Globalization and Human Capital Investment: Export Composition Drives Educational Attainment*

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Abstract

Human capital is among the most important drivers of long-run economic growth, but its macroeconomic determinants are still not well understood. This paper demonstrates the importance of a key demand-side driver of education, using exports as a lens to study how shifting patterns of production affect subsequent educational attainment. Using a panel of 102 countries and 45 years, we find that growth in less skill-intensive exports depresses average educational attainment while growth in skill-intensive exports increases schooling. Our results provide insight into which types of sectoral growth are most beneficial for long-run human capital formation and suggest that trade liberalization could exacerbate initial differences in factor endowments across countries.

Keywords: Exports; Education; Human Capital; Skill-Intensity

JEL Codes: F14; F16; J24

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1 Introduction

Human capital ranks among the most important determinants of growth and income. Recent work by Jones (2014) and Lucas (2015) goes so far as to suggest that differences in the stock of human capital could account for potentially all of the cross-country variation in incomes between rich and poor countries. Despite these powerful implications, the drivers of human capital investment are still not well understood.[1] Much of the existing research focuses on supply-side determinants of skill acquisition, including access to schools and education spending, but the demand-side matters too:[2] macroeconomic conditions drive wages and job opportunities, which shape individuals' decisions to invest in human capital. In this paper, we use exogenously driven changes in a country's exports as a lens to identify the extent to which shifting patterns of aggregate production influence citizens' subsequent educational attainment. Our proposed strategy offers a new and powerful window for exploring the demand-side determinants of human capital acquisition in a long horizon, cross-country setting.

A body of theoretical work in the trade literature formalizes the underlying mechanism, but the intuition is straightforward: trade influences labor market opportunities and wages, which in turn determines individuals' incentives to invest in education.[3] Theory indicates that the *skill-composition* of trade flows is what matters: an increase in skill-intensive exports can boost workers' incentives to acquire more training and education, while expanded opportunities in less skill-intensive sectors may exacerbate school attrition and dropout rates.[4]

The sharpness of these predictions belies the difficulty of empirical testing in practice. Endogeneity presents a first order concern. First, causality can run in both directions: skill-abundant countries will have a comparative advantage in relatively skill-intensive goods, and vice versa. Second, both educational attainment and export patterns are influenced by a host of often-unobserved domestic characteristics including local policy reforms, technological progress, or institutional changes.

[1] Banerjee and Duflo (2005) suggest that this question is one of the most important issues in growth and development economics.

[2] For detailed analysis of the supply-side drivers of cross-country educational attainment, see, e.g., Hanushek and Woessmann (2011, 2012); for the balance of demand and supply-side drivers, see Becker (1964) and Goldin and Katz (2008).

[3] The seminal contribution is Findlay and Kierzkowski (1983). More recent theoretical work on endogenous human capital responses to trade includes Vogel (2007), Jung and Mercenier (2008), and Blanchard and Willmann (2013).

[4] Consistent with earlier work (e.g. Atkin 2012), we emphasize the potential role of exports over imports, but we account for both directions of trade in our study.

Recognizing these challenges, we propose a new strategy to identify the causal effect of changes in a country's export patterns on subsequent educational attainment using rich panel data, spanning 102 countries and 45 years, and a gravity-based instrumental variables technique. Our empirical approach offers important advantages relative to existing work. First, exports offer a consistent measure of economic activity across countries and a clean separation of production by skill-intensity, both of which are crucial for taking the theory to the data. Furthermore, unlike previous work, our focus is on the *skill composition* of exports. While a handful of cross-country studies have looked at the relationship between aggregate exports and educational attainment (Wood and Ridao-Cano 1999, Redding and Schott 2003, and Galor and Mountford 2008), none have measured the skill-composition of trade.

By focusing on exports rather than explicit measures of labor market returns, we circumvent the long-standing limitations posed by sporadic cross-country wage and labor market data.[5] Exploiting variation in a key driver of labor market demand (exports), rather than relying on less-consistently available measures of labor market characteristics such as wages and job vacancies, allows us to capture the effects of labor market changes on educational attainment for a broad, long horizon, cross-country panel.

The dimensionality of our panel, in turn, offers sufficient breadth to include both year and country fixed effects throughout. Our analysis uses only *within-country* variation for identification, which immediately controls for all time-invariant country characteristics that typically raise omitted variables concerns in existing (static) cross-country analysis. To address remaining endogeneity concerns, we adopt a gravity-based IV technique that allows us to form causal inference. We instrument for the composition of exports by identifying variation in *bilateral* export flows that is driven by exogenous geographic factors and time-varying conditions in the foreign importing country.[6] The resulting instruments are correlated with observed trade flows, but are by construction independent of conditions in the exporting country, which mitigates concerns that reverse causality or omitted variables are driving our results. We demonstrate the robustness of our results to several distinct instruments: three based on conditions in the trading partner country including GDP, death rate, and natural disasters; and a fourth instrument proposed by Feyrer (2009), which

[5] See Goldberg and Pavcnik (2007) for an overview of the data limitations.

[6] We aggregate the predicted bilateral trade flows across a country's trading partners to construct our instrument for country-level exports.

exploits time-varying effects of bilateral air and sea distances.

Previewing the results, we find that the skill-composition of exports has a significant and robust impact on educational decisions.[7] Growth in agricultural and unskill-intensive manufactured exports reduces average years of schooling, while growth in skill-intensive manufactured exports increases schooling. In the baseline specification, we estimate that doubling agricultural exports depresses per capita education by an average of 0.6 school years, while doubling skill-intensive manufactured exports boosts average educational attainment by roughly 0.3 school years. Our results suggest, for example, that if Brazil had been in the 75th percentile of skill-intensive export growth in the 1990s, instead of the 25th, its per capita average education would have been roughly .25 years higher by 2000; this decade of counterfactual export-growth would have moved Brazil from the 43rd to the 47th percentile of educational attainment at the millennium.

Extensions demonstrate that the results are strongest where sensibility would suggest. We find that less skill-intensive exports reduce schooling most sharply at the primary school level, while the positive effect of skill-intensive exports on schooling manifests itself higher up the educational ladder. The impact of exports on schooling is similar across genders but differs according to the level of development of the country; not surprisingly, the negative impact of agricultural exports on average years of schooling is limited to less-developed countries. A placebo test confirms that exports have no discernible effect on the educational decisions of older individuals as we would expect. In robustness tests, we show that including additional explanatory variables or using alternative lag structures leaves our results qualitatively unchanged.

Together these findings point to the troubling possibility that trade liberalization could induce economic divergence.[8] Less-developed countries that specialize in agricultural goods may see a relative decline in educational attainment, which will only slow growth further in these countries. At the same time, developed countries that export skill-intensive manufactured goods will see an increase in educational attainment, which will accelerate future growth. These findings lend support to the stark theoretical predictions of Ventura (1997) and Bajona and Kehoe (2010), who

[7] We define educational attainment by years of schooling. We readily acknowledge that quality-adjusted measures of educational achievement would be preferable, but these data are far more limited in cross-country scope and time horizon, and would preclude the empirical approach we adopt here. See, e.g, Hanushek and Woessmann (2011) for a comprehensive review of the data and limitations.

[8] This line of reasoning traces its roots back more than a century, as is nicely summarized by Wood and Ridao-Cano (1999).

demonstrate that incorporating trade into standard growth models can dramatically change the convergence prediction to the detriment of poor countries.[9]

This paper builds on and ties to several important lines of research. Most closely related are three existing studies that pursue a cross-country examination of the relationship between exports and educational attainment. Wood and Ridao-Cano (1999), Redding and Schott (2003), and Galor and Mountford (2008) are motivated by the same Heckscher-Ohlin intuition, but are limited by important empirical challenges that we overcome.[10] Our paper is the first to use a direct measure of the skill composition of exports. Earlier studies *infer* the type of goods each country exports by assigning whole countries as having comparative advantage in either skill or unskilled intensive goods based on factor endowments (Wood and Ridao-Cano 1999), level of development (Galor and Mountford 2008), or geographical remoteness (Redding and Schott 2003). In effect, this earlier work takes the two-good model literally, since total exports and export composition are synonymous when countries have comparative advantage in just one good. Our approach, in contrast, is to leverage the predictions of the many-good setting from Blanchard and Willmann (2013), which allows for comparative advantage in multiple goods, and thus emphasizes the importance of actually *measuring* the skill composition of exports. Our panel setting also offers immediate advantages relative to the cross-sectional analyses in Redding and Schott (2003) and Galor and Mountford (2008), who cannot control for country level fixed effects. Finally, our IV approach allows us to form causal inferences about the effect of export composition on educational attainment.

Our findings also knit together a series of country-specific studies of demand-side drivers of educational attainment. Most closely related are four papers that focus explicitly on the link between trade and educational attainment. Using detailed census data from Mexico, Atkin (2012) finds evidence that expanded export-sector job opportunities caused an increase in the high school drop-out rate during the period of rapid trade liberalization from 1986 and 2000. Using recent US data and broadening the focus to include offshoring and immigration, Hickman and Olney (2011) demonstrate that certain US workers have responded to global competition by increasing their schooling. In a set of companion studies, Edmonds, Pavcnik, and Topalova (2009, 2010) find

[9] In closed economy growth models, convergence occurs because poor countries have less physical capital or human capital and thus have higher returns to these factors that are important for growth. Trade alters the terms of trade, decreases the returns to these factors, and thus reduces the tendency for poorer countries to converge.

[10] In a related cross-country analysis, Pavcnik and Edmonds (2006) find evidence that openness leads to less child labor.

that imports reduce educational attainment in both rural and urban areas within India, operating primarily through a negative income effect.[11]

These papers are part of a broader literature examining how educational decisions respond to the growth of local industries. Jensen (2012), Shastry (2012), and Oster and Steinberg (2013), find compelling evidence that school enrollments in India increased with local IT jobs, while Heath and Mobarak (2014) find that enrollments in Bangladesh increased in response to manufacturing growth. Emphasizing the impact of labor-saving technology, Foster and Rosenzweig (1996) demonstrate that educational attainment increased in India with technological change in agriculture. On the other side of the globe, Black, McKinnish, and Sanders (2005) show that enrollments in Appalachian states within the U.S. decreased with the coal boom.

These country specific studies generate compelling evidence that education can and does respond to demand-side drivers, including openness to trade. At the same time, the narrow scope and wide range of results make it hard to draw broad conclusions from this micro-level evidence. For instance, Atkin (2012) finds that globalization decreases educational attainment in Mexico while Hickman and Olney (2011) find that globalization increases educational attainment in the U.S. An important contribution of our paper is that we reconcile these conflicting results in the literature using a broad cross-country long-horizon data set. We show that taking into account the composition of a country's exports is the key factor that can unify these country specific findings: growth in unskill-intensive exports reduces educational attainment, while growth of skill-intensive exports induces better schooling outcomes.

The paper proceeds as follows. In the next section, we outline briefly the theoretical justification for our approach. Section 3 then describes the data, while section 4 outlines our empirical strategy and the construction of the instruments. Results are presented in section 5. Section 6 concludes.

2 Theory

This section outlines the theoretical basis for our empirical approach. We use existing work in trade theory to show how the pattern of a country's exports drives local investment in human capital.

[11] We find little evidence of an aggregate income effect using our cross-country panel data. While we are unable to identify income and substitution effects at the individual household, our aggregate results suggest that the latter effect dominates. See the discussion in Section 3.

Weaving together several modeling approaches, we first identify the basic theoretical predictions using a workhorse Heckscher-Ohlin framework, and then draw out additional empirical predictions that arise in more recent theoretical work. This theoretical framework should not be viewed as the main contribution of our paper but rather is useful in formalizing our intuition and motivating our empirical analysis.

We begin by tracing the link between the skill-intensity of exports and human capital investment using a model of endogenous skill acquisition based on Findlay and Kierzkowski (1983). Intuitively, trade affects the relative wages paid to skilled versus unskilled workers through standard Stolper-Samuleson (SS) effects. Trade-induced wage changes subsequently alter the incentives to go to school and hence equilibrium schooling decisions. In the absence of reliable cross-country wage data, this mechanism provides a theoretical foundation for studying the empirical relationship between exports and schooling outcomes directly.

A second subsection outlines several key empirical implications that stem from more recent work in trade theory. We discuss income effects and the potential for heterogenous effects of exports on education in a many-good, heterogenous-agents model. The resulting theoretical predictions further inform our empirical approach.

