Globalization and Human Capital Investment: How Export Composition Drives Educational Attainment[1]

Emily Blanchard[2] William W. Olney[3]

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Abstract

This paper demonstrates that the composition of a country's exports is an important driver of educational attainment. Using detailed trade data and a gravity based IV technique, we identify the causal impact of changes in the pattern of a country's exports on subsequent educational attainment. Relying on within-country variation over 45 years for 104 countries, we find that exporting lower-skill goods depresses average years of schooling, particularly at the primary level, while exporting higher-skill goods increases schooling at higher educational levels. Our results provide new insight into which types of sectoral growth are most beneficial for long-term human capital formation.

Keywords: Exports; Education; Human Capital; Structural Change

JEL Codes: F14; F16; J24

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[2] Tuck School of Business, Dartmouth College, Hanover, NH 03755 (email: emily.blanchard@tuck.dartmouth.edu)

[3] Department of Economics, Williams College, Williamstown, MA 01267 (email: william.w.olney@williams.edu). This project was supported by the Class of 1945 World Fellowship grant at Williams College.

1 Introduction

Human capital ranks among the most important drivers of growth and income, yet its determinants remain poorly understood. It is notoriously difficult to measure the extent to which schooling and investment in human capital respond to changes in overall economic conditions, the pattern of production across sectors, and the returns to education. Country specific event studies offer only limited scope for drawing broad conclusions, while a lack of consistent wage data makes cross-country studies virtually impossible;[4] reverse causality and difficult-to-measure confounding factors pose additional challenges for identifying causal relationships outside of narrow case studies. Thus, despite the powerful implications for growth and inequality, the literature has yet to find robust cross-country evidence of a causal link between what countries produce and their citizens' educational attainment.

This paper adopts a new approach to address these challenges by focusing on exogenously-driven changes in a country's export patterns as a way to identify how shifts in the structure of production influence schooling outcomes. A body of theoretical work in the trade literature formalizes the underlying mechanism, but the intuition is straightforward: export markets influence labor market opportunities and wages, which in turn determine individuals' incentives to go to school.[5] Crucially, theory indicates that it is the composition of exports, rather than the overall level, that should matter most: skill-intensive exports can increase workers' incentives to acquire more training and education, while expanded opportunities in less skill-intensive sectors may exacerbate school attrition and drop-out rates.

Based on this logic, we propose a strategy to disentangle the effects of the composition of exports from the overall volume of trade, using rich panel data and a gravity-based instrumental variables technique in the spirit of Frankel and Romer (1999) and Feyrer (2009). In the process, we reconcile the disparate country-level findings of Atkin (2012) and Hickman and Olney (2011), who demonstrate (respectively), skill-downgrading in response to trade

[4] Goldberg and Pavcnik (2007)

[5] 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).

liberalization in Mexico, and skill-upgrading in the US.[6] Our findings support both earlier studies. We find that growth in low-skill intensive exports reduces educational attainment, while export growth in high-skill sectors increases schooling outcomes. At the same time, our results add new texture to the literature by demonstrating that different types of exports affect schooling decisions systematically at different points in the educational ladder.[7]

Our empirical approach offers several appealing features. First, by focussing on export composition, rather than explicit measures of labor market returns, we circumvent the sporadic and often poor cross-country wage data. Moreover, as Atkin (2012) demonstrates, educational decisions may be shaped as much by (often unobserved) job opportunities (e.g. vacancies) as by wages. By focussing on a key driver of labor market demand (exports), rather than hard-to-measure labor market characteristics such as wages and vacancies, we are better positioned to capture a wide set of potential labor market changes across a broad set of countries.

Second, exports provide a consistent measure of economic activity across countries and a relatively clean separation of different classes of production by skill-intensity. This separation allows us to examine how educational decisions depend on the skill-intensity of different types of exports. Specifically, we can test whether exports of less skill-intensive goods (e.g. agricultural products) reduces educational attainment of workers who face a higher opportunity cost of schooling. And likewise, we can test whether exporting skill intensive goods (e.g. skill-intensive manufactured products) induces greater investment in human capital. Thus, the detailed trade data allow us to move past simply examining the impact of total exports on education to focus on how specific types of exports alter individual-level incentives to go to school, as suggested by theory.

Third, a rich panel data set allows us to focus on only within-country variation to examine the link between educational attainment and export patterns. The dimensionality of our panel allows us to include country fixed effects and year fixed effects which represents a significant econometric improvement over existing cross-sectional analyses. At the same

[6] Edmonds, Pavcnik and Topalova (2010) also find a negative schooling response to trade liberalization for certain households in India, but they argue that the mechanism works primarily through the negative income effects of lower import protection for adversely affected households, rather than through the labor market incentives that are the focus of Atkin (2012) and Hickman and Olney (2011).

[7] This last point is consistent with recent theory by Blanchard and Willmann (2013).

time, the scope of our data set allows us to draw broad conclusions about the relationship between exports and education, which is something that country specific case studies have struggled to do.

Finally, we draw causal inference by focusing on the effects of only exogenously-driven changes in export composition. We construct an instrument that identifies variation in exports that is unrelated to potentially confounding domestic factors, including political reforms, local technological changes, and (crucially) educational attainment itself. Modifying a gravity technique developed by Frankel and Romer (1999) and Feyrer (2009), we exploit variation in bilateral trade that is driven by exogenous geographic factors and (time-varying) conditions in each of a country's trading partners. Aggregating across trading partners yields a set of exogenous instruments for the pattern of a country's exports. We extend this approach to construct separate instruments for each of our export components – in effect, exploiting the non-homotheticity in bilateral import demand for different classes of traded goods. To the best of our knowledge, we are the first to use this technique.[8]

Our analysis proceeds in three stages. First, we briefly outline the theoretical basis for our study, based on existing models that link the pattern of a country's exports directly to human capital acquisition. We then combine data on exports and educational attainment spanning 104 countries and 45 years to examine the relationship between the pattern of a country's exports and educational attainment. In the third section of the paper, we work through a series of extensions and robustness checks to develop additional insights into the underlying mechanisms, the key sources of variation driving the results, and the broader applicability of our findings.

We find that exports have a significant and robust impact on educational decisions. Our results show that the *skill-composition* of exports plays an important role in educational attainment: agricultural and low-skill manufactured exports reduce average years of schooling while exports of skill-intensive manufactured goods increases schooling.[9] The results are

[8] Specifically, we find that a country's bilateral exports of agricultural, low- and high-skill manufactured goods respond quite differently to changes in trading partners' incomes. This heterogeneity in import demand-elasticities generates sufficient variation to separately identify exogenously-driven changes in a country's export composition.

[9] Estimates from the baseline specification, suggest that doubling agricultural exports decreases average years of schooling by 0.6 years, while doubling skill-intensive manufactured exports increases schooling by 0.3 years on average.

similar whether or not we control for the total level of exports or GDP, which emphasizes the importance of the compositional effect relative to the potential influence of the overall volume of exports or trade-induced changes in aggregate income.

