^2	***0.92***	***0.93***	***0.90***	***0.91***	***0.91***	***0.93***	***0.92***	***0.91***	***0.91***
Countries	***36***	***36***	***36***	***36***	***36***	***36***	***36***	***36***	***36***
Observations	***125***	***125***	***125***	***125***	***125***	***125***	***125***	***125***	***125***

NOTES: Dependent Variable is the log of Low-Skill Wages. Estimates obtained using fixed effects.
Standard errors in parentheses. * is significant at the 5 percent level and ** is significant at the 1 percent level. Period dummies not reported.
(a) All classifications based on EDUC divisions.
(b) Also excludes period dummies.

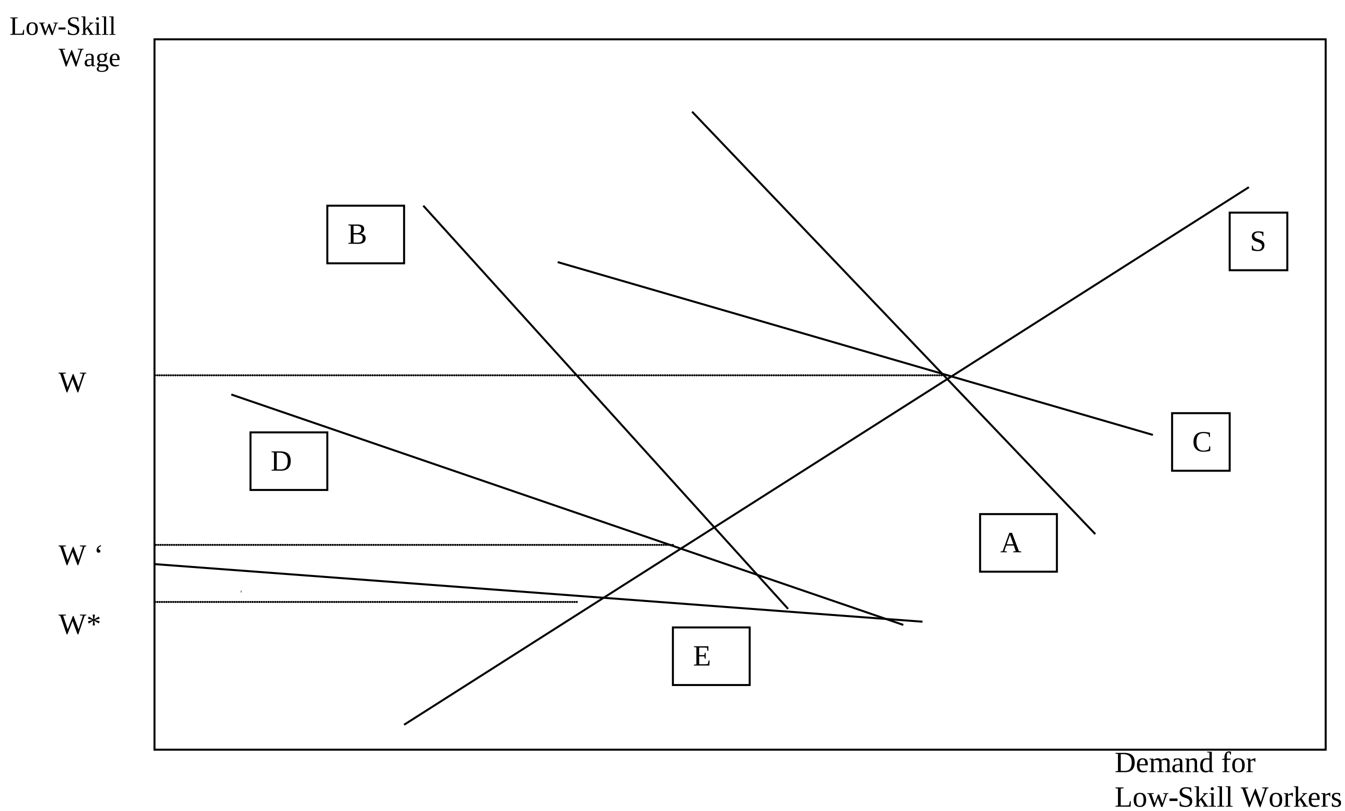
Table 9
Sensitivity Analysis: Effect of Trade Flows on Low-Skill Wages[a]