2.1 A Simple Model of Exports and Skill Acquisition

The following is a simplified version of Findlay and Kierzkowski (1983), which demonstrates the mechanism by which trade drives human capital investment. Begin with a standard two country, two good, two factor Heckscher-Ohlin (HO) model. Two countries, Home and Foreign, produce and trade two goods, agriculture, A, and manufactures, M. Production of both goods requires skilled-labor (L_S) and unskilled labor (L_U). Following custom, assume that the manufactured good is relatively skill-intensive.[12]

The population consists of finitely-lived agents who endogenously choose to become skilled or unskilled based on expected future earnings. At each instant, a mass N of ex-ante identical individuals is born, each of whom live for time T. A given individual can remain unskilled and immediately start earning the prevailing unskilled wage for the rest of his life, or he can go to school

[12] That is, for any internal vector of factor prices, the ratio of skilled-to-unskilled labor use is higher for production of M than A.

for an exogenous period of time θ, after which he will earn the prevailing skilled wage.

At any point in time there is a mass of NT (atomistic) individuals who can be divided into three types according to:

$$NT = UT + E\theta + E(T - \theta), \tag{1}$$

where UT are unskilled, $E\theta$ are those individuals currently in school, and $E(T-\theta)$ are skilled workers who have completed school.

A (non-traded) education sector converts individuals into skilled workers via the following production function:

$$Q = F(K, E; \theta), \tag{2}$$

where Q is the output of skills measured in efficiency units, K is the exogenous educational input (e.g. teachers, facilities, etc.), and E is the mass of students, each of whom spends duration θ in school. Assuming constant returns to scale with θ fixed, the production function may be rewritten as $q = f(k)$, where we let $q \equiv Q/E$ represent the number of skill units a student acquires (i.e. the per-capita skill level) if she has access to $k \equiv K/E$ units of the per-student educational input for the entire θ period of education. Assume that the return to education is diminishing in k so that: $f'(k) > 0$ and $f''(k) < 0$.

Definitionally, $Q = f(k)E$. Thus:

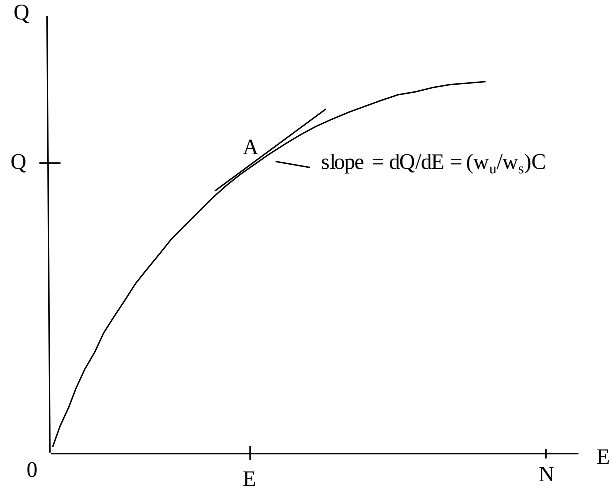
$$\frac{\partial Q}{\partial E} = f(k) - f'(k)k > 0 \text{ and} \tag{3}$$

$$\frac{\partial^2 Q}{\partial E^2} = \frac{1}{E}k^2 f''(k) < 0. \tag{4}$$

Or in other words, the output of skills is increasing with the number of skilled workers, but at a diminishing rate as more students squeeze into the fixed educational facilities, K. Figure 1 presents a graphical representation of Q as a function of E. Notice that determining where on this curve the economy operates in equilibrium will pin down the values of E and Q.

FIGURE 1

Total efficiency units of skill (Q) and number of educated workers (E)



2.1.1 Education Decisions

Each individual decides whether to acquire skills by weighing the future benefits of education against the direct and opportunity costs of going to school. Following Findlay and Kierzkowski (1983), we assume that the fees associated with going to school from time 0 to θ are equal to the present discounted value of marginal product of school over a skilled worker's life, from θ to T.

Let w_u denote the (endogenous) wage paid to unskilled workers, and w_s denote the price of a unit of skill. An unskilled worker earns income of w_u, while a skilled worker with a skill level of $q = f(k)$ earns $w_s f(k)$. Taking wages, E, $f(k)$, and the market interest rate, r, as given, each individual chooses to go to school if the lifetime benefits outweigh the cost:

$$(5) \qquad \int_\theta^T w_s f(k) e^{-rt} dt - \int_\theta^T w_s f'(k) k e^{-rt} dt \geq \int_0^T w_u e^{-rt} dt.$$

The first term on the left reflects the present value of all future income earned as a skilled worker from θ to T, while the second term represents the direct school fees over the period 0 to θ. The term on the right hand side reflects the opportunity cost of education– i.e. the present discounted value of a lifetime of unskilled income (from 0 to T).

The net benefit of education can be defined as the present value of future skilled wages minus the direct costs of school and foregone unskilled wages. Using π to denote this net benefit of education, equations (5) and (3) can be combined to yield:

$$\pi = \frac{1}{r}\left[w_s \frac{\partial Q}{\partial E}(e^{-r\theta} - e^{-rT}) - w_u(1 - e^{-rT})\right]. \tag{6}$$

The net benefit of education is increasing with the skilled wage, decreasing with the unskilled wage, and decreasing with the number of educated workers E.[13] Together, this last condition and free entry into schooling imply that the equilibrium net benefit of education is zero. Thus, setting (6) to zero and rearranging generates the following expression:

$$\frac{\partial Q}{\partial E} = \frac{w_u}{w_s}\underbrace{\frac{(1 - e^{-rt})}{(e^{-r\theta} - e^{-rT})}}_{\equiv C} = \frac{w_u}{w_s}C. \tag{7}$$

This equilibrium condition is reflected in Figure 1, which shows that the education level (E) and aggregate skills (Q) are determined where the slope of the function equals the wage ratio (scaled by a constant, C). The horizontal distance $0E$ reflects the mass of individuals that choose to become educated, while $U = N - E$ individuals choose to remain unskilled.

2.1.2 Trade

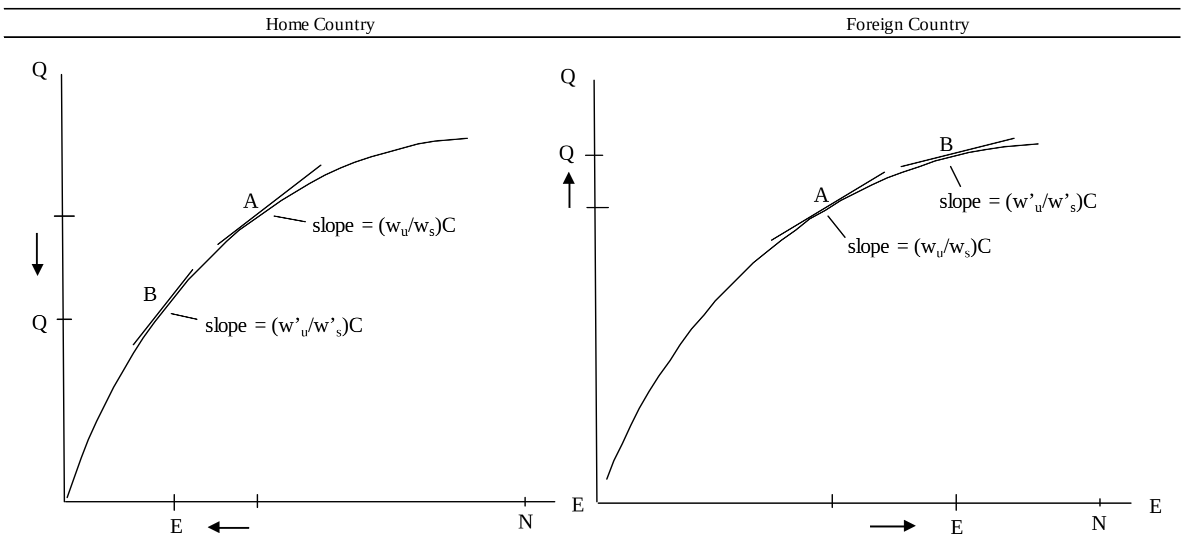
Suppose that a Home country trades freely with Foreign (*), which has identical technologies, tastes, and educational sectors, but differs in its educational input such that $K < K^*$. Home has weaker educational facilities, teachers, etc. It is immediate that in autarky, Home will be relatively abundant in unskilled labor, which (by the Hecksher-Ohlin theorem) gives Home comparative advantage in agriculture. Therefore, after opening to trade, Home will export agriculture while Foreign will export manufactures.

With trade, world relative prices converge to some point in between the two autarky relative prices. Trade thus causes the relative price of agriculture to increase at Home and decrease in Foreign. These price changes translate directly to changes in relative wages. By the SS Theorem, the relative unskilled wage will increase at in Home and decrease in Foreign. From equation (7) it follows immediately that educational attainment will decline at Home and rise in Foreign.

[13] Specifically, $\frac{\partial \pi}{\partial w_s} > 0$ and $\frac{\partial \pi}{\partial w_u} < 0$ and $\frac{\partial \pi}{\partial E} < 0$.

Figure 2 illustrates the impact of trade on the educational decisions in both Home (on the left) and Foreign (on the right). At Home, as the relative unskilled wage increases, the point of tangency shifts to the left, commensurate with a fall in educational investment. Exporting unskill-intensive agriculture goods reduces the equilibrium mass of skilled workers, E. The intuition is straightforward. As the relative unskilled wage increases after trade, the opportunity cost of going to school increases, and thus fewer individuals decide to become skilled. The opposite effect arises in the Foreign country, where the relative skilled wage increases, driving up the equilibrium education level, E.

FIGURE 2



The relationship between the output of efficiency units of skill (Q) and the number of educated workers (E) in the Home and Foreign countries. Point A represent the autarky equilibrium point while B represents equilibrium after trade in each country.

These contrasting results in Home and Foreign generate clear testable predictions. Countries that export unskill-intensive goods will see a decline in average educational attainment. However, countries that export skill-intensive goods will experience an increase in educational attainment. The key insight is that the skill composition of exports alters relative wages and thus changes the incentives to go to school. The remainder of the paper examines whether there is empirical evidence supporting this basic prediction. First, however, we pause to introduce additional predictions based on more recent empirical and theoretical work in the literature.

2.2 Additional Empirical Implications from Recent Work

Income Effects. Absent from the theory so far is the empirically demonstrated point that exports can generate income effects that may influence schooling. Empirical work by Edmonds, Pavcnik and Topalova (2009, 2010) show the importance of this channel, finding evidence that household income effects have outweighed the incentive effects of trade liberalization in certain very poor households in rural and urban India. The logic is straightforward: export growth, regardless of skill intensity, can increase (decrease) household real income for export-oriented (import-competing) workers. As families become wealthier, they may opt to send their children to school longer even if the opportunity cost of schooling is also rising. Conversely, households that suffer a decline in income may reduce educational investment even if the opportunity cost of schooling has also fallen.

At the national level, it is reasonable to postulate that exports, regardless of type, could generate a positive *aggregate* income effect by increasing GDP (as in Feyrer, 2009). A positive aggregate income effect could in turn induce greater educational attainment even absent the Stolper-Samuelson incentive mechanism highlighted so far. To evaluate and control for this possibility, we include empirical specifications both with and without controls for aggregate income and aggregate export levels, which provide insight into the relative magnitude of these competing effects.[14]

Many sectors, Many workers. In recent theoretical work, Blanchard and Willmann (2013) develop a model of trade and endogenous skill acquisition with the same fundamental mechanisms outlined above. In place of dynamics, their model allows for ex-ante heterogenous agents and a continuum of tradeable sectors, each of which requires a specific differentiated skill level. The resulting multisector heterogeneous worker framework offers additional insight relevant for our empirical analysis.

First, trade liberalization can induce simultaneous skill upgrading and skill downgrading in a many-sector model. This is because a country can have comparative advantage in multiple distinct skill-intensity sectors (for example, a country could export both skill-intensive pharmaceuticals and low-skill fresh produce). In the model, trade liberalization will increase relative wages in these export sectors, which will induce some workers to upgrade skills (those entering into pharmaceuticals)

[14] We cannot of course control for *household* income effects without household data. Our results thus reflect the average household response to changes in export composition, including both individual-level income and incentive effects.

while inducing others to reduce skill attainment (those entering agricultural work). The incentive effects of export growth may also have heterogenous effects across different sets of workers, who initially may be at different levels of the educational ladder. When individuals face different costs of education, some workers find will skill upgrading relatively easy, while others will not. Ex-ante heterogenous abilities may be reflected in the distribution of educational outcomes along a continuous educational ladder.