Using more detailed data on primary, secondary, and tertiary education levels, we find that different types of exports affect educational attainment at different points within the schooling system. Specifically, unskill-intensive exports reduce primary schooling, while skill-intensive exports increase schooling higher up the educational ladder. In other words, the results are strongest where we expect the relationships to be most important. The differential responses in educational attainment by workers at various points on the educational ladder are both intuitive and consistent with existing theoretical predictions (Blanchard and Willmann 2013).

To better understand the underlying mechanisms, we utilize different dimensions of the data to conduct a series of extensions. A placebo test confirms that exports have no effect on the educational decisions of older individuals, which offers additional support for our posited mechanism. We find that the impact of exports on schooling is similar across genders[10] but differs according to the level of development of the country. Perhaps unsurprisingly, we find that the negative impact of agricultural exports on average years of schooling is limited to less-developed countries. In contrast, the impact of manufactured exports on educational attainment is similar across rich and poor countries, although slightly larger in magnitude in developed countries.

Finally, we conduct a number of sensitivity checks. For instance, we demonstrate the robustness of our results to alternate lag structures and the inclusion of a variety of additional controls, including both national spending on education and foreign direct investment. As a further check on our IV strategy, we reconstruct the instrument in a variety of different ways to alleviate potential concerns about the validity of the exclusion restriction.

Together, our findings raise a troubling possibility. Taken to the logical conclusion, our results suggest that the impact of trade on educational attainment could induce economic divergence. Less-developed countries that export agricultural goods may experience declines

[10] We find modest evidence that unskilled manufactured exports have a more negative impact on male educational achievement than female achievement; differences in the responsiveness to agricultural and skilled manufacturing exports are negligible.

in educational attainment, which will only sharpen comparative advantage in agricultural goods. At the same time, developed countries that tend to export skill-intensive manufactured goods will experience an increase in educational attainment, further increasing comparative advantage in those goods. This is particularly troubling in light of recent work (e.g. Jones, 2014) that suggests human capital is the most important driver of economic growth.[11] Our empirical findings also lend support to the stark theoretical predictions of Ventura (1997) and Bajona and Kehoe (2010), who demonstrate that incorporating trade into standard growth models can dramatically change the convergence prediction to the detriment of poor countries.[12]

Our work relates to an important body of specific event studies that demonstrate 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) found 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.

Several more closely related studies focus explicitly on the link between trade and educational attainment. Edmonds, Pavcnik, and Topalova (2009, 2010) find that imports reduce educational attainment in both rural and urban areas within India, operating primarily through a negative income effect.[13] As noted earlier, Atkin (2012) finds evidence of skill downgrading in Mexico while Hickman and Olney (2011) find evidence of skill upgrading in the U.S. Our findings provide a plausible explanation for these conflicting results.

More broadly, while country specific studies generate compelling findings, their narrow

[11] Jones (2014) argues that differences in the stock of human capital could account for potentially *all* of the variation in income between rich and poor countries.

[12] 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. However, trade alters the terms of trade, decreases the returns to these factors, and thus reduces the tendency of poorer countries to converge.

[13] 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.

scope necessarily limits the extent to which broader cross-country inferences can be drawn. Our paper takes an alternative but complementary approach, sacrificing some of the precision of case-studies in order to generate a broad cross-country long-horizon set of results that ultimately knit together the existing literature on educational attainment and local labor market changes.

To the best of our knowledge, the only other papers that have pursued a cross-country examination of the relationship between trade and educational attainment are Wood and Ridao-Cano (1999), Redding and Schott (2003), and Galor and Mountford (2008).[14] Relative to these earlier papers, our panel setting offers immediate advantages relative to the cross-sectional analyses in Redding and Schott (2003) and Galor and Mountford (2008). Additionally, we use a direct measure of exports in our analysis which improves upon Wood and Ridao-Cano (1999) and Galor and Mountford's (2008) technique of using a country's initial factor endowments or level of development to form assumptions about the types of goods they export. Most importantly, we use an IV approach to identify the causal impact of exports on educational attainment, which allows us to directly address concerns over reverse causality and omitted factors that would otherwise challenge econometric inference.

The next section presents the theoretical justification for our approach, based largely on existing work in the trade literature. Section 3 lays out the reduced-form empirical specification. Section 4 introduces the data and describes our instrumentation strategy. Section 5 presents the baseline empirical results, while section 6 discusses a number of extensions and robustness checks. Section 7 concludes.

2 Theory

In this section, we outline the theoretical basis that underpins our empirical approach. We use existing work in trade theory to sketch how the pattern of a country's exports drives local investment in human capital. Weaving together several modeling approaches, we first formalize the intuition driving our basic empirical strategy using a workhorse Heckscher-Ohlin model, and then draw out additional predictions that arise in a richer framework.

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

This modeling exercise thereby provides a useful way of motivating and setting up the empirical analysis that follows; it should not be interpreted as a stand-alone contribution of the paper.

We begin by clarifying 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 short second subsection then discusses income effects and summarizes additional insights from more recent work in the trade literature. In particular, we demonstrate the possibility of non-monotonic skill change – the idea that increased trade could both increase and decrease educational attainment at different points along the educational ladder. We use this basic insight to inform how we measure skill attainment within and across countries.

2.1 A Simple Model of Exports and Skill Acquisition

In what follows, we present a simplified version of Findlay and Kierzkowski (1983) to demonstrate the mechanism by which trade drives incentives for 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.[15]

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 of N 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 her life, or she can go

[15] 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.

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

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

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

where UT is the number of unskilled people, $E\theta$ are individuals who are 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 which reflects teachers, classrooms, facilities, etc., and E is the number of students, each of whom spend θ time 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 educational input for the entire θ period of her education. Assume that the returns to education are diminishing in k so that: $f'(k) > 0$ and $f''(k) < 0$.

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

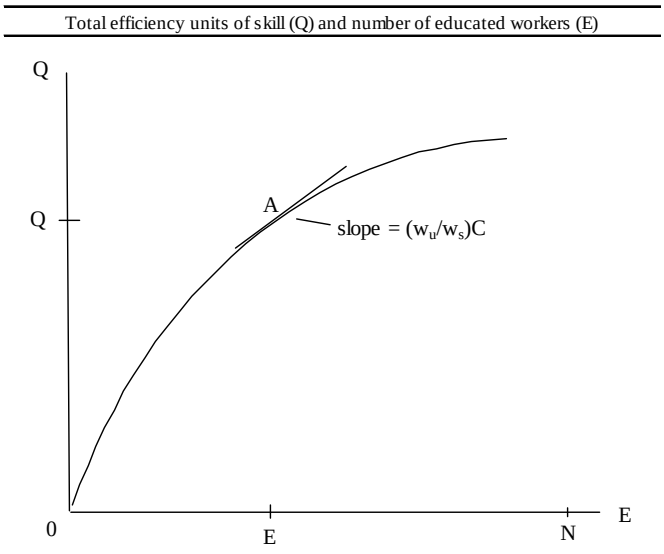
$$\frac{\partial Q}{\partial E} = f(k) - f'(k)k > 0 \text{ and} \tag{3}$$

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

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



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 (direct) equilibrium school fees associated with going to school from time 0 to θ are equal to the present discounted value of marginal product of school over the skilled workers 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 then earns income of w_u, while a skilled worker with a skill level of $f(k)$ earns $w_s f(k)$. Taking the 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:

$$\int_{\theta}^{T} w_s f(k) e^{-rt} dt - \int_{\theta}^{T} w_s f'(k) k e^{-rt} dt \geq \int_{0}^{T} w_u e^{-rt} dt. \tag{5}$$

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.[16] This latter condition and free entry implies that the equilibrium net benefit of education is zero. Thus, setting (6) to zero and rearranging generates the following expression:

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

Thus, in equilibrium the slope of the curve in Figure 1 is equal to the relative wage scaled by a constant, C. Equation (7) therefore pins down the equilibrium value of E. The horizontal distance $0E$ reflects the number of individuals that choose to become educated, while $U = N - E$ individuals choose to remain unskilled.