	Standard Results (1)	*10% Educ. Divisions (2)*	*50% Educ. Divisions (3)*	*SKILL is Toted/Prim (4)*	*Drop TRSIMIL (5)*	*Add GDP & GDP²* (6)*	*Add Avg. Wages (7)*	*No Period Dummies (8)*	*Add Time Trend[b] (9)*
TRLOSK	-2.41	-7.91	-18.91*	-3.71	-0.21	-3.93**	-2.90	-1.89	-2.74
	(1.53)	(4.79)	(7.88)	(1.91)	(1.31)	(1.31)	(1.49)	(1.47)	(1.61)
TRHISK	2.68	-3.79	-3.05	7.73	5.70	5.98	2.95	0.82	2.12
	(5.31)	(2.66)	(2.21)	(7.91)	(7.45)	(4.18)	(5.22)	(5.39)	(5.21)
TRSIMIL	0.66	3.16	1.53	0.76		0.61	0.73*	0.41	0.59
	(0.36)	(1.87)	(0.91)	(0.41)		(0.33)	(0.36)	(0.33)	(0.37)
CAP	-0.62	-4.93	-3.13	0.26	0.13	-0.20	-0.49	-0.72	-0.84
	(1.79)	(3.01)	(1.76)	(2.50)	(2.40)	(1.61)	(1.76)	(1.79)	(1.77)
SKILL	-0.54*	-0.85*	-0.47	4.20	-0.63*	-0.50	-0.56**	-0.65**	-0.61**
	(0.22)	(0.40)	(0.29)	(6.97)	(0.28)	(0.26)	(0.22)	(0.23)	(0.23)
$SKILL^2$	0.04*	0.07*	0.03	-0.69	0.04	0.05**	0.04**	0.04*	0.04*
	(0.02)	(0.03)	(0.02)	(1.92)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
RIGID	0.01	0.05	0.03	-0.03	0.01	0.03	0.01	0.01	0.01
	(0.02)	(0.04)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
						-0.38**	0.00		-0.07
						(0.12)	(0.00)		(0.05)
						-0.00**			
						(0.00)			
Adj. R^2	***0.91***	***0.76***	***0.85***	***0.86***	***0.86***	***0.91***	***0.91***	***0.91***	***0.91***
Countries	***36***	***36***	***36***	***36***	***36***	***36***	***36***	***36***	***36***
Observations	***121***	***121***	***121***	***121***	***121***	***121***	***121***	***121***	***121***

NOTES: Dependent Variable is the log of Low-Skill Wages. Estimates obtained using fixed effects.
Standard errors in parentheses. * is significant at the 5 percent level and ** is significant at the 1 percent level. Period dummies not reported.
(a) All classifications based on EDUC divisions. Instruments for TRHISK and TRLOSK are: total trade to GDP, population, and GDP.
(b) Also excludes period dummies.

Figure 1
Effects of Increased Trade with
Countries of Similar and Different Relative Skill Abundance