From here we draw two insights that inform our subsequent empirical approach. First, aggregation across sectors can obscure trade's true effects; it is imperative to measure the skill composition of exports.[15] If an increase in aggregate exports would induce some workers to increase education and others to drop out, then regressing educational outcomes on total exports could yield evidence of no causal relationship when the underlying effects of trade are acute but heterogeneous. Here we go further than Findlay and Kierzkowski (1983), and recognize the substantial heterogeneity in skill-intensity within manufacturing products. In our analysis, we therefore differentiate exports by skill-composition to the extent the data allows, which yields three categories: agriculture, less skill-intensive manufactures, and skill-intensive manufactures.[16]

Second, we expect changes in export composition to influence educational attainment at different points along the educational ladder. One might reasonably anticipate changes in unskill-intensive exports to have a stronger affect on enrollment decisions at lower rungs of the educational ladder, while skill-intensive exports are felt at higher educational rungs. Empirically, we therefore adopt a more flexible approach, measuring educational attainment not only by average years of schooling at the country level, but also at the primary, secondary, and tertiary levels too.[17]

3 Data

The goal of our empirical exercise is to evaluate the effect of the composition of exports on educational attainment, for the broadest possible sample of countries over a long time horizon. To

[15] In contrast, Wood and Ridao-Cano (1999) and Galor and Mountford (2008) effectively impose monotonic comparative advantage by assuming countries' exports are either low- or high-skill based on initial capital endowment or level of development.

[16] While our data shows that agricultural exports are homogenous in terms of skill intensity, we recognize that this approach may understate the (potentially heterogenous) effects of agricultural exports on human capital accumulation.

[17] While the definitions of 'primary', 'secondary,' and 'tertiary' vary slightly across countries, country fixed effects should capture these differences.

this end, we have combined detailed export data with broadly available measures of educational outcomes for a sample that ultimately covers 104 countries in 5-year intervals from 1965 to 2010. The data are derived from the following publicly available sources.

3.1 Educational Attainment

Data on educational attainment are from Barro and Lee (2013) and are appealing for a number of reasons. First and foremost the coverage is excellent with data covering over one hundred countries over five year intervals, beginning in 1950. The broad scope of countries included and the time period covered are of course central to the spirit of this cross-country, long-horizon panel analysis.

Second, it has a variety of more disaggregated data that proves useful for us. For instance, it reports average years of schooling and initiation and completion rates at the primary, secondary, and tertiary levels. It also has educational data for different age cohorts. We focus our analysis on young workers (15-29 year-olds), since these workers are in the process of making educational decisions and thus potentially the most sensitive to changes in local labor markets. Younger workers are also more likely to respond to changing economic conditions because they have their full working careers to amortize the cost of incremental schooling. In a robustness test, we leverage data on older individuals to conduct a quasi-placebo test, in which we confirm that older individuals are less sensitive to changes in export patterns. Finally, the data also break out educational attainment by gender, which we pursue in another extension.

An important qualification of the Barro and Lee data is that they represent a *quantity-based* measure of education (years of school) rather than a *quality-based* measure (e.g. test scores). Quantity- and quality-based measures are correlated, but the latter has proven to be a more powerful predictor of growth in those instances when comparable data exists (Lucas 2015; Hanushek and Woessmann 2011). Unfortunately, quality-based measures of educational achievement are limited, particularly before 1990, and are not suited for panel analysis, since test-scores generally are not comparable across years.[18] Note too that some of the discrepancy between quality and quantity-based measures of education could reflect fiscal or institutional investments in education, rather than students' incentives, which is not the mechanism we are trying to identify. Absent a comprehensive,

[18] See Hanushek and Woessmann (2011) for careful accounting of the available data and their attendant strengths and weaknesses.

long-horizon many-country panel measure of quality of education, we proceed with the standard caveat that our estimates of the link between exports and education may be only partially captured by our quantity-based measure.

3.2 Export Data

Trade data come from the World Trade Flows data set constructed by Feenstra et al. (2005). This data set has export data by country and 4-digit SITC (revision 2) industry for the years 1962-2008.[19] The data include both country-level exports by industry, which constitutes our dependent variable, and also bilateral trade flows for every pair of countries in the world, which we use to construct our instruments. Values are reported in nominal U.S. dollars and are converted to real U.S. dollars using the Consumer Price Index provided by the Bureau of Labor Statistics.

We define three distinct components of exports: agriculture, unskill-intensive manufactures, and skill-intensive manufactures (the balance of exports include natural resources which are explored in the extensions). Agricultural exports are the sum of exports in SITC industries 0, 1, 2, and 4, and manufactured exports are the sum of exports in SITC industries 6, 7, and 8. We decompose these manufacturing industries into those that are less skill-intensive and those that are more skill-intensive using UNCTAD data on the skill and technology content of HS 6-digit industries (Basu, forthcoming). Agricultural industries are homogenous in the UNCTAD data, and so we treat agriculture as undifferentiated by skill, with the caveat that average estimated effects could mask underlying heterogeneity in the effects of particular categories of agricultural trade. In the appendix, we describe these skill-classifications in detail, and demonstrate the robustness of our results to alternate skill-intensity classifications based on the NBER-CES U.S. Manufacturing Industry Database. We also consider an alternative specification in which we allow developed and developing countries to have different skill-intensity classifications, and find our main results to be robust.

[19] Relative to the raw UN Comtrade data, a number of corrections and improvements have been made in this data. These include, among other things, using importer records rather than export reports when possible, relying on the more accurate U.S. trade data, and correcting a number of inconsistencies in the UN data (Feenstra et al. 2005). These adjustments have not been made to the extended 2001-2008 data provided by Robert Feenstra and Greg Wright, but the results that follow are comparable if the post-2000 trade data is excluded.

3.3 Control Variables

Our empirical specifications control for country and year fixed effects throughout, which eliminates the need for many of the typical (time-invariant) controls. The set of time varying country-level control variables is limited by data availability, since relatively few data series span the set of countries and years included in the education and trade data. Our baseline specifications maximize sample size subject to including the most relevant controls; extensions demonstrate the robustness of the results to including additional (less-widely available) control variables.

In baseline specifications, we include the following time-varying country-level control variables: (real) imports, which are obtained from the World Trade Flows data set; population and GDP, from the Penn World Tables; death rate per 1,000 people, from the World Development Indicators (WDI); and the immigrant share of the population, also from the WDI.[20] In extensions, we include controls for fiscal expenditures on education and foreign direct investment (both from the WDI and available for slightly different subsamples of countries), neither of which change the results.

3.4 Descriptive Statistics

Combining these variables generates an unbalanced panel data set that spans the years 1965-2010 at five year intervals.[21] Table 1 reports summary statistics for our baseline sample. To demonstrate the extent of cross-country variation in schooling and export patterns, Table 2 reports the average years of schooling, average total exports, and the average export composition over the 1965-2010 period by country.

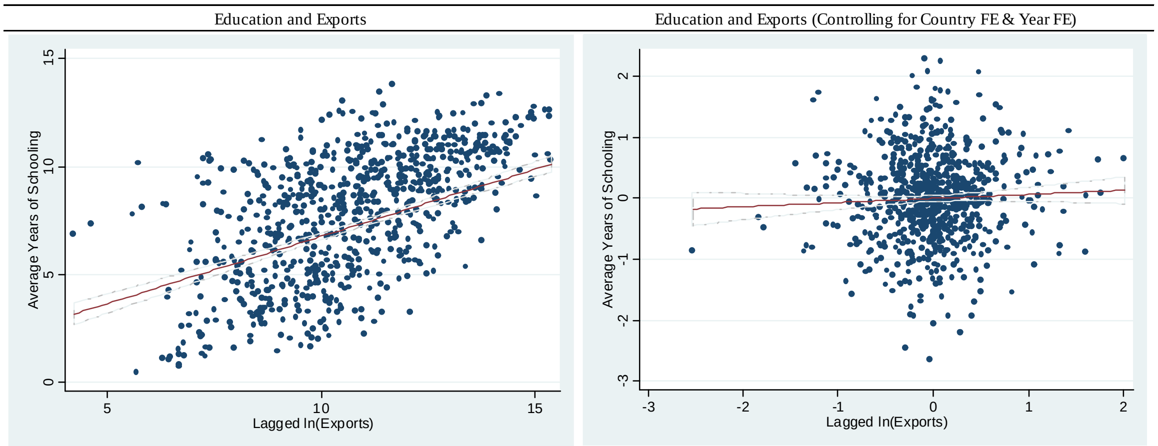
Figure 3 offers insight into our data by plotting the average years of schooling against the natural logarithm of lagged total exports. In the left most panel, we plot the raw years of schooling against aggregate exports, and see a clear positive and significant relationship. This should be interpreted with caution, however, since it is likely that exports and average years of schooling are higher in more developed countries and higher in more recent years. To account for this most obvious source

[20] The death rate in a country could capture a variety of negative shocks, such as wars, health epidemics, and natural disasters, that could affect both exports and educational attainment. More generally, the WDI has an enormous number of variables but relatively few span the countries and years used in this analysis.

[21] Following Hanson et al. (2013), we exclude extremely small countries from our baseline sample (countries with population below one million or average real GDP below 5 million USD). We also drop countries that report a decline in manufacturing or agricultural exports of over 85% from one five year period to the next to avoid potential contamination by conflict-driven outliers (such as Iraq, Cambodia, and Nicaragua). Our results are robust to alternate samples of countries.

of bias, we control for country and year fixed effects and plot the residuals on the right side of Figure 3. Immediately, we see the importance of using a panel setting, as the relationship between years of schooling and total exports vanishes. At least in this raw cut of the data, there is little evidence that the total level of exports is significantly tied to overall educational attainment (even before controlling for GDP). Together these two scatter plots highlight the importance of controlling for country-level fixed effects, something the previous literature has not always done.

FIGURE 3

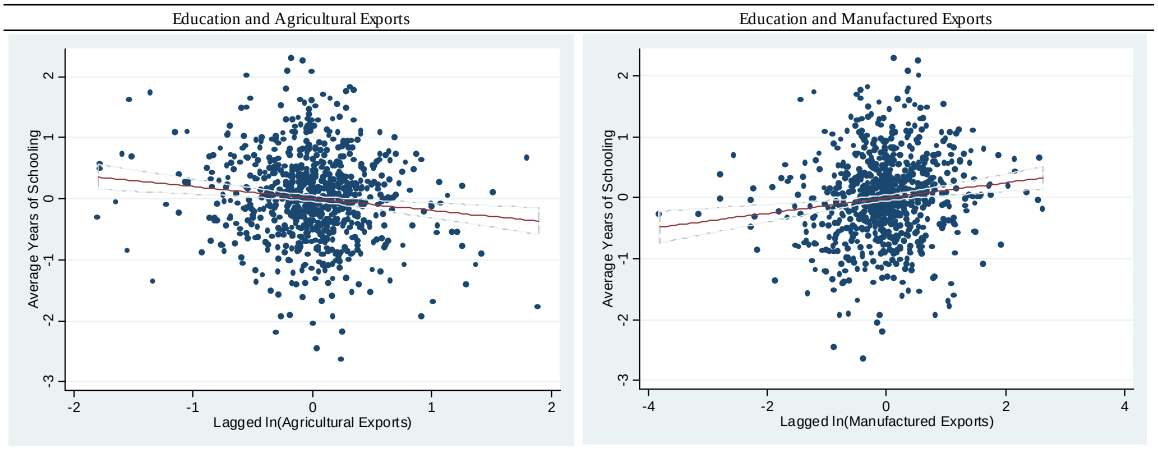


The left panel plots average years of schooling of 15-29 year olds against lagged real exports. The right panel is an anologous scatter plot after controlling for country fixed effects and year fixed effects. Schooling data is from Barro and Lee (2013) and the trade data is from the NBER-UN Trade Dataset.

Theory predicts that the composition, not the overall volume, of exports is what matters for educational attainment. In Figure 4, we therefore plot agricultural exports and manufacturing exports separately against average years of schooling, again controlling for country and year fixed effects. The left scatter plot reveals a significant negative relationship between agricultural exports and average years of schooling, while on the right side we see a significant positive relationship between manufactured exports and schooling.[22] These opposing relationships are consistent with the theoretical prediction that less skill-intensive agricultural exports are likely to increase the opportunity cost of school and thus decrease educational attainment, while exports of higher skilled manufactured goods drive up the returns to skill and thus increase educational attainment. It is encouraging that these predictions are confirmed in such a raw cut of the data.

[22] As demostrated in the empirical resutls, when we later decompose manufacturing by skill-intensity level these distinctions grow even sharper.

FIGURE 4



Average years of schooling of 15-29 year olds is plotted against lagged real agricultural exports on the left and against lagged real manufacturing exports on the right. Both scatter plots control for country and year fixed effects. Schooling data is from Barro and Lee (2013) and the trade data is from the NBER-UN Trade Dataset.