2.1.2 Trade

Suppose that both Home and Foreign have identical technologies, tastes, and educational sectors, but differ in their 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 HO theorem) gives Home a comparative advantage in agriculture. Therefore, opening to trade, Home exports agriculture while Foreign exports manufactures, since (in the short run) the country's endowment of human capital is initially fixed.

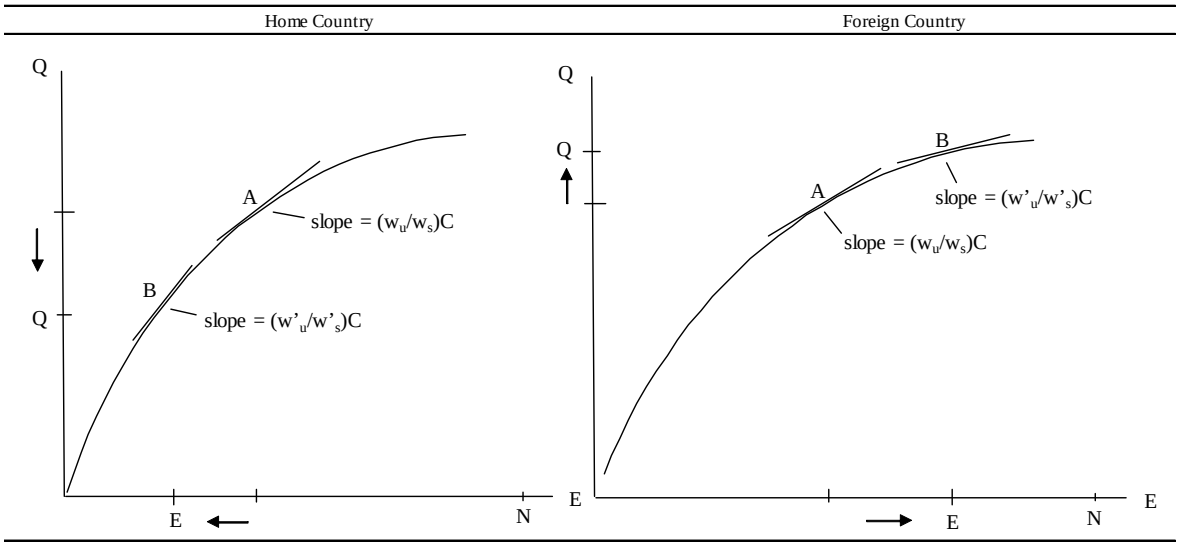
With trade, world relative prices converge to some point in between the two autarky relative prices. Opening to trade thus causes the relative price of agriculture to increase at

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

Home and decrease in Foreign. These price changes translate directly to changes in relative wages. By the SS Theorem, the relative unskilled wage increases in Home and decreases in Foreign. From equation (7) it follows immediately that educational attainment will decline at Home and rise in Foreign.

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 less skill-intensive agriculture goods reduces the equilibrium number 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 important testable predictions. Countries that export less skill-intensive (e.g. agricultural) goods will see a decline in average educational attainment. However, countries that export skill-intensive (e.g. manufactured) goods will experience an increase in educational attainment. The key insight is that trade alters relative wages and thus changes the incentives to go to school. The remain-

der of the paper examines whether there is empirical evidence supporting these intuitive predictions.

2.2 Extensions to the Baseline Theoretical Framework

Our empirical approach is motivated primarily by the Stolper-Samuleson intuition formalized above. Before we continue to the empirical specification, however, we pause to introduce some additional testable predictions based on more recent empirical and theoretical work in the literature.

First, while the simple theoretical framework above emphasizes how different components of trade alter the incentives to go to school, it is important to recognize that exports can also generate income effects that may influence schooling. Empirical work by Edmonds, Pavcnik and Topalova (2009, 2010) demonstrates the importance of this channel, finding evidence that household income effects have outweighed the 'direct' 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 (or decrease) household real income for export-oriented (import competing) workers. Richer families may opt to send their children to school longer, even when the opportunity cost of schooling rises, just as households that suffer a decline in income may reduce educational investments, even if the opportunity cost of schooling falls. Stepping back to the national level, it is reasonable to postulate that exports, regardless of type, could generate a positive *aggregate* income effect (which would be consistent with Frankel and Romer (1999) or Feyrer's (2009) findings that trade increases GDP). This would induce greater educational attainment if overall GDP gains are broadly shared. Our empirical analysis includes specifications both with and without controls for aggregate income, which together provide insight into the relative magnitude of these competing effects.[17]

In recent theoretical work, Blanchard and Willmann (2013) develop a model of trade and endogenous skill acquisition with the same fundamental mechanisms found in Findlay and Kierzkowski (1983) and outlined above. In place of dynamics, their model allows for

[17] We cannot, however, 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.

ex-ante heterogenous agents and a continuum of sectors (or 'occupational tasks'), each of which requires a specific skill level. Relative to the framework reviewed in the previous subsection, their model offers several additional insights relevant for our empirical analysis.

Trade liberalization can induce simultaneous skill upgrading and skill downgrading in a many-sector model. Intuitively, a country can have comparative advantage at multiple points along the job-skill ladder – for instance, in high tech pharmaceuticals and also in fresh produce. Trade liberalization will increase relative wages in these export sectors, which can induce some workers to upgrade skills (entering into pharmaceuticals) while others to reduce skill attainment (entering agricultural work).

Another closely related point is that the incentive effects of trade will affect different types of workers differently. In Blanchard and Willmann's model, individuals face ex-ante heterogeneous costs of education: some workers find skill upgrading relatively easy, while others do not. These individual level differences affect both the equilibrium self-selection of agents into different skill levels and occupations, and the aggregate response to trade liberalization. Even a substantial increase in the average return to skill upgrading may not be sufficient to induce some agents to acquire more education.

From here we draw two insights that shape our subsequent empirical approach. First, we expect that an increase in exports may induce both an increase and decrease in educational attainment in the same country, at the same time. It is the skill-composition of exports – not the volume of trade itself – that should matter for educational attainment. Indeed, it is entirely possible that regressing educational outcomes on total exports could yield evidence of no causal relationship even if the underlying effects of trade are acute: aggregate exports can obscure trade's true effects. Thus, our empirical work focuses on the skill composition of exports at the country-level.