Demand and Supply for Low-Skill Workers



Endnotes

[1] Slaughter (1998: 32).
[2] For detailed surveys of empirical work on this topic, see: Cline (1997), Freeman (1995), Gottschalk and Smeeding (1997), Lawrence (1996), Richardson (1995), Rodrik (1997), and Slaughter and Swagel (1997).
[3] Lawrence (1996: 14).
[4] Rodrik (1997).
[5] See Cline (1997), Chapter 2, for an excellent survey of these arguments and counter-arguments.
[6] The classification procedure is described in more detail in Section III. I do not extend this analysis to include the ratio of nonproduction to production workers because I have not been able to find this data for a large enough sample of countries across time.
[7] Two exceptions are: Robbins (1996) which tests for the impact of trade liberalization on wage inequality in several developing countries and Robertson (1998) which tests for Stolper-Samuelson effects in Mexico.
[8] Although this assumption is frequently utilized in empirical work, evidence supporting it is mixed. The Leontief paradox suggests that this assumption does not hold for the US before 1970, and Bowen *et al.* (1987) argue that this assumption does not hold well in their sample of 27 countries. On the other hand, recent work argues that the Leontief paradox can be explained by incorporating measures of human capital and/or natural resources. (See Deardorff, 1984). Moreover, empirical tests by Yahr (1968), Hufauer (1970), and Balassa (1979) support this assumption for a variety of countries, and Wood (1994) supports this assumption for trade between the "North" and "South". See Deardorff (1984) for an overview of this debate and empirical work testing the relationship between relative factor abundance and the factors embodied in trade flows.
[9] Knight *et al.* (1993) and Islam (1995) have shown the importance of using panel estimation to control for omitted-variable bias in estimates of the neoclassical growth model. Forbes (2000) has made the same point in estimates of the relationship between inequality and growth.
[10] For example, see Cline (1997), Chapter 4.
[11] In each case, if the relevant statistic is not available for a country in a given year, I use the average value of that statistic for all “similar” countries, where “similar” is defined according to how the country is classified in the IMF Trade data. Specifically, the eight groupings utilized are: Africa, Asia, Former Communist/Soviet Economies (including Eastern Europe), Industrial Countries, Latin American Mainland (including Central and South America), Latin American Islands, Middle East, and Pacific Islands.
[12] From Barro and Lee (1996).
[13] This apparently random formula is used to balance the need to have a distinct difference between skill levels in the two groups, with the need to keep the sample size in each group large enough to obtain meaningful results. The sensitivity analysis shows that adjusting this formula does not have a significant effect on the results.
[14] This data was obtained from Martin Rama at the World Bank. Rama obtained these statistics from the International Labour Office. This data is not used in other parts of the analysis (such as for the dependent variable) since it is only available starting in 1985.
[15] See Wood (1994, 1995).
[16] Simultaneity is still a potential concern if the error terms are correlated across time. This is addressed in more detail below.
[17] Slaughter (1998) discusses this fact that short-run frictions could lead to a lagged impact of trade on wages.
[18] The null hypothesis is that the country-specific effect is independent of the other regressors. The χ^2 test statistics are: 46.0, 781.2, 169.6 and 203.7, for estimates using income, education, wages, or the index, respectively, as a measure of skills.
[19] More specifically, the ratio of trade with lower skilled countries to GDP in 1990 is 0.12 for Germany and 0.03 for Spain. The ratio of wage inequality in 1990 is 2.2 for Italy and 0.9 for Sweden. Note, however, that changes of these magnitudes within a given country are unlikely in a short period of time.
[20] For example, I use the gini coefficient as reported by Deininger and Squire (1996), or I use other wages reported by the Union Bank of Switzerland (such as earnings of unskilled female textile workers for low-skilled wages.)
[21] For example, I replace years of total education with the ratio of enrollment in higher education to enrollment in primary education, or the ratio of the number of years of total education to the number of years of primary or secondary education. I also test for different functional forms in the relationship between education and wages by excluding the squared term and/or adding a cubed term for total education.

[22] For example, I add: GNP per capita and/or GNP per capita squared and/or economic growth (to control for a Kuznets effect); the share of production in agriculture, industry, manufacturing, and services (to control for changes in the productive structure of the economy); and average wages in the economy as a whole (to control for any country-specific changes in aggregate wages).

[23] The exceptions are when trade flows are classified by education or wages with 50 percent (instead of 25 percent) divisions used to rank countries and trade flows (such as in column 4). The coefficient on TRLOSK continues to be positive, although it is insignificant. The coefficient on TRSIMIL, however, becomes significantly positive. A closer examination of the data suggests that when the stringent 50 percent divisions are utilized, most trade flows previously classified as TRLOSK become TRSIMIL.

[24] I focus on results based on educational classifications because: (a) these have the largest number of observations (excluding estimates based on income divisions, which are problematic as described above); and (b) of all the skill measures used in this paper, average years of education is most likely to accurately capture relative skill abundance.

[25] See Rodrik (1997) or Slaughter (1997) for a further explanation of this elasticity argument.

[26] Slaughter (1997).

[27] See Acemoglu (1998) for a complete model.

[28] For example, see Fortin and Lemieux (1997), Gottschalk and Smeeding (1997) and Topel (1997).