4 Empirical Strategy

4.1 Baseline Specification

Our theory is sufficiently general that we choose to adopt a reduced form empirical specification to test our key predictions. Specifically, we test the extent to which the composition of a country's exports affects educational attainment using the following specification:

(8)

$$Ed_{it} = \beta_0 + \beta_1 \ln Ag\_Ex_{it-5} + \beta_2 \ln Man^U\_Ex_{it-5} + \beta_3 \ln Man^S\_Ex_{it-5} + \beta_4' X_{it-5} + \gamma_i + \gamma_t + \varepsilon_{ct}.$$

Recall from the data that educational attainment is measured as the average years of schooling in country i in year t (and in later specifications as educational attainment at the primary, secondary, and tertiary levels). The key independent variables of interest are the (log of) agricultural exports, Ag_Ex_{it-5}, unskill-intensive manufactured exports, $Man^U\_Ex_{it-5}$, and skill-intensive manufactured exports, $Man^S\_Ex_{it-5}$, of country i in year $t-5$. In the first set of regressions, the vector X consists of time-varying country-level control variables for imports, population, death rate, and migrant share, that could influence educational attainment; later specifications also control for each country's total exports and GDP. The independent variables are lagged five years to account for the time that it takes for economic factors to affect average years of schooling. In all specifications, we include time and country fixed effects, indicated by γ_i and γ_t. Standard errors are clustered at the country level to address potential serial correlation.

Theory predicts that an increase in agricultural and unskilled manufactured exports will reduce the incentive to go to school (so that $\beta_1, \beta_2 < 0$), while an increase in skill-intensive manufactured exports will induce greater educational attainment ($\beta_3 > 0$). In contrast, if exporting leads to a positive income effect that increases demand for education, then all three coefficients in equation (8) should be positive.[23] Accordingly, the signs of β_1 and β_2 offer preliminary insight into the magnitude of the income and incentive effects. To control for aggregate income effects more carefully, we also estimate versions of equation (8) that include total exports and GDP.

To the extent that the skill intensity of agricultural and manufacturing exports varies systematically across countries or over time, the country fixed effects and year fixed effects control for these differences. We address concerns about more idiosyncratic differences in the skill-intensity of industries across developed and less-developed countries in section 6.4 and appendix A1.

While the lag structure, controls, and fixed effects alleviate some of the concerns about omitted variable bias and reverse causality, they cannot completely eliminate endogeneity. Thus, we adopt the instrumental variable approach outlined below.

4.2 Instrument

The goal of our IV strategy is to isolate the variation in a country's export components (agriculture and unskill- and skill-intensive manufactures) that is driven only by exogenous factors. We first describe how to instrument for total exports, which facilitates comparison with the existing literature. We then apply these techniques to construct the instruments for the individual export components that are used in our analysis.

We build on a well-established method of constructing instruments for trade flows based loosely on the gravity model (e.g. Feyrer 2009).[24] This section describes how the instruments are constructed using bilateral trade data. The results from this section thus represent a preliminary step necessary to construct the instruments and should not be confused with the typical first-stage and second-stage IV results that will follow.

[23] As noted earlier, our aggregate level data is unable to address the relative strength of income and substitution effects at the *household level*; See Edmonds and Pavcnik (2005); Edmonds (2006); and Edmonds, Pavcnik and Topalova (2009, 2010) for important work on this topic.

[24] See Frankel and Romer 1999 for an early approach in a cross-sectional analysis.

The gravity model is one of the most successful empirical relationships in economics and is remarkably good at predicting bilateral trade flows (Anderson 2011, Anderson and van Wincoop 2003). Fundamentally, the gravity model predicts that bilateral trade is a function of exporter characteristics, importer characteristics, and resistance factors such as distance. In the present context, variation in bilateral trade that is due to exporter characteristics is potentially problematic because it could be correlated with educational attainment. Thus, our goal in constructing the instruments is to eliminate any variation in predicted bilateral trade that is driven by exporter characteristics. The instruments therefore rely on only the variation in trade due to plausibly exogenous factors such as geography and conditions in a country's foreign trading partners.[25]

Anderson and van Wincoop (2003) derive the following theoretically consistent gravity model:

$$x_{ijt} = \frac{y_{it} y_{jt}}{y_{wt}} \left(\frac{\tau_{ijt}}{P_{it} P_{jt}} \right)^{1-\sigma}, \tag{9}$$

where x_{ijt} denotes exports from country i to country j in year t;[26] y_{it} , y_{jt} , y_{wt} are real GDP in country i, country j, and in the world; τ_{ijt} is the bilateral resistance term; and P_{it} and P_{jt} are the multilateral resistance terms in country i and j. $\sigma > 1$ is the elasticity of substitution between goods. Taking logs of equation (10) generates the following equation, which we take to our bilateral trade data:

$$ln(x_{ijt}) = ln(y_{it}) + ln(y_{jt}) - ln(y_{wt}) + (1 - \sigma)(ln(\tau_{ijt}) - ln(P_{it}) - ln(P_{jt})). \tag{10}$$

In the first two columns of Table 3, we quickly confirm that our data and analysis can replicate the standard gravity results now common in the literature. Column 1 reports a simple gravity specification to predict total bilateral export flows using only importer and exporter GDP, distance, year fixed effects, importer fixed effects, and exporter fixed effects. Column 2 adds a (more rigorous) set of bilateral pair fixed effects that subsume all other time-invariant bilateral fixed effects (distance, geography, language, colonial relationships, etc.) that are often found to be important determinants of bilateral trade.[27] The results confirm that larger countries in terms of GDP and

[25] Unlike Frankel and Romer (1999) and Feyrer (2009), which focus exclusively on geographic factors, we also explore instrument variants based on economic shocks in the foreign importing country.

[26] Focusing on uni-directional trade is more relevant for this analysis and also avoids the "silver medal mistake" discussed by Baldwin and Taglioni (2006).

[27] Baldwin and Taglioni (2006) argue that, relative to importer and exporter fixed effects, bilateral pair fixed effects

more proximate countries trade more with each other.

Our goal here is not to test the gravity model, however, but to identify the variation in bilateral exports that is unrelated to conditions in the exporting country (which is potentially problematic). As such, we cannot use exporter GDP to predict bilateral export flows, since it could be correlated with educational attainment. Thus, we estimate the following equation:

$$ln(x_{ijt}) = \alpha ln(y_{jt}) + \gamma_t + \gamma_{ij} + \epsilon, \quad (11)$$

where γ_t are year fixed effects and γ_{ij} are bilateral pair fixed effects.

Column 3 reports the estimates from equation (11).[28] The within sample fitted values from this regression capture variation in bilateral exports that is driven by importer GDP, time effects, and bilateral pair effects for each pair of countries in each year. These fitted values are by construction not a function of conditions in the exporting country and are therefore used to construct our instrument.

To the extent that bilateral pair fixed effects inadvertently capture time-invariant characteristics of the exporting country, the country fixed effects in the main IV analysis will account for these factors.[29] Another potential concern is that importer GDP could be correlated with exporter GDP outside of the time fixed effects (which are already included), especially if the two countries are geographically proximate or economically integrated. If true, our fitted values may still be correlated with characteristics in the exporting country (that said, it is reassuring that the coefficient on importer GDP does not change from columns 2 to 3, which alleviates concerns that importer GDP is inadvertently picking up variation in exporter GDP).

To address this possibility, we utilize three additional, complementary IV approaches, each of which leverages a distinct source of plausibly exogenous variation in bilateral trade flows. The first of these uses changes in the death rate in the importing country, instead of importer GDP, to identify changes in bilateral exports. This alternative diverges from the more familiar and micro-founded gravity concept, by identifying exogenous shocks in the importing country caused

are preferable when using a panel data set and are better at dealing with the "gold medal error" associated with the multilateral resistance terms.

[28] For brevity, we report only the predictions for total exports. When we take this approach to the data, we separately predict agricultural, unskilled manufactured, and skill manufactured exports. These estimates are available by request.

[29] Feyrer (2009) describes this issue in greater detail.

by war, disease, famine, or demographics. Taking this logic one step further, we develop a third instrument based on an even more clearly exogenous source of variation in the importing country: natural disasters. For this instrument, we compile data on natural disasters from EM-DAT, which covers a wide span of countries, years, and disaster types.[30] Estimates for predicting total bilateral exports using these alternate importer country shocks are reported in columns 4 and 5 of Table 3. In column 4, we see that a surge in the death rate in an importing country is associated with a decrease in bilateral trade flows, as one might expect. The negative coefficient signals that acute negative shocks reduce trade flows. Column 5 offers a more nuanced reading, and shows that some kinds of natural disasters (e.g. floods and landslides) increase bilateral imports, while others have little or no effect on bilateral trade.[31]

As a further check on our identification strategy we also pursue a fourth and conceptually distinct IV approach proposed by Feyrer (2009).[32] Rather than using shocks in the importing country, Feyrer exploits the time varying effects of air and sea distances to identify an exogenous source of variation in bilateral trade flows. Specifically, he interacts sea and air distance with year fixed effects to identify the impact of improved aircraft technology over time that affects some pairs of countries more than others. The result is a set of sixteen estimated coefficients that identify the effect of time-varying geography on bilateral trade flows. These coefficients are then used to predict bilateral trade flows.[33]

Using each of these different approaches, we can construct the predicted bilateral trade volumes based on a distinct source of plausibly exogenous variation: changes in importer GDP, importer death rate, importer natural disasters, or time-varying geography. The last step in constructing our instrument for country-level exports is then simply to aggregate the bilateral fitted values across all of a country's trading partners within a given year. Following standard procedure, the (unlogged) bilateral fitted values from columns 3-6 are summed in the following manner to construct our

[30] We quantify natural disasters based on damages (in U.S. $) but the results are similar if instead we use total deaths or total number of people affected.

[31] When we decompose the effect of natural disasters on different *types* of imports, we find sensible responses. For example, imports of machinery and transportation equipment (e.g. rebuilding materials, SITC 7) is the most responsive to natural disasters, while beverages and tobacco (STIC 1) and miscellaneous goods (STIC 9) show little or negative response.

[32] Feyrer graciously provided his sea distance data to us. For landlocked countries not included in Feyrer's analysis, we use sea distances from the closest neighboring country.

[33] Coefficient estimates are not reported due to space constraints, but are available by request.

instruments:

$$(12) \qquad export\_IV_{it} = \sum_{j \in \Omega_i} e^{\widehat{\alpha} ln(y_{jt}) + \widehat{\gamma}_t + \widehat{\gamma}_{ij}},$$

where Ω_i represents the set of country i's trading partners.

Finally, we take several additional steps in our empirical strategy to limit further concerns about the exclusion restriction. To address the possibility that importer GDP could affect domestic educational attainment through a channel other than exports, we control for both imports and migration in all specifications. We also control for FDI in an extension and find the results little changed (though the sample is much smaller because of limited data on FDI).

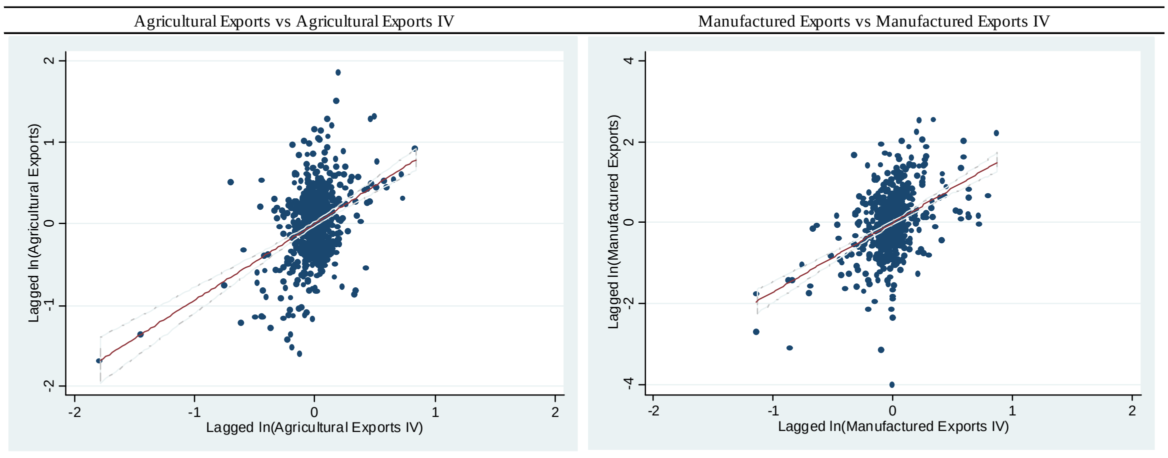
4.3 Export Component Instruments

We use the methodology described above to construct separate instruments for each of the export components. Thus, agricultural exports, unskill-intensive manufactured exports, and skill-intensive manufactured exports are used in turn as the dependent variables in equation (11) and the three additional IV variations. To use in the figures below (and later to emphasize the importance of distinguishing unskill- and skill-intensive manufactures), we also construct an instrument for aggregate manufactured exports.

Constructing separate instruments for each of the export components represents a novel feature of our IV analysis relative to existing studies. Our first instrument exploits variation in importer GDP to identify changes in the composition of a country's exports. This approach takes advantage of two sources of variation across different types of exports. First, it leverages differences in the *set* of a country's active trading partners for each type of good. Second, by using changes in importers' GDP, this approach exploits the potential non-hometheticity of preferences across different types of exports by recognizing the differential effect of income changes on import demand across different trading partners. For example, growth in one country (i.e. China) may lead to relative greater demand for agricultural exports while the growth of another country (i.e. Germany) could lead to greater demand for manufactured goods.