Second, we anticipate the effects different components of exports to influence educational attainment at different points along the educational ladder. For instance, a high school dropout is unlikely to reenroll following an increase in pharmaceutical exports, while the valedictorian is unlikely to drop out following an improvement in potato exports. We predict that low skill-intensity exports are likely to affect decisions at lower rungs of the educational ladder while changes in exports of more skill-intensive goods are likely to influ-

ence educational outcomes at higher rungs. Empirically, we therefore measure educational attainment not only by average years of schooling at the country level, but also by primary, secondary, and tertiary completion rates.[18]

3 Empirical Specification

We use the following reduced form specification to test the extent to which the composition of a country's exports affects its residents' educational attainment:

$$(8) \quad Educ_{it} = \beta_0 + \beta_1 \ln Agr_Exp_{it-5} + \beta_2 \ln Man_Exp_{it-5} + \beta_3' X_{it-5} + \gamma_i + \gamma_t + \varepsilon_{ct}.$$

Educational attainment is measured as either the average years of schooling in country i in year t or, in later specifications, the rate of school completion at the primary, secondary, and tertiary levels. The key independent variables of interest are the (log of) agricultural exports, Agr_Exp_{it-5}, and manufactured exports, Man_Exp_{it-5}, of country i in year $t-5$. The vector X consists of time-varying country-level control variables including imports, population, death rate, and migrant share, that could influence educational attainment. 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 addition, equation (8) is estimated at five year intervals.[19] 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 throughout to address the potential for serial correlation.

Theory predicts that an increase in agricultural exports reduces the incentive to go to school, so that $\beta_1 < 0$, while an increase in manufactured exports induces greater educational attainment, $\beta_2 > 0$. In contrast, if exporting leads to a positive aggregate income effect that increases demand for education, then both coefficients in equation (8) should be positive.[20] So the sign of β_1 will provide preliminary insight into the magnitude of the

[18] While the definitions of 'primary', 'secondary,' and 'tertiary' vary somewhat across countries, the country fixed effects will capture these differences. Our categories of exports by skill-intensity are also sufficiently coarse that we cannot make more specific predictions. To improve upon the specificity afforded by cross-country data would require a country-specific case study, along the lines of Atkin (2012).

[19] This is because education data is only available every five years. However, given the nature of our question five year intervals is probably preferable to a high frequency annual analysis.

[20] As noted earlier, our aggregate level data is unable to address the relative strength of income and

income and incentive effects. To control for these aggregate income effects more carefully, we also estimate a version of equation (8) that includes total exports or GDP. Comparing the results with and without GDP, for instance, offers insight into the magnitude of these competing effects.

In the theory, we adopted the customary assumption that agriculture is unskilled-intensive and manufacturing is skill-intensive. Although this seems plausible (at least in the developing world), the empirical analysis further decomposes manufactured exports into those that are skill-intensive and those that are unskill-intensive using standard industry classifications. To the extent that the skill intensity of agricultural and manufacturing exports varies across countries or over time, the country fixed effects and year fixed effects control for these differences. Finally, we address the potential that the skill intensity of industries could vary systematically between developed and less-developed countries in an extension.

While the lag structure and the inclusion of numerous controls and fixed effects alleviates some of the concerns about omitted variable bias and reverse causality, they may not completely eliminate endogeneity. Thus, we rely on an instrumental variable approach to identify the causal impact of exports on educational attainment. The specific construction of the instrument will be discussed in greater detail in the next section of the paper.

4 Data

4.1 Educational Attainment

Data on educational attainment come from Barro and Lee (2013) and are appealing for a number of reasons. First and foremost, it has educational attainment data for over one hundred countries over five year intervals from 1950-2010. The broad scope of countries included and the time period covered is central to the spirit of this cross-country, long horizon analysis.

Second, it offers educational attainment data for different age cohorts. In the baseline

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.

specification, we focus on average years of schooling of 15-29 year olds. This younger cohort is the focus of the empirical analysis, because, by definition, these are the individuals in the process of making their educational decisions. Younger workers are also more sensitive to changing economic conditions since they have their full working careers ahead of them. Utilizing data on older individuals, we also pursue a placebo test where we examine how exports affect the average years of education of older individuals.

One more key attribute of the Barro and Lee (2013) data is the inclusion of average schooling years and completion rates at the primary, secondary, and tertiary levels. The data also break out educational attainment by gender, which we study in another extension.

4.2 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 by 4-digit SITC revision 2 industry for the years 1962-2008.[21] The data set also reports bilateral trade flows by industry for every pair of countries in the world, which we use to construct the instrument. 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 agricultural exports as the sum of exports in SITC industries 0, 1, 2, and 4, and manufactured exports as the sum of exports in SITC industries 6, 7, and 8. We further decompose these manufacturing industries into those that are unskill-intensive and those that are skill-intensive using data UNCTAD data (Basu forthcoming) on the skill and technology content of HS 6 digit industries and a HS - SITC concordance from the Center for International Data at UC Davis.[22] As a robustness check (available by request), we instead construct skill-intensity classifications using the NBER-CES U.S. Manufacturing

[21] We utilize a version of this data that has been extended to 2008 by Robert Feenstra and Gregory Wright.

[22] Specifically, SITC 2-digit manufacturing industries are defined as unskill intensive if they primarily consist of "Non-Fuel Primary Commodities", "Resource-Intensive Manufactures", or "Mineral Fuels." If the SITC 2-digit manufacturing industry primarily consist of "Technology-Intensive Manufacturing", then they are defined as skill-intensive manufactured industries. In contrast, the agricultural group of industries are completely uniform. All 2-digit SITC industries that constitute the Agricultural sector defined above are classified as "Non-Fuel Primary Commodities" by UNCTAD.

Industry Database[23] and find the results little changed.[24]

Finally, relative to the raw UN Comtrade data, a number of corrections and improvements have been made in this data set. 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).[25]

4.3 Control Variables

We control for both country and year fixed effects throughout. To account for factors that may vary over time within a country, the empirical specification adds addition time varying country-level control variables. The set of potential controls is limited by data availability; relatively few data series span the set of countries and years included in the education and trade data. Thus, we face a trade-off between maximizing the set of control variables and maximizing sample size. We begin by including in the baseline analysis those control variables that are most relevant to our study and also the most comprehensive. Then in Section 6.4 we include additional controls that may be important but whose coverage is poor.

Specifically, the set of controls in the baseline analysis consists of: real imports, which are obtained from the World Trade Flows data set; population, from the Penn World Tables; the death rate per 1,000 people, from the World Development Indicators (WDI) data produced by the World Bank; and the immigrant share of the population, also from the WDI.[26] In some specifications we also control for total exports obtained from the World Trade Flows data set and GDP from the Penn World Tables. All control variables are logged and lagged five years.

[23] The downside of using the NBER U.S. Manufacturing database is 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.

[24] While it would be informative to explore heterogeneity in industry skill-classifications across countries, we would need more disaggregated data to do so. In our context, heterogeneity in estimates across developed versus developing countries thus may in part reflect differences in skill intensity across industries.