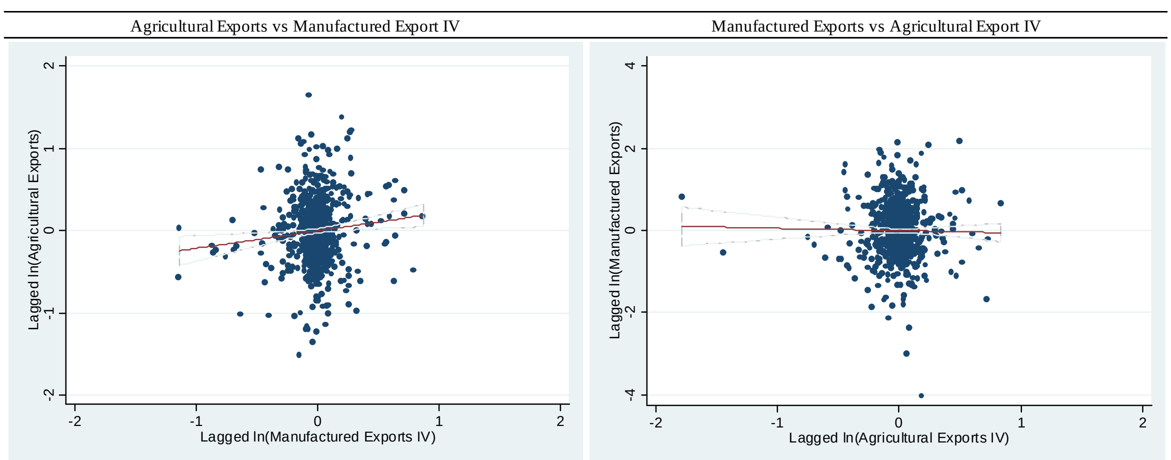
Figures 5 and 6 shows that there is sufficient variation in import demand elasticities across export types and trading partners' to separately predict these different export components. Figure 5 demonstrates that the agricultural and manufactured instruments have a significant positive impact on the type of exports they were designed to predict after controlling for the other instrument, country FE, and year FE. Figure 6 then shows that the off diagonal instruments are not successful: the right side of Figure 6 demonstrates that the agricultural instrument is not a good predictor of manufactured exports after controlling for the manufactured instrument, country FE, and year FE. Likewise, in the left side panel, we see that the instrument for manufactured exports offers little help in predicting agricultural exports.

FIGURE 5



On the left, lagged real agricultural exports is plotted against the agricultural export IV after controlling for the manufactured export IV, country FE, and year FE. On the right, lagged real manufactured exports is plotted against the manufactured export IV after controlling for the agricultural export IV, country FE, and year FE. The trade data is from the NBER-UN Trade Dataset.

FIGURE 6



On the left, lagged real agricultural exports is plotted against the manufactured export IV after controlling for the agricultural export IV, country FE, and year FE. On the right, lagged real manufactured exports is plotted against the agricultural export IV after controlling for the manufactured export IV, country FE, and year FE. The trade data is from the NBER-UN Trade Dataset.

To avoid repetition, we do not delve into commensurate graphical exercises for the three alternative IV approaches, which use importers' death rates, importers' natural disasters, and time-varying geography. Each variant proves to be capable of identifying different sources of variation across distinct export components and performs well in first stage tests. In the next section, we present parallel results for each set of instruments, and find all of them to be qualitatively and quantitatively consistent. In the extensions, we focus on the instrument based on importer GDP, since it has the clearest micro foundations (gravity model) relative to the three other alternatives.

5 Results

Our results are sequenced as follows. We begin in Table 4 by demonstrating the broad contours of the relationship between export composition and educational attainment in a simple, Ordinary Least Squares (OLS) setting. Here, we demonstrate the importance of distinguishing manufacturing exports by skill intensity and work through a series of alternatives to arrive at our preferred specification. To more carefully identify a causal relationship, we then turn to our four different IV specifications and report these results in Tables 5 and 6. Finally, a variety of extensions and robustness checks are pursued in the subsequent section.

5.1 OLS

Table 4 reports results from estimating equation (8) using OLS. Each regression in the table uses average years of schooling as the dependent variable; includes country and year fixed effects; and controls for imports, population, death rate, and migrant share (while columns 3-5 also control for total exports and GDP). Standard errors are clustered at the country level and reported in brackets. We build from the least sophisticated specification in column 1 to our preferred specification in column 5.

Column 1 demonstrates the importance of differentiating manufactures by skill-intensity. In this first regression, we estimate the relationship between average years of schooling and exports of agriculture and manufactures. Average years of schooling are negatively correlated with exports of agricultural goods as predicted, but the relationship with manufacturing exports is insignificant. The latter finding is inconsistent with a literal interpretation of a two sector Heckscher-Ohlin model, but as emphasized earlier (and formalized in a multi-sector trade model) it is entirely plausible in practice given the marked heterogeneity among manufacturing industries.

Column 2 reruns the empirical specification decomposing manufactured exports by skill-intensity using the classifications described earlier. As predicted, the two components of manufactured exports demonstrate sharp and opposing relationships with average schooling. Agriculture and unskill-intensive manufacturing exports are associated with lower schooling, while skill-intensive manufactured exports are associated with higher average schooling levels.

The initial results in column 2 point clearly to the association between schooling and exports suggested by theory. At the same time, however, they conflate the level effects of exports with the compositional effects of exports. Since higher exports are associated with higher levels of GDP (e.g. Feyrer, 2009), the specification in column 2 potentially captures not only the compositional influence of exports, but also an aggregate income effect.

To examine this issue more carefully, columns 3-5 experiment with controls for total exports and GDP. In column 3, we find that the volume of total exports has an insignificant impact on educational attainment and leaves the coefficients on the export components virtually unchanged.[34] This result again emphasizes the theoretical prediction that what matters for educational attainment is the composition of exports and not necessarily the total volume of trade. In column 4, we control for potential aggregate income effects more carefully by also including GDP. As expected, GDP has a significant positive impact on educational attainment but it does not significantly alter the export component coefficients of interest and total exports offers no explanatory power above and beyond GDP. Column 5, which is our preferred specification, confirms that the results are unchanged when we omit the control for total exports and include only GDP as a control.[35]

Focusing on column 5, the OLS results suggest that doubling skill-intensive manufactured exports will increase average years of schooling by roughly two months. Conversely, doubling unskill-intensive manufactured exports will decrease school outcomes by roughly the same magnitude. The negative and significant association between agricultural exports and schooling is more than twice as large. While these coefficients may seem small, it is important to remember that the educational decisions of only a subsample of the population are directly affected by exports. In this light, it is

[34] Given the log specification, this is equivalent to regressing education on the shares of agricultural, unskilled manufactured, and skilled manufactured exports.

[35] We prefer to focus on exports in levels, rather than shares, to facilitate economic interpretation. We find it more intuitive to think about the effect of a 5 percent increase in a country's agricultural exports than, say, a 5 percentage point shift in the composition of exports (which, if we hold total export fixed, would require non-agricultural exports to fall).

perhaps remarkable that differences in the pattern of exports are reflected in overall average years of schooling of the entire population.[36]

5.2 IV

We remain concerned about potential endogeneity, even after lagging the independent variables and including a variety of controls and fixed effects. Thus, we adopt a 2SLS approach to test the causal predictions of the theory. As described earlier, our instruments are constructed using variation in a country's bilateral export patterns that is driven by exogenous factors.

Table 5 reports the first stage IV results using importer GDP to construct the instruments (the first stage results using the other three IV approaches are also strong; see Table A2 in the appendix). In every column of Table 5, the relevant instrument has a large, positive, and significant impact on the component of exports it was designed to predict. The F-stat on the excluded instruments is well above 10 in every specification, which indicates a relatively strong first stage. As an interesting aside, notice that agricultural exports are increasing with migrants while manufacturing exports are increasing with GDP, both of which we find plausible.

Table 6 reports the second stage results using our four different IV approaches.[37] Column 1 uses importer GDP to construct the instrument and finds that educational attainment is decreasing with agricultural exports and unskilled manufactured exports but is increasing with skilled manufactured exports. The magnitudes of these coefficients indicate that doubling agricultural exports reduces average years of schooling by roughly two-thirds of a year. Doubling skilled manufactured exports increases average years of schooling by about a third of a year, while doubling unskilled manufactured exports decreases average schooling by about roughly the same measure. To put these estimates in context, suppose that in the 1990s, Brazil had been in the 75th percentile of skill-intensive export growth (1.3 log points), instead of the 25th (.47 log points). Our results suggest that (all else equal) Brazil's average educational attainment would have been roughly .25

[36] This finding that trade exposure can have a substantial effect on aggregate labor market outcomes is consistent with existing work, including important early findings by Bernard and Jensen (1997) and more recent work by Hakobyan and McLaren (2010) and Autor, Dorn, and Hanson (2013).

[37] Typically the IV standard errors should be adjusted to account for the fact that the instrument was constructed (Frankel and Romer 1999). However, as Feyrer (2009) points out this adjustment is impractical when over 5,000 pair fixed effects are used in the bilateral trade regression, as is the case in our analysis. Furthermore, Frankel and Romer (1999), Rajan and Subramanian (2008) and Feyrer (2009) all find that this adjustment is extremely small and never affects the significance of the coefficients.

years higher by 2000, which would have moved it from the 43rd to the 47th percentile of per capita education at the millennium. These results are similar to our OLS findings, but now carry a causal interpretation consistent with theory.

Columns 2 and 3 construct the instruments using changes in trading partners' death rates and natural disasters. Results are reassuringly consistent across columns 1-3, which mitigates the concern that the first approach (using importer GDP) is inadvertently contaminated by unobserved changes in the exporting country. In a fourth, very different IV approach reported in column 4, we use the time-varying geography method proposed by Feyrer (2009). The resulting second stage estimates for the export components remain statistically significant and quantitatively consistent with our earlier estimates in columns 1-3.

We are reassured to find that our results are remarkably similar across four distinct IV approaches. Although the four sets of instruments in Table 6 are constructed using very different sources of exogenous variation, they share the common goal of eliminating variation in exports that is driven by domestic factors that could be correlated with educational attainment. No instrument is perfect, but taken together these four IV approaches provide compelling evidence that the composition of exports has a causal effect on educational attainment.

Finally, notice that the key estimates in Table 6 are larger in magnitude than the OLS results in Table 4. This is consistent with the existing literature (Frankel and Romer 1999, Feyrer 2009). We posit that this difference may be due to the higher variance of the export measures relative to the instruments, which would attenuate the OLS results. To the extent that our instruments identify a more permanent, structural source of variation in exports, and individuals respond more to systemic, structural shifts in the pattern of exports than to idiosyncratic temporary changes, smaller variation in the instruments would induce a greater educational response, while larger fluctuations in the noisy export components will have less of an effect on education in the OLS specifications. Consistent with this hypothesis, the scatter plots in Figure 5 show that the variation in the export components is higher than the variation in the analogous instruments. More formally, we confirm that the standard deviations of the measured export components are substantially larger than then the standard deviation of the instruments, after controlling for country and year fixed effects.

Overall, the results in Table 6 provide compelling support for the predictions of the theory.

Educational attainment is decreasing with less skill-intensive exports and increasing with more skill-intensive exports. The magnitudes are small but plausible given that export-oriented jobs are often a relatively small component of the aggregate labor market. We find that a country's exports affect aggregate labor markets enough to change individuals' incentives to go to school, and that these effects depend critically on the skill-intensity of the export sector. Next, we ask whether these effects vary systematically across different points along the educational ladder.

6 Extensions

6.1 Heterogeneous Effects along the Educational Ladder

By focusing only on average years of schooling, our baseline specification could mask heterogeneous effects of exports on different levels of schooling. The results so far indicate overall average years of schooling are affected by exports, but is this driven by changes in primary, secondary, or college education? Both common sense and formal theory suggest that agricultural exports may be more likely to decrease primary education while exports of skilled manufactured products may drive up achievement at the secondary or tertiary levels.

Table 7 explores this possibility by examining how exports affect average years of primary, secondary and tertiary schooling.[38] We find that agricultural exports have a significant negative impact on primary schooling, but little influence on secondary and tertiary education. Students in grade school appear to be more sensitive to changes in the agricultural sector than are students pursing more advanced education.[39] Likewise, we find that unskilled manufactured exports also negatively affect primary schooling but have little impact on secondary and tertiary education. Conversely, skilled manufactured exports have a positive impact further up the education ladder, particularly at the secondary school level.[40]

Table 8 pursues a similar analysis using a richer measure of the distribution of educational attainment, also from the Barro and Lee (2013) data. We redefine the dependent variable to be

[38] All extensions are modifications of the baseline IV specification in Column 1 of Table 6.

[39] Although we include country fixed effects, it is possible that the only variation in the primary education variable occurs in developing countries, which would subsequently drive our results. We address this point in an extension in which we look separately at developed and less developed countries.

[40] The lack of a discernible effect on tertiary education is perhaps not surprising given the extent of heterogeneity even in the skilled-manufacturing category: many sub-sectors in this category may hire workers out of high school, especially in the developing world.

the percent of the 15-29 year old population with no schooling, at least some primary schooling, at least completed primary schooling, at least some secondary schooling, at least completed secondary schooling, at least some tertiary schooling, and at least completed tertiary school. This specification provides greater insight into how exports affect the distribution of education. The results are broadly consistent with those from Table 7, and show that agricultural and unskilled manufactured exports influence educational decisions negatively and toward the bottom end of the education distribution while skilled manufacturing exports affect decisions positively and somewhat higher up the education ladder. Interestingly, the strongest effects for agricultural and skill-intensive exports are seen during the primary completion/secondary initiation period, which suggests (perhaps unsurprisingly) that students are most sensitive to economic conditions at the time of transition between elementary and high school.

The results in Tables 7 and 8 are consistent with theory, but they also serve as a plausibility check on our main results. We would be concerned, for instance, if agricultural exports significantly affected college level education decisions. We find it reassuring that our results are strongest in the anticipated places.

6.2 Age

The analysis so far focuses on the average years of schooling of 15-29 year olds. We expect that this younger cohort will be most sensitive to export-induced changes in the labor market, since they are in the process of making educational decisions and have their entire working careers to amortize investments in human capital. As a placebo test, we examine instead how exports affect educational attainment of older cohorts within the same 5-year time horizon. Since older individuals have already made their educational decisions and chosen careers, we expect that they should be less responsive to changing economic conditions, and thus to the pattern of exports.

Table 9 shows the results from this placebo test. For ease of comparison, column 1 re-reports the baseline results (Table 6, column 1) using the average years of schooling of 15-29 year olds as the dependent variable. Column 2 reports the estimated impact of exports on the average years of schooling of 30-49 year olds. As expected, the average years of schooling of this older cohort is virtually unaffected by changes in the pattern of exports. Comparing the results in columns 1 and 2 confirms our expectation that the results should hold almost exclusively for younger individuals.

6.3 Gender

The Barro and Lee (2013) data also report educational attainment by gender. Although theory does not have strong predictions about how exports might differentially affect educational decisions of males and females, we nonetheless find it to be an interesting dimension to investigate. Perhaps exporting affects one gender more than another or perhaps the responsiveness of educational decisions to market forces differs across genders. Table 10 indicates that the educational decisions of both males and females respond to exports in broadly the same way. However, comparing columns 1 and 2 we see that males are if anything slightly more responsive to agricultural exports and unskilled manufactured exports, while skilled manufactured exports have a similar impact on males and females.

6.4 Level of Development

This section examines whether there are differences in how exports affect years of schooling in developed versus less-developed countries. Time invariant differences across countries are captured by the country fixed effects in the baseline specification, but there could be, for instance, systematic differences in the skill-intensity of agricultural and manufactured exports across developed and less developed countries.

The results of this extension are reported in Table 11, where developed countries are defined as those designated as "High Income" or "Upper Middle Income" by the World Bank in year 2000 and less developed countries are those designated "Lower Middle Income" or "Low Income". While the IV specification is generally preferable, in this case splitting the sample in half leads to a sufficiently weak first stage that we report instead the OLS results.

Overall, we see that exports affect educational decisions in both developed and less developed countries. There are some interesting differences, however. Agricultural exports continue to exhibit a strong negative effect on years of schooling in less developed countries, but we find no such evidence when restricting attention to only developed countries. This finding is consistent with the idea, that the agricultural sector may be more capital intensive (and may attract very little formal-sector labor) in developed economies, or that (especially primary) education in developed countries is less sensitive overall to macroeconomic changes. This result indicates that the negative coefficient on agricultural exports in the baseline results is primarily driven by less developed countries.[41]

We find that manufactured exports have roughly an equivalent effects on educational attainment in both developing and developed countries. Overall, the results in Table 11 show that there is support for the predictions of the theory in both developed and less-developed countries, and that our results are again strongest where common sense would suggest.

6.5 Sensitivity Analysis

Table 12 reports a series of sensitivity checks that test the robustness of the baseline results. To address the concern that 5 year lags could be too short to capture the schooling responses of the youngest cohorts, column 1 lags the independent variables by 10 years (the downside of using the longer lags is that we lose more than ten percent of our observations). Despite the smaller sample, the results are of the expected sign, significant, and quantitatively similar to the baseline results. Thus, we find no evidence that our results are sensitive to different lag structures.

Columns 2-5 include a variety of additional controls. In Column 2, we add region-year specific fixed effects to the baseline IV specification, which addresses the potential concern that time-varying trends in regional development (e.g. emergence of the East Asian Tigers) could be driving our results. This specification exploits only contemporaneous intra-regional variation in export composition and educational attainment, and finds our results only slightly attenuated. This is perhaps not surprising given that our baseline specification already includes country and year fixed effects, which together with time-varying export characteristics like GDP, are likely to absorb most regional development trends.

In Column 3, we control for national educational expenditures as a percent of gross national income using data from the World Bank's World Development Indicators. Unfortunately, this variable has limited coverage, which significantly reduces the sample. As expected, educational expenditures have a strong positive relationship with the average years of schooling. Because educational expenditures are likely endogenous to the demand for education, however, we are careful not to draw causal inference. The important point is, rather, that including educational expenditures as a control does not change the estimated coefficients of interest on the export

[41] In additional cuts of the data by region or time period (not reported), we found that this negative relationship between agricultural exports and educational achievement is widespread, and not driven by a particular region or time period.

variables, which remain of the expected sign and significant. This should not be surprising given our IV approach eliminates variation in exports that is driven by domestic conditions such as educational policies.

To address concerns that a shock in the importing country could affect domestic educational attainment through a channel other than exports, Column 4 controls for foreign direct investment. Again, coverage is limited for this measure of inward FDI, which is from the World Development Indicators (otherwise we would have included it in our baseline specification). The coefficient on FDI is not statistically significant. Despite the fact that the sample is more than twenty percent smaller, the estimated coefficients on the export components remain similar in sign, magnitude, and significance level.

In column 5, we explore the thus-far omitted exports of natural resources (like oil). For some countries these exports represent a substantial share of total exports, even if the share of the labor market is more limited. Column 5 includes exports of coal, oil, and gas (SITC 3) as well as the baseline export components. The data indicate that natural resource exports have no discernible impact on average years of schooling, and importantly that their inclusion does not affect the agricultural or manufacturing export coefficients.

Following the export definitions, the import control variable is decomposed into analogous agricultural and manufacturing components in column 6. Including these separate import controls does not change the export coefficients of interest. Only unskilled manufactured imports have a significant impact on years of schooling, and as we would expect, it is opposite in sign from the analogous export component.

Column 7 then instruments for these import components. Specifically, for each import component an instrument is constructed using the same methodology discussed in section 4.2 but using exporter (i.e. the trading partner's) GDP rather than importer GDP. The first stages (available upon request) are strong with all six of the first stage F-stats well above 10. Column 7 shows that import components have no causal effect on educational attainment while export components remain significant and of the expected sign. Together, columns 6 and 7 show that the baseline results are robust to the inclusion of these import components and that educational decisions are far more sensitive to exports than to imports.

7 Conclusion

This paper demonstrates that educational attainment responds to exogenously-driven changes in the composition of a country's exports, and thus offers insight into how investment in human capital responds to changing patterns of production. We construct a panel data set that spans 102 countries and 45 years and adopt IV approaches based on exogenous drivers of bilateral trade. Our results indicate that educational attainment is decreasing with agricultural exports and unskilled manufactured exports, and is increasing with skilled manufactured exports. We find that these results are strongest where we most expect, and are robust to a variety of extensions and sensitivity checks.

These findings carry important policy implications. First, while the benefits of international trade are often stressed, we examine the more complex question of what types of exports are most beneficial for human capital accumulation. Since most countries are already integrated into world markets, the relevant policy question is how best to engage in trade with the rest of the world. Our results suggest that exporting skill-intensive goods may carry important long-run benefits via an empirically demonstrated increase in human capital.

Accordingly, we find empirical support for the long-standing concern, voiced by Bajona and Kehoe (2010) among others, that trade may exacerbate economic differences across countries through its impact on endogenous educational attainment. Our results provide evidence that less developed countries that export low skill-intensive goods may see a decline in average educational attainment. To the extent that human capital is a key driver of economic growth, as demonstrated yet again in compelling terms by Jones (2014) and Lucas (2015), this mechanism may undermine the development process. The same logic suggests that developed countries that export skill-intensive goods may continue to experience an increase in educational attainment that would reinforce initial economic advantages. These implications are striking and warrant additional research.

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TABLE 1
Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Average Years of Schooling	787	7.8	2.9	0.5	13.8
ln (Agr. Exports)$_{t-5}$	787	9.3	1.7	3.8	13.5
ln (Man. Exports)$_{t-5}$	787	9.3	2.8	0.6	15.2
ln (Unskilled Man. Exports)$_{t-5}$	787	8.6	2.5	0.5	14.2
ln (Skilled Man. Exports)$_{t-5}$	787	8.0	3.4	0.1	14.9
ln (Imports)$_{t-5}$	787	10.8	1.9	3.0	15.9
ln (Population)$_{t-5}$	787	9.5	1.4	6.6	14.1
ln (Death Rate)$_{t-5}$	787	2.2	0.4	0.4	3.5
ln (Migrant Share)$_{t-5}$	787	1.0	1.5	-4.6	4.4
ln (GDP)$_{t-5}$	787	18.1	1.7	14.3	23.3

TABLE 2

Average Years of Schooling and Average Exports by Country 1965-2010

Country	Schooling	Total Exports	Agr Exp (%)	U Man Exp (%)	S Man Exp (%)	Country	Schooling	Total Exports	Agr Exp (%)	U Man Exp (%)	S Man Exp (%)
Afghanistan	3.1	2	65	21	3	Libya	9.3	93	0	0	1
Albania	9.9	2	35	37	11	Lithuania	9.6	31	22	29	27
Algeria	6.4	119	2	0	1	Malaysia	9.4	351	20	12	52
Argentina	9.0	115	62	8	13	Mali	1.5	2	62	5	4
Armenia	9.8	3	21	43	31	Mauritius	7.9	7	44	46	7
Australia	11.5	342	49	11	10	Mexico	7.6	438	10	13	53
Austria	8.3	269	10	26	51	Moldova	9.9	6	48	25	24
Bangladesh	5.1	23	12	84	1	Mongolia	7.8	2	60	19	2
Belgium-Lux	10.6	731	12	23	39	Morocco	4.0	39	49	28	10
Benin	3.0	1	80	6	2	Nepal	3.0	2	22	69	4
Bolivia	8.7	7	46	16	1	Netherlands	10.3	985	22	12	32
Brazil	6.1	297	48	14	28	New Zealand	12.8	74	69	12	9
Bulgaria	9.3	26	20	29	27	Norway	10.3	255	11	13	16
Cameroon	5.5	15	51	7	1	Pakistan	4.0	41	24	69	3
Canada	11.2	1063	21	16	39	Panama	8.7	15	35	16	34
Chile	9.3	84	52	38	3	Papua New Guinea	3.9	11	71	1	1
China	7.8	1210	7	41	43	Paraguay	7.0	7	83	7	1
Colombia	6.9	59	44	13	7	Peru	8.1	41	50	31	2
Costa Rica	7.6	21	50	16	29	Philippines	8.0	123	24	16	56
Cote Divoire	4.0	25	87	5	2	Poland	9.4	159	16	26	38
Croatia	8.7	29	17	31	31	Portugal	8.2	100	16	41	31
Czech Rep	11.5	269	7	19	64	Romania	10.0	58	13	35	31
D.R. Congo	3.2	19	18	59	0	Russian Fed	10.5	1281	8	10	13
Denmark	9.6	237	31	17	31	Saudi Arabia	8.6	723	1	1	2
Dominican Rep.	6.8	20	33	41	19	Senegal	4.4	5	76	5	4
Ecuador	7.7	31	49	2	2	Singapore	9.0	359	5	8	62
Egypt	5.7	43	20	17	6	Slovakia	9.8	113	7	19	59
El Salvador	6.5	10	49	38	8	Slovenia	11.1	69	5	28	51
Estonia	10.8	33	16	22	38	South Africa	7.2	161	28	26	19
Finland	9.1	193	14	35	41	Spain	9.4	415	19	18	48
France	8.9	1369	16	16	50	Sri Lanka	10.4	18	38	50	7
Germany	9.7	3815	6	13	60	Sudan	3.2	9	48	1	1
Greece	10.3	61	34	34	16	Sweden	11.0	407	13	19	56
Haiti	4.2	3	24	58	13	Switzerland	9.8	435	5	20	44
Honduras	5.9	12	58	36	3	Syria	4.8	19	19	6	3
Hong Kong	11.3	319	3	45	46	Tajikistan	8.9	3	30	65	3
Hungary	10.7	106	15	16	55	Tanzania	4.8	6	76	11	2
India	4.3	138	29	48	13	Thailand	7.0	225	27	23	42
Indonesia	5.5	268	22	23	11	Trinidad & Tobago	9.3	26	5	1	4
Iran	7.0	240	3	3	1	Tunisia	6.3	28	16	41	13
Ireland	11.0	228	19	11	33	Turkey	6.1	118	24	39	30
Israel	10.7	102	11	39	31	U Arab Emirates	9.3	333	3	8	10
Italy	9.4	1071	9	31	47	UK	9.4	1258	8	16	49
Japan	11.4	2056	2	9	81	USA	12.2	3071	17	11	55
Jordan	8.2	7	38	21	12	Uganda	4.2	4	92	4	2
Kazakhstan	10.1	106	12	10	11	Ukraine	10.4	128	21	10	52
Kenya	6.0	11	68	10	4	Uruguay	8.4	13	52	29	7
Korea Rep.	11.3	543	4	23	63	Venezuela	6.5	170	4	4	4
Kuwait	6.5	134	1	1	1	Vietnam	6.3	45	26	38	11
Kyrgyzstan	8.0	3	35	16	10	Yemen	4.2	21	5	0	1
Latvia	10.3	21	29	26	19	Zambia	5.7	14	8	90	2