[25] These adjustments have not been made to the 2001-2008 data, but the results that follow are remarkably similar if the post 2000 trade data is excluded.

[26] 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.

4.4 Descriptive Statistics

Combining these different variables generates an unbalanced panel data set that spans the years 1965-2010 at five year intervals. Educational attainment covers the years 1970-2010 while the trade and control variables are lagged five years and thus span the years 1965-2005. This lag structure makes the best use of the available trade data; however, later we show that the results are robust to other lag specifications.

Following Hanson et al. (2013), we exclude extremely small countries from our baseline sample.[27] In addition, we 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.[28] Our results are robust to alternate samples of countries, but we find this cut of the data to be the most sensible.

Table 1 reports summary statistics for the variables included in 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 share of agricultural and manufactured exports over the 1965-2010 period by country.

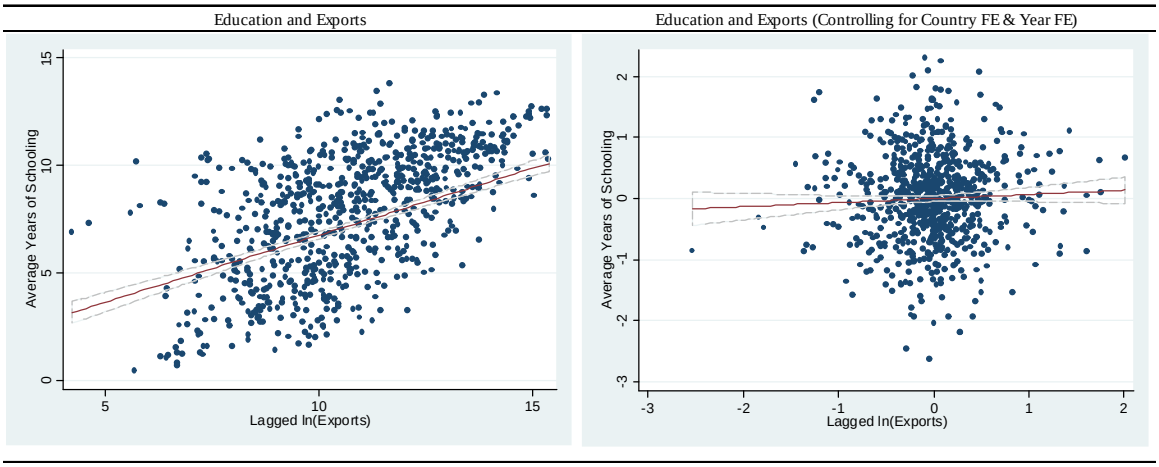
The left panel of Figure 3 offers a first look at the data, plotting the average years of schooling against the natural logarithm of lagged total exports. A clear positive and significant relationship is evident. This should be interpreted with caution, however, since it is likely that exports and average years of schooling are higher in more developed countries and higher in more recent years. To account for this most obvious source of bias, we regress exports and years of schooling on country and year fixed effects, and plot the residuals on the right side of Figure 3. These residuals represent the variation exploited in our empirical analysis and show that there is no significant relationship between years of schooling and total exports. Therefore, at least in this raw cut of the data, there is little evidence that the total level of exports are significantly tied to overall educational attainment. Rather, the positive relationship between exports and educational attainment observed on the left side is largely due to fixed country and year factors. Together these two scatter plots highlight

[27] Countries with less than a million people or with GDP of less than five million dollars on average were dropped.

[28] For instance, conflict and wars in Iraq, Cambodia, and Nicaragua led to a dramatic decline in exports in these countries at various points in time.

the importance of controlling for country and year fixed effects, something the previous literature has not always done.

FIGURE 3

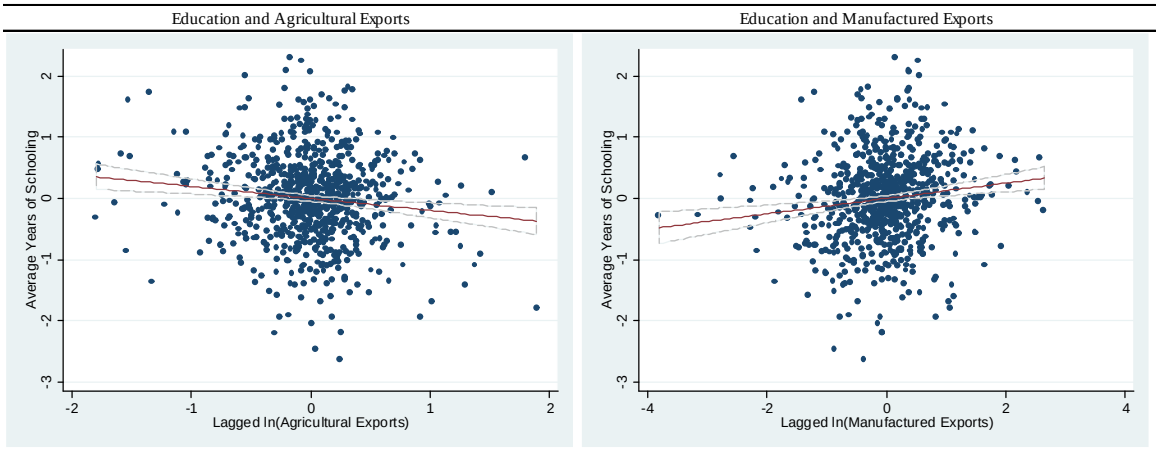


The left panel plots average years of schooling of 15-29 year olds against lagged real exports. The right panel is an anologous scatter plot after controlling for country fixed effects and year fixed effects. Schooling data is from Barro and Lee (2013) and the trade data is from the NBER-UN Trade Dataset.

The theory predicts that the composition, not necessarily 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.[29] These opposing relationships are consistent with the theoretical prediction that lower skill (e.g. agricultural) exports are likely to increase the opportunity cost of school and thus decrease educational attainment, while exports of higher skill (e.g. 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. Next we examine whether these relationships can survive a more rigorous econometric analysis.

[29] When we later decompose manufacturing by skill-intensity level, these distinction grow even sharper as demonstrated by the empirical results.

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.

4.5 Instrument

Our IV strategy is based on a well-established method of constructing an instrument using the gravity model (Frankel and Romer 1999 and Feyrer 2009 among others). This section describes specifically how the instrument is constructed using bilateral trade data; later, we use this instrument in our standard two-stage least squares (2SLS) estimation procedure. The results from this section thus represent a preliminary step necessary to construct the instrument and should not be confused with the typical first-stage and second-stage IV results that will follow afterwards.