Average years of schooling of 15-29 year olds, average real exports (in millions of real US $), and the share of agricultural, low-skilled manufactured, and high-skilled manufactured exports over the sample (1965-2005). Schooling data is from Barro and Lee (2013) and the trade data is from the NBER-UN Trade Dataset.

TABLE 3
Construction of Instrument using Bilateral Trade Data

	ln (Bilateral Exports)					
	(1)	(2)	(3)	(4)	(5)	(6)
ln (Imp. GDP)	1.265***	1.370***	1.389***			
	[0.039]	[0.035]	[0.035]			
ln (Exporter GDP)	1.326***	1.376***				
	[0.037]	[0.034]				
ln (Distance)	-1.260***					
	[0.011]					
ln (Imp. Death Rate)				-0.711***		
				[0.041]		
ln (Imp. Drought)					0.006*	
					[0.003]	
ln (Imp. Earthquake)					0.001	
					[0.003]	
ln (Imp. Extreme Temp)					0.001	
					[0.004]	
ln (Imp. Flood)					0.006***	
					[0.002]	
ln (Imp. Landslide)					0.031***	
					[0.006]	
ln (Imp. Storm)					0.003	
					[0.002]	
ln (Imp. Volcano)					0.014**	
					[0.007]	
ln (Imp. Wildfire)					-0.004	
					[0.003]	
ln (Sea Dist) * Year FE						Yes
ln (Air Dist) * Year FE						Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	No	No	No	No	No
Exporter FE	Yes	No	No	No	No	No
Bilateral Pair FE	No	Yes	Yes	Yes	Yes	Yes
Observations	50,692	50,692	52,014	53,678	53,260	53,443
R-squared	0.727	0.874	0.859	0.848	0.847	0.847

Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010.

TABLE 4

Impact of Exports on Average Years of Schooling (OLS)

	Average Years of Schooling				
	(1)	(2)	(3)	(4)	(5)
ln (Agr. Exports)$_{t-5}$	-0.305**	-0.338***	-0.374***	-0.329***	-0.336***
	[0.123]	[0.117]	[0.124]	[0.117]	[0.110]
ln (Man. Exports)$_{t-5}$	0.047				
	[0.065]				
ln (Unskilled Man. Exports)$_{t-5}$		-0.135**	-0.145**	-0.156***	-0.158***
		[0.059]	[0.061]	[0.055]	[0.054]
ln (Skilled Man. Exports)$_{t-5}$		0.204***	0.193***	0.170***	0.169***
		[0.065]	[0.064]	[0.058]	[0.058]
ln (Imports)$_{t-5}$	0.248*	0.213*	0.169	0.058	0.052
	[0.142]	[0.126]	[0.143]	[0.137]	[0.125]
ln (Population)$_{t-5}$	0.913*	0.820*	0.849*	0.447	0.456
	[0.489]	[0.477]	[0.490]	[0.485]	[0.471]
ln (Death Rate)$_{t-5}$	-1.419***	-1.487***	-1.468***	-1.472***	-1.469***
	[0.416]	[0.393]	[0.402]	[0.392]	[0.386]
ln (Migrant Share)$_{t-5}$	0.016	0.059	0.050	0.045	0.044
	[0.131]	[0.126]	[0.129]	[0.134]	[0.133]
ln (Total Exports)$_{t-5}$			0.105	-0.019	
			[0.156]	[0.155]	
ln (GDP)$_{t-5}$				0.747***	0.739***
				[0.243]	[0.237]
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	787	787	787	787	787
R-squared	0.953	0.955	0.955	0.957	0.957

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variable is the average years of schooling of 15-29 year olds.

TABLE 5
First Stage IV Results

	Importer GDP		
	Agr. Exports	Unskilled Man. Exports	Skilled Man. Exports
	(1)	(2)	(3)
ln (Agr. Exports IV)$_{t-5}$	0.759***	-0.684***	-0.541**
	[0.128]	[0.246]	[0.230]
ln (Unskilled Man. Exports IV)$_{t-5}$	0.022	0.993***	-0.153
	[0.103]	[0.147]	[0.165]
ln (Skilled Man. Exports IV)$_{t-5}$	0.015	0.309*	1.322***
	[0.089]	[0.166]	[0.119]
ln (Imports)$_{t-5}$	0.294***	0.429***	0.486***
	[0.070]	[0.106]	[0.126]
ln (Population)$_{t-5}$	-0.546**	-0.886**	-0.025
	[0.264]	[0.415]	[0.480]
ln (Death Rate)$_{t-5}$	-0.113	-1.099***	-0.406
	[0.251]	[0.348]	[0.291]
ln (Migrant Share)$_{t-5}$	0.133**	-0.046	-0.175*
	[0.066]	[0.112]	[0.098]
ln (GDP)$_{t-5}$	0.086	0.756**	0.899***
	[0.168]	[0.292]	[0.218]
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	787	787	787
R-squared	0.958	0.951	0.97
F-Stat, Instrument	12.8	21.0	55.4

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. This table shows the first stage IV results from the specification listed in Column 1 of Table 6.

TABLE 6

Impact of Exports on Average Years of Schooling (IV)

	Imp. GDP	Imp. Death Rate	Imp. Natural Disasters	Sea & Air Distance
	(1)	(2)	(3)	(4)
ln (Agr. Exports)$_{t-5}$	-0.655***	-0.663***	-0.632***	-0.616***
	[0.202]	[0.170]	[0.141]	[0.170]
ln (Unskilled Man. Exports)$_{t-5}$	-0.293***	-0.262**	-0.252**	-0.327***
	[0.107]	[0.123]	[0.129]	[0.122]
ln (Skilled Man. Exports)$_{t-5}$	0.295***	0.252**	0.216**	0.291***
	[0.103]	[0.100]	[0.105]	[0.110]
ln (Imports)$_{t-5}$	0.189	0.204	0.210	0.195
	[0.149]	[0.134]	[0.130]	[0.129]
ln (Population)$_{t-5}$	0.283	0.286	0.288	0.266
	[0.454]	[0.444]	[0.438]	[0.458]
ln (Death Rate)$_{t-5}$	-1.596***	-1.588***	-1.595***	-1.630***
	[0.360]	[0.367]	[0.371]	[0.367]
ln (Migrant Share)$_{t-5}$	0.108	0.100	0.087	0.098
	[0.109]	[0.109]	[0.112]	[0.113]
ln (GDP)$_{t-5}$	0.744***	0.765***	0.792***	0.771***
	[0.215]	[0.211]	[0.214]	[0.218]
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	787	787	787	787
R-squared	0.955	0.955	0.955	0.955
F-Stat, Agr. Exp. IV	12.8	15.1	16.4	17.9
F-Stat, U. Man. Exp. IV	21.0	21.4	22.8	19.9
F-Stat, S. Man. Exp. IV	55.4	45.5	41.7	34.4

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variable is the average years of schooling of 15-29 year olds.

TABLE 7

Impact of Exports on Average Years of Schooling by Education Level (IV)

	Primary	Secondary	Tertiary
	(1)	(2)	(3)
ln (Agr. Exports)$_{t-5}$	-0.607***	-0.106	0.058
	[0.144]	[0.188]	[0.050]
ln (Unskilled Man. Exports)$_{t-5}$	-0.221*	-0.051	-0.022
	[0.113]	[0.101]	[0.021]
ln (Skilled Man. Exports)$_{t-5}$	0.114	0.164*	0.017
	[0.088]	[0.094]	[0.018]
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	787	787	787
R-squared	0.911	0.915	0.839

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variables are average years of primary schooling, average years of secondary schooling, and average years of tertiary schooling of 15-29 year olds.

TABLE 8
Impact of Exports on Completion Rates (IV)

	% No Schooling	% Primary	% Compl. Primary	% Seconday	% Compl. Secondary	% Tertiary	% Compl. Tertiary
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln (Agr. Exports)$_{t-5}$	3.342*	-3.328*	-7.419***	-10.952***	-3.641	2.148	0.757
	[1.807]	[1.809]	[2.019]	[2.990]	[2.493]	[1.677]	[0.851]
ln (Unskilled Man. Exports)$_{t-5}$	2.468**	-2.456**	-2.560*	-1.398	-0.162	-0.589	-0.492
	[1.143]	[1.142]	[1.369]	[1.424]	[1.482]	[0.732]	[0.380]
ln (Skilled Man. Exports)$_{t-5}$	-1.058	1.063	2.710**	3.370**	1.407	0.369	0.482
	[0.939]	[0.938]	[1.155]	[1.544]	[0.981]	[0.658]	[0.312]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	787	787	787	787	787	787	787
R-squared	0.941	0.941	0.938	0.915	0.914	0.827	0.837

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variables are the percent of the 15-29 year old population with no schooling, at least some primary school, at least completed primary school, at least some secondary school, at least completed secondary school, at least some tertiary school, and at least completed tertiary school.

TABLE 9

Impact of Exports on Average Years of Schooling by Age (IV)

	Age 15-29	Age 30-49
	(1)	(2)
ln (Agr. Exports)$_{t-5}$	-0.655***	-0.427
	[0.202]	[0.277]
ln (Unskilled Man. Exports)$_{t-5}$	-0.293***	0.214
	[0.107]	[0.146]
ln (Skilled Man. Exports)$_{t-5}$	0.295***	-0.055
	[0.103]	[0.116]
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	787	787
R-squared	0.955	0.972

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variables are the average years of schooling of 15-29 year olds and the average years of schooling of 30-49 year olds.

TABLE 10

Impact of Exports on Average Years of Schooling by Gender (IV)

	Male	Female
	(1)	(2)
ln (Agr. Exports)$_{t-5}$	-0.709***	-0.597**
	[0.208]	[0.233]
ln (Unskilled Man. Exports)$_{t-5}$	-0.413***	-0.165
	[0.114]	[0.123]
ln (Skilled Man. Exports)$_{t-5}$	0.301**	0.289***
	[0.121]	[0.105]
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	787	787
R-squared	0.934	0.961

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variable in column 1 is average years of schooling of 15-29 year old males and in column 2 it is average years of schooling of 15-29 year old females.

TABLE 11

Impact of Exports on Average Years of Schooling by Level of Development (OLS)

	Developed	Less Developed
	(1)	(2)
ln (Agr. Exports)$_{t-5}$	0.051	-0.430***
	[0.165]	[0.126]
ln (Unskilled Man. Exports)$_{t-5}$	-0.201**	-0.144**
	[0.096]	[0.062]
ln (Skilled Man. Exports)$_{t-5}$	0.222*	0.151**
	[0.131]	[0.065]
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	384	403
R-squared	0.896	0.960

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. Developed countries are those designated High Income or Upper Middle Income by the World Bank in 2000. Less Developed countries are those designated Lower Middle Income or Low Income by the World Bank in 2000.