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 an instrument for export volumes is to eliminate any variation in bilateral trade that is driven by exporter characteristics. The instrument therefore relies on only the variation in trade due to more plausibly exogenous factors such as geography and economic conditions in a country's foreign trading partners.[30]

[30] Unlike Frankel and Romer (1999) and Feyrer (2009), which focus exclusively on geographic factors, we

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} are exports from country i to country j in year t.[31] 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. Finally, $\sigma > 1$ is the elasticity of substitution between goods. Taking logs of equation (10) generates:

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

Thus, bilateral export flows are a function of log real GDP in the importing country, $ln(y_{it})$. Real GDP in the exporting country, $ln(y_{jt})$, will not be included in the subsequent empirical specification, since it could be correlated with educational attainment. Again, the goal of this IV strategy is to identify the variation in bilateral trade that is unrelated to conditions in the exporting country. Year fixed effects, γ_t, will absorb changes in world GDP, $ln(y_{wt})$, and common trends in the bilateral and multilateral resistance terms. Finally, a full set of bilateral pair fixed effects, γ_{ij}, will control for all time-invariant resistance factors such as distance, language, and colonial relationships that are often found to be important determinants of bilateral trade. Baldwin and Taglioni (2006) argue that, relative to importer and exporter fixed effects, bilateral pair fixed effects are preferable when using a panel data set and are better at dealing with the "gold medal error" associated with the multilateral resistance terms. Thus, we obtain the following equation:

$$ln(x_{ijt}) = \alpha ln(y_{it}) + \gamma_t + \gamma_{ij} + \epsilon. \tag{11}$$

To estimate (11), we use bilateral export flows between every pair of countries in our

also exploit variation due to economic shocks in the foreign importing country. We explore several alternative strategies of instrument construction in robustness checks.

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

sample over five year intervals from 1965-2005.

In the first two columns of Table 3, we confirm that our data and analysis can replicate the gravity results now common in the literature. Column 1 reports a simpler gravity specification with year fixed effects, importer fixed effects, and exporter fixed effects. Consistent with the existing literature, we find that bilateral export flows are increasing with importer GDP and exporter GDP, but decreasing with distance. Column 2 then includes a (more rigorous) set of bilateral pair fixed effects, which subsume the distance variable and all other time invariant factors. We see that both importer GDP and exporter GDP still have a significant positive impact on exports, consistent with existing work.

Column 3 then reports the estimates from equation (11). The within sample fitted values from this regression capture variation in bilateral trade that is driven by importer GDP, time effects, and bilateral pair effects for each pair of countries in each year. Again, these fitted values are by construction not a function of conditions in the exporting country. We find it reassuring that the coefficient on importer GDP does not change from columns 2 to 3, which alleviates concerns that importer GDP could inadvertently be picking up variation in exporter GDP. While it is possible that the bilateral pair fixed effects could inadvertently capture some time-invariant characteristics of the exporting country, the country fixed effects in the main IV analysis will account for these factors.

The fitted values from column 3 are at the bilateral-year level, while the unit of observation in our main empirical specification is at the country-year level. The last step in constructing our instrument is then simply to aggregate the bilateral fitted values across all trading partners within a year, to generate total exports abroad for each country in each year. Following Frankel and Romer (1999) and Feyrer (2009), the (unlogged) bilateral fitted values are summed in the following manner to construct our instrument:

$$export_IV_{it} = \sum_{j \neq i} e^{\widehat{\alpha} ln(y_{it}) + \widehat{\gamma}_t + \widehat{\gamma}_{ij}} \tag{12}$$

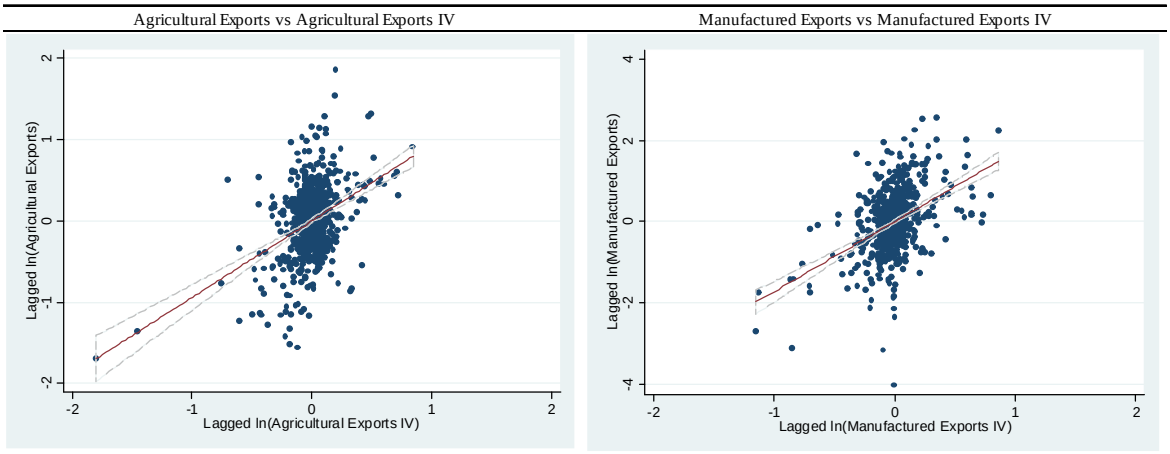
Analogous instruments are constructed for each of the export components using this same methodology. Specifically, agricultural exports, manufactured exports, unskilled manufactured exports, and skilled manufactured exports are used in turn as the dependent

variables in equation (11). The results from these estimations are reported in columns 4-7 of Table 3. The fitted values are then summed according to equation (12) to create the instruments for each export type.

Constructing separate instruments for each of the export components represents a novel feature of our IV analysis relative to existing studies which simply focus on total exports (Frankel and Romer 1999, Feyrer 2009). Specifically, our approach takes advantage of the non-hometheticity of preferences where foreign shocks can have differential effects on the demand for agricultural and manufactured exports. For instance, growth in one country (i.e. China) may lead to greater demand for agricultural exports while the growth of another country (i.e. Germany) could lead to greater demand for manufactured exports. While intuitive, Figures 5 and 6 then investigate whether there is actually enough variation in this IV approach to separately predict these different export components.

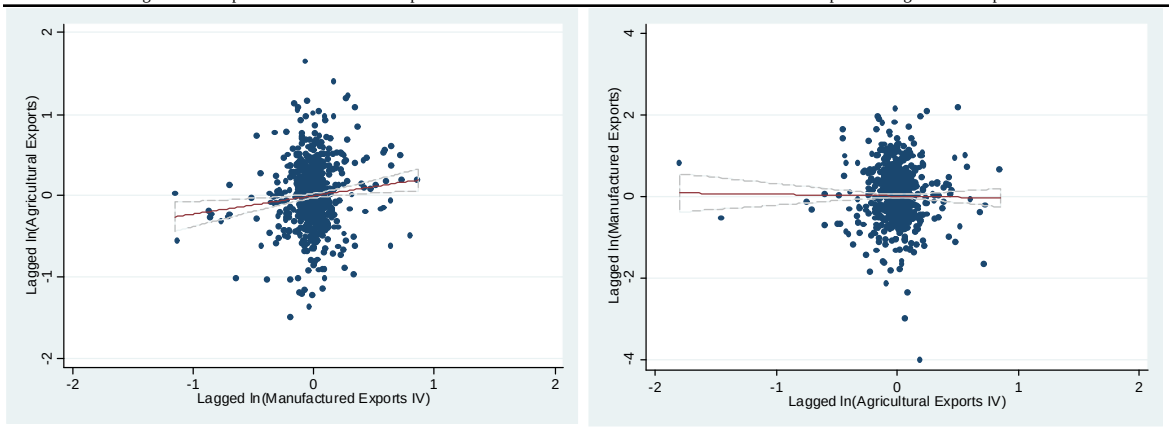
Figure 5 shows that the agricultural and manufactured instruments have a significant positive impact on the type of exports they were designed to predict after controlling for the other instrument, country FE, and year FE. Figure 6 then shows that the other instrument is not successful at predicting the export component of interest. For instance, on the right side of Figure 6 we see that the agricultural instrument is not a good predictor of manufactured exports after controlling for the manufactured instrument, country FE, and year FE. Thus, despite the similarity in how the instruments are constructed, Figures 5 and 6 show that this approach is successful at separately identifying the different components of 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.

Finally, we note that our empirical strategy offers several additional features that limit 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). Another potential concern is that importer GDP could be correlated with exporter GDP in some unobserved way (outside of the time fixed effects, which are already included), especially if the two countries are geographically proximate or are economically

integrated. That said, the results in Columns 2 and 3 of Table 3 argue against this possibility since the coefficient on importer GDP does not change when exporter GDP is excluded. Nonetheless, in a robustness check, we use the importing-country's death rate, rather than importer GDP, to construct the instrument. This alternative is less consistent with a gravity model approach but could be better at identifying an exogenous shock in the importing country. In Section 6.6, we also use bilateral trade agreements to construct the instrument rather than importer GDP. Overall, we find that our baseline results are robust to these alternative IV specifications, which limits concerns about the exclusion restriction.[32]

5 Results

5.1 OLS

We report baseline results using Ordinary Least Squares (OLS) in Table 4. All regressions include country fixed effects, year fixed effects, and have robust standard errors clustered at the country level in brackets. Column 1 estimates the relationship between average years of schooling and agricultural and manufacturing exports. As expected, exporting unskill-intensive agricultural goods is negatively correlated with average years of schooling. Specifically, doubling agricultural exports is associated with a decline in average schooling within a country of 0.3 years.[33]

In the next row of column 1, we find that the relationship between manufacturing exports and educational attainment is insignificant. At first glance, this result seems surprising, since the theory predicts that exporting relatively more skill-intensive goods should increase the relative wage of skilled workers, and thus provide an incentive to go to school. There is, however, marked heterogeneity among these manufacturing industries. For instance, textile

[32] We also tried constructing an instrument using the distance weighted average tariff rates of a country's foreign trading partners. Unfortunately, TRAINS tariff data by country and industry are only available after 1988. Unsurprisingly, drastically limiting the number of years in the sample weakens this IV.

[33] While this coefficient may seem small, it is important to remember that the educational decisions of only a subsample of the population are affected by agricultural exports. In this light, it is perhaps remarkable that a change in exports is large enough to show up in the overall average years of schooling of the entire population. 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).

yarn and fabric (SITC 65) and office and automatic data processing machines (SITC 75) are both classified as manufactured goods but, according to UNCTAD, the former is resource and unskill-labor intensive while the latter is technological and skill-intensive. To disentangle these effects, column 2 reruns the empirical specification decomposing manufactured exports into unskilled and skilled components using the classifications described earlier.

In this new specification in Column 2, the coefficient on agricultural exports is still negative and significant as before. In contrast, the two components of manufactured exports demonstrate sharp and opposing relationships with schooling. Unskill-intensive manufactured exports are negative and significantly related to average years of schooling, while the coefficient on skill-intensive manufactured exports is positive and significant, consistent with the predictions generated by theory. These contrasting results explain why the estimated coefficient on aggregate manufactured exports in column 1 is insignificant.

Notice that the results in column 2 combine a potentially positive aggregate income effect of exports with the compositional effects outlined in our theoretical section. The fact that the coefficients on agricultural exports and unskilled manufactured exports are negative suggest that the compositional effects dominate any potential aggregate income effect. However, to examine this issue more carefully, columns 3 and 4 control for total exports and GDP respectively. In column 3, total exports has an insignificant impact on educational attainment, while the coefficients on the export components remain virtually unchanged.[34] This indicates that what matters for educational attainment is the composition of exports and not necessarily the total volume of exports. In column 4, we control for potential aggregate income effects more carefully be including GDP. As expected, GDP has a significant positive impact on educational attainment. While the manufactured export coefficients in column 4 are slightly less positive, as expected, controlling for aggregate income does not significantly alter the coefficients of interest. Thus, while there is little evidence of an aggregate income effect associated with exports, the compositional effect appears to be quite strong which is consistent with our theoretical predictions. We have not yet demonstrated causality, however, and thus we turn to the instrumental variables results now.

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

5.2 IV

Despite lagging the independent variables and including a variety of controls and fixed effects, there are still potential endogeneity concerns. Thus, we implement an IV approach to test the causal predictions of the theory. As described earlier, our instrument is constructed using the variation in a country's bilateral export pattern that is driven by exogenous factors.

Table 5 reports the first stage IV results.[35] 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. Consistent with the findings in Figures 5 and 6, these results indicate that the IV components are successfully capturing different variation that is useful in predicting actual export flows. To address the potential violation of the exclusion restriction whereby a foreign shock in the importing country affects the domestic economy through a channel other than trade, we specifically control for imports and migration throughout.[36] Finally, 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 IV results. The results are similar to our OLS findings, but now carry a causal interpretation consistent with theory. In column 1 agricultural exports depress average years of schooling while aggregate manufactured exports do not have a significant impact on educational attainment. When, in column 2, manufacturing is separated by skill intensity, we find evidence of a sharp causal relationship between manufacturing exports and educational attainment. Educational attainment is decreasing with unskill-intensive manufactured exports and increasing with skill-intensive manufactured exports. Both coefficients are significant at the one percent level.[37] Finally, the results in-

[35] These are the first stage IV results from the baseline specification in column 4 of Table 6. The other first stage IV results are very similar.

[36] As noted earlier, we control for FDI in an extension in Section 6.4 and find the results to be robust despite the limited sample size.

[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 effects the significance of the coefficients.

cluding total exports (column 3) and GDP (column 4) are again similar and indicate little evidence of an aggregate income effect.

Consistent with the existing literature (Frankel and Romer 1999, Feyrer 2009), our IV results in Table 6 are larger in magnitude than the OLS results in Table 4. We posit that this difference is likely driven by the higher variance of the export measures (relative to the instruments), which would attenuate the OLS results. Specifically, the instruments may identify a more permanent, structural source of variation in exports and thus strip away idiosyncratic variation our export variables. To the extent that young 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. The scatter plots in Figure 5 offer evidence along these lines, where we see 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 unskill-intensive exports and increasing with 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 the 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.

5.3 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 a 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 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. As expected, agricultural exports have a significant negative impact on primary schooling, but have little impact on secondary and tertiary education. This indicates that, as expected, students in grade school are more affected by growth in the agricultural sector than those pursing a college education.[38] 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 skill distribution, particularly at the secondary school level.[39]

Table 8 pursues a similar type of analysis but utilizes a different measure of educational attainment from the Barro and Lee (2013) Dataset. Specifically, in Table 8 the dependent variable is 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. However, the results are broadly consistent with those from Table 7. Agricultural and unskilled manufactured exports influence educational decisions negatively and toward the bottom end of the skill distribution while skilled manufacturing exports affect decisions positively and higher up the skill distribution.

Not only are the results in Tables 7 and 8 consistent with theory, they also serve as a quasi-placebo test of our main results. We would be concerned, for instance, if agricultural exports significantly affected college level education decisions. The fact that the results are strongest in the most logical places is reassuring.

[38] 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 developing and less developed countries.

[39] The lack of a discernable 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.

6 Extensions

6.1 Age

The analysis so far has focused 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 to recoup 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, 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 convenience, column 1 re-reports the baseline results 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 30-49 year olds is unaffected by changes in the pattern of exports. Comparing the results in columns 1 and 2 confirms our expectation that the results should hold for only younger individuals.

6.2 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.

6.3 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 relationship with years of schooling in less developed countries as in the baseline analysis, but we find no such evidence when restricting attention to only developed countries. This finding is consistent with the idea, for instance, that the agricultural sector is less skill-intensive in developing countries but is more capital intensive (and may attract very little formal-sector labor) in developed economies. Furthermore, this result indicates that the negative coefficient on agricultural exports in the baseline results is primarily driven by less developed countries. Notably, 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.

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.

6.4 Sensitivity Analysis

Table 12 reports a number of sensitivity checks that test the robustness of the baseline results. Specifically, column 1 lags the independent variables by 10 years, rather than the 5 year lags that are used in the baseline specification. This specification addresses the concern that the 5 year lags may be too short to capture the schooling responses of some of the youngest cohorts. The downside of using the longer lags is that we lose more than ten percent of our observations. Despite the smaller sample, the results in column 1 of Table 12 are of the expected sign, significant, and quite similar to the baseline results. Thus, we find no evidence that our results are sensitive to the lag structure used in the baseline specification.

Columns 2-5 include a variety of additional controls. In Column 2, we include a control for national educational expenses 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 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 3 controls for foreign direct investment. This measure of inward FDI was obtained from the World Development Indicators but it has relatively poor coverage and thus was not included in the baseline specification. 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. At the same time, the coefficient on FDI is not statistically significant. This provides yet more support for the exclusion restriction and thus our IV approach.

In column 4, 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 4 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.

Finally, following the export definitions, the import control variable is decomposed into analogous agricultural and manufacturing components. As is evident in column 5, including these separate import controls does not change the export coefficients of interest. In addition, the import components have a minimal impact on educational attainment. 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. Overall, column 6 shows that the baseline results are robust to the separate inclusion of these import components and that educational decisions are far more sensitive to exports than to imports.

6.5 Alternative Instruments

Our IV approach identifies variation in exports that is driven by foreign country shocks and exogenous geographic factors. Specifically, in the baseline analysis the instrument is constructed by regressing bilateral trade values on importer GDP, year fixed effects, and bilateral pair fixed effects. The fitted values from this regression are used to construct the instrument. Although this is a logical way of identifying an exogenous source of variation in exports and it is consistent with the insights from the gravity model, there are other ways to accomplish this goal. This section constructs the instrument in a few different ways to test the robustness of the results. In the process, our findings below offer more support for the validity of the exclusion restriction.

Similar to Table 3, Table 13 reports the gravity style regressions that are used to create the alternate instruments. Column 1 reports the baseline results again, while column 2 instead uses the death rate in the importing country. This captures various negative shocks in the importing country (such as natural disasters, epidemics, etc.) which are plausibly exogenous. In addition, this method alleviates concerns that importer and exporter GDP

could be correlated. Not surprisingly, we see that an increase in the death rate in the foreign country reduces exports to that country. Column 3 instead includes indicator variables for whether the pair of countries are part of a free trade agreement. Not surprisingly, we see that exports are increasing with WTO, NAFTA, and EU membership. Finally, column 4 includes importer GDP, the importer death rate, and the trade agreement variables. Using the fitted values from these different specifications, the instruments are then constructed in the manner outlined in section 4.5.

Table 14 then reports the second stage IV results. Column 1 shows the baseline results while columns 2-4 report the results obtained using the alternate instruments. Although the construction of the instruments vary substantially, they all share the common goal of eliminating variation in exports that is driven by domestic factors which could be correlated with educational attainment. Furthermore, columns 2 and 3 specifically address the concern that importer and exporter GDP could be correlated in some unobserved way which would be problematic for our exclusion restriction. The results in Table 14 show that the impact of exports on average years of schooling is similar across these different IV approaches. Educational attainment is decreasing with unskill-intensive exports and increasing with skill-intensive exports regardless of which IV approach is used. Overall, these results demonstrate that our baseline results are robust to a variety of different IV approaches.

7 Conclusion

This paper investigates how educational attainment responds to exogenously-driven changes in the pattern of a country's exports and uses the results to gain insight into how investment in human capital responds to the pattern of production across different sectors. We construct a panel data set that spans 104 countries and 45 years and we use an IV approach that utilizes bilateral trade data to identify the variation in exports that is unrelated to domestic factors. Both our OLS and IV results indicate that educational attainment is decreasing with agricultural exports, decreasing with unskill-intensive manufacturing exports, and increasing with skill-intensive manufacturing exports. We find that these results are

strongest where we most expect, and are robust to a variety of extensions and sensitivity checks.

Our 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 has important long-run benefits via an empirically demonstrated increase in human capital.

Accordingly, we find empirical support for the concern voiced by Bajona and Kehoe (2010) and others that trade may exacerbate economic differences across countries through its impact on 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), 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	Years of Schooling	Total Exports	Agr Exp (%)	Man Exp (%)	Country	Years of Schooling	Total Exports	Agr Exp (%)	Man Exp (%)
Afghanistan	3.1	2	65	24	Lithuania	9.6	31	22	56
Albania	9.9	2	35	48	Malaysia	9.4	351	20	64
Algeria	6.4	119	2	1	Mali	1.5	2	62	9
Argentina	9.0	115	62	22	Mauritius	7.9	7	44	53
Armenia	9.8	3	21	74	Mexico	7.6	438	10	66
Australia	11.5	342	49	21	Moldova	9.9	6	48	50
Austria	8.3	269	10	77	Mongolia	7.8	2	60	21
Bangladesh	5.1	23	12	85	Morocco	4.0	39	49	38
Belgium-Lux	10.6	731	12	62	Nepal	3.0	2	22	73
Benin	3.0	1	80	9	Netherlands	10.3	985	22	44
Bolivia	8.7	7	46	17	New Zealand	12.8	74	69	22
Brazil	6.1	297	48	42	Norway	10.3	255	11	29
Bulgaria	9.3	26	20	55	Pakistan	4.0	41	24	72
Cameroon	5.5	15	51	7	Panama	8.7	15	35	50
Canada	11.2	1063	21	55	Papua New