TABLE 12
Impact of Exports on Average Years of Schooling - Sensitivity Analysis (IV)

	10 Year Lags	Region*Year FE	Educ. Expenditures	FDI	NR Exports	Import Comp.	Import Comp. (IV)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln (Agr. Exports)	-0.555***	-0.572***	-0.498**	-0.581**	-0.655***	-0.645***	-0.474***
	[0.206]	[0.201]	[0.223]	[0.263]	[0.206]	[0.196]	[0.182]
ln (Unskilled Man. Exports)	-0.342***	-0.268**	-0.382***	-0.323**	-0.293***	-0.293***	-0.248**
	[0.120]	[0.117]	[0.142]	[0.143]	[0.104]	[0.107]	[0.108]
ln (Skilled Man. Exports)	0.368***	0.257***	0.308***	0.263**	0.296***	0.274***	0.328**
	[0.129]	[0.099]	[0.106]	[0.113]	[0.105]	[0.099]	[0.128]
ln (Educ. Expenditures)			0.491***				
			[0.138]				
ln (Inward FDI)				-0.031			
				[0.033]			
ln (Coal, Oil, Gas Exports)					-0.001		
					[0.031]		
ln (Agr. Imports)						-0.019	0.072
						[0.104]	[0.462]
ln (Unskilled Man. Imports)						0.330**	-0.264
						[0.135]	[0.956]
ln (Skilled Man. Imports)						-0.137	0.066
						[0.115]	[0.566]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region*Year FE	No	Yes	No	No	No	No	No
Observations	682	787	660	591	787	787	787
R-squared	0.955	0.96	0.957	0.955	0.955	0.956	0.953

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variable is the average years of schooling of 15-29 year olds. Column 1 lags the independent variables 10 years (rather than 5 years) and column 2 includes region*year fixed effects. Column 3 controls for educational expenditures, Column 4 controls for inward FDI, and Column 5 controls for coal, oil, and gas exports (SITC 3). Column 6 controls for the type of imports and Column 7 instruments for these import components using the same strategy used to instrument for the export components.

A Appendix

A.1 Industry Skill Intensity

As discussed in section 3.2, we classify manufacturing industries as either unskill- or skill-intensive based on publicly available UNCTAD classifications described in Basu (forthcoming).[42] Based on the skill and technology content of goods, UNCTAD assigns each HS-6 category to a basic skill-intensity designations. These HS-6 industries are then mapped to SITC industries using the HS-SITC concordance from the Center for International Data at UC Davis. SITC 2-digit manufacturing industries (SITC codes 6, 7, and 8) are defined as unskill-intensive if they consist primarily of "Non-Fuel Primary Commodities", "Resource-Intensive Manufactures", "Mineral Fuels". SITC 2-digit manufacturing industries that consist primarily of "Technology-Intensive Manufacturing", are instead designated as skill-intensive manufactured industries.

In contrast to manufacturing, agricultural industries are treated as homogenous, since UNCTAD designates all industries in the Agricultural sector (SITC codes 0,1,2,4) as "Non-Fuel Primary Commodities". We cannot, therefore, separate more and less skill-intensive agricultural exports. To the extent that there is heterogeneity in skill intensity across different agricultural sectors, our coarse classification will blunt the estimated effects of agricultural trade on education.

For consistency and transparency, we apply the same definitions of skilled and unskilled manufacturing industries to every country and every year of our analysis. We view this symmetric treatment as the most conservative approach, but readily acknowledge that this blanket approach may mask underlying heterogeneity in skill-intensity across countries or over time, which (in general) would mute the estimated response of education to export composition. Indeed, the observed heterogeneity in estimates between developed and developing countries found in Table 11 may in part reflect underlying differences in skill intensity across industries between rich and poor countries.

In robustness checks, we also construct skill-intensity classifications using the NBER-CES U.S. Manufacturing Industry Database, which may better reflect the technology and skill content of goods produced in the industrialized world.[43] The downside of using the NBER U.S. Manufacturing

[42] The classification data are available here: http://www.unctad.info/en/Trade-Analysis-Branch/Data-And-Statistics/Other-Databases

[43] We first concord the data (from U.S. SIC to SITC) using UC Davis industry concordances. If an SITC industry concords with multiple SIC industries, the frequency of HS10 links within that SITC-SIC pair are used as weights. We then calculate the share of employment that consists of production workers for each 2-digit SITC industry. Those

database is, of course, that it relies on data from the U.S. which is less relevant for many countries in our sample. For instance, according to the U.S. data, cars (i.e. "Road Vehicles" SITC 78) are defined as an unskilled industry whereas UNCTAD, which takes a more global view, defines car production as skill intensive. For this reason, we tend to prefer the UNCTAD data for our baseline analysis.

Table A1 lists 2-digit manufacturing industries by skill classification under the UNCTAD and NBER-CES classifications. The third column, 'NBER-CES (Cars)', simply redefines the autos as skill-intensive, which we use in a robustness test described below.

TABLE A1
Definitions of Skill-Intensive Manufactured Industries

SITC Code	SITC Description	UNCTAD	NBER-CES	NBER-CES (Cars)
60	MANUFACTURED GOODS CLASSIFIED CHIEFLY BY MATERIAL	0	0	0
61	LEATHER, LEATHER MANUFACTURES, N.E.S., AND DRESSED FURSKINS	0	0	0
62	RUBBER MANUFACTURES, N.E.S.	1	0	0
63	CORK AND WOOD MANUFACTURES OTHER THAN FURNITURE	0	0	0
64	PAPER, PAPERBOARD, AND ARTICLES OF PAPER PULP, PAPER OR PAPER BOARD	0	0	0
65	TEXTILE YARN, FABRICS, MADE-UP ARTICLES, N.E.S., AND RELATED PRODUCTS	0	0	0
66	NONMETALLIC MINERAL MANUFACTURES, N.E.S.	0	0	0
67	IRON AND STEEL	1	0	0
68	NONFERROUS METALS	0	0	0
69	MANUFACTURES OF METALS, N.E.S.	1	0	0
70	MACHINERY AND TRANSPORT EQUIPMENT	1	1	1
71	POWER GENERATING MACHINERY AND EQUIPMENT	1	1	1
72	MACHINERY SPECIALIZED FOR PARTICULAR INDUSTRIES	1	1	1
73	METALWORKING MACHINERY	1	1	1
74	GENERAL INDUSTRIAL MACHINERY AND EQUIPMENT, N.E.S., AND MACHINE PARTS, N.E.S.	1	1	1
75	OFFICE MACHINES AND AUTOMATIC DATA PROCESSING MACHINES	1	1	1
76	TELECOMMUNICATIONS AND SOUND RECORDING AND REPRODUCING APPARATUS AND EQUIPMENT	1	1	1
77	ELECTRICAL MACHINERY, APPARATUS AND APPLIANCES, N.E.S., AND ELECTRICAL PARTS THEREOF	1	1	1
78	ROAD VEHICLES (INCLUDING AIR-CUSHION VEHICLES)	1	0	1
79	TRANSPORT EQUIPMENT, N.E.S.	1	1	1
80	MISCELLANEOUS MANUFACTURED ARTICLES	0	0	0
81	PREFABRICATED BUILDINGS; SANITARY, PLUMBING, HEATING AND LIGHTING FIXTURES AND FITTINGS, N.E.S.	1	1	1
82	FURNITURE AND PARTS THEREOF; BEDDING, MATTRESSES, MATTRESS SUPPORTS, CUSHIONS AND STUFFED FURNISHINGS	0	1	1
83	TRAVEL GOODS, HANDBAGS AND SIMILAR CONTAINERS	0	1	1
84	ARTICLES OF APPAREL AND CLOTHING ACCESSORIES	0	0	0
85	FOOTWEAR	0	0	0
87	PROFSSIONAL, SCIENTIFIC AND CONTROLLING INSTRUMENTS AND APPARATUS, N.E.S.	1	1	1
88	PHOTOGRAPHIC APPARATUS, EQUIPMENT AND SUPPLIES AND OPTICAL GOODS, N.E.S.; WATCHES AND CLOCKS	1	1	1
89	MISCELLANEOUS MANUFACTURED ARTICLES, N.E.S.	0	0	0

The "A" and "X" industries from the World Trade Flows data set (see Feenstra et al. 2005) are defined as skilled or unskilled based on the overall 1-digit industry level skill intensity.

Table A2 compares the results of our baseline analysis using different skill-classification schemes. Column 1 simply restates the baseline specification results using the UNCTAD classifications for ease of comparison. Column 2 instead uses the NBER-CES definitions of skill-intensity, and finds that the estimated coefficients of interest are similar in sign and magnitude to the baseline results, but are less significant (indeed the coefficient on unskilled manufacturing exports is no longer significantly different from zero). In column 3, we instead use the NBER-CES definitions but simply

industries with a production share greater than the median are defined as unskilled and those with a production share less than the median are defined as skilled industries.

switch car production (SITC 78) from unskilled to skilled; here, all the coefficients of interest are now significant.[44] Column 4 presents a hybrid classification system in which we use the UNCTAD data to define manufacturing industries in less-developed countries and the NBER-CES data to define manufacturing industries in developed countries. Here we again find strong significant results that are similar to the baseline results. Overall, we conclude from Table A1 that our results are robust to alternate definitions of manufactured industries.

TABLE A2
Impact of Exports on Average Years of Schooling - Alternate Manufacturing Definitions (IV)

	Baseline	NBER-CES	NBER-CES (Cars)	Hybrid
	(1)	(2)	(3)	(4)
ln (Agr. Exports)	-0.655***	-0.561**	-0.515**	-0.623***
	[0.202]	[0.224]	[0.208]	[0.207]
ln (Unskilled Man. Exports)	-0.293***	-0.181	-0.288*	-0.244**
	[0.107]	[0.113]	[0.151]	[0.106]
ln (Skilled Man. Exports)	0.295***	0.288*	0.372**	0.283***
	[0.103]	[0.149]	[0.179]	[0.102]
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	787	785	786	787
R-squared	0.955	0.954	0.953	0.954

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. The dependent variable is the average years of schooling of 15-29 year olds. Column 1 reports the baseline results that use UNCTAD data to define manufacturing industries. Column 2 uses the production share of employment from the NBER-CES US Manufacturing Industry Database to define manufacturing industries. Column 3 also uses the NBER-CES US Manufacturing definitions but simply redefines Road Vehicles (SITC 78) as skilled rather than unskilled. Finally Column 4 uses UNCTAD data to define manufacturing industries for less-developed countries and uses NBER-CES data to define manufacturing industries for developed countries.

A.2 Additional First Stage IV Results

Due to space constraints Table 5 only reports the first stage results for the importer GDP instrument. Table A3 reports additional first-stage IV results. Specifically, columns 1-3 in Table A3 report the first stage IV results using the death rate in the importing country as an instrument. Columns 4-6 report the first stage results using natural disasters in the importing country as an instrument. Finally, columns 7-9 report the first stage results using Feyrer's (2009) sea and air distance IV approach. These first stage results correspond to the second stage results presented in columns 2-4 of Table 6 respectively. Throughout Table A3, the instruments are strong positive pre-

[44] Using the share of non-production workers as a proxy for skill-intensity overlooks any differences in the skill sets held by those production workers. The potential for this sort of miscoding seems particularly acute in autos.

dictors of the components of exports that they were designed to predict. Additionally, the F-stats are all well above 10 indicating a strong first stage.

TABLE A3
First Stage IV Results

	Importer Death Rate			Importer Natural Disasters			Sea and Air Distance		
	Agr. Exports	U Man. Exports	S Man. Exports	Agr. Exports	U Man. Exports	S Man. Exports	Agr. Exports	U Man. Exports	S Man. Exports
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ln (Agr. Exports IV)$_{t-5}$	0.817***	-0.338*	-0.467**	0.917***	-0.339*	-0.385*	0.920***	-0.306*	-0.199
	[0.130]	[0.176]	[0.216]	[0.133]	[0.181]	[0.200]	[0.126]	[0.178]	[0.253]
ln (Unskilled Man. Exports IV)$_{t-5}$	0.113	1.269***	0.022	0.125	1.229***	0.086	0.099	1.089***	-0.096
	[0.113]	[0.169]	[0.159]	[0.106]	[0.157]	[0.168]	[0.121]	[0.150]	[0.165]
ln (Skilled Man. Exports IV)$_{t-5}$	-0.018	0.207	1.265***	-0.045	0.211	1.210***	-0.044	0.309*	1.217***
	[0.086]	[0.158]	[0.124]	[0.079]	[0.161]	[0.127]	[0.097]	[0.162]	[0.127]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	787	787	787	787	787	787	787	787	787
R-squared	0.958	0.952	0.970	0.959	0.951	0.970	0.958	0.951	0.969
F-Stat, Instrument	15.1	21.4	45.5	16.4	22.8	41.7	17.9	19.9	34.4

Robust standard errors clustered at the country level in brackets. *** p<0.01, ** p<0.05, * p<0.1. All regressions are estimated using data at 5 year intervals from 1965-2010. Columns 1-3 show the first stage IV results from the specification listed in column 2 of Table 6. Columns 4-6 show the first stage IV results from the specification listed in column 3 of Table 6 and columns 7-9 show the first stage results from the specification in column 4 of Table 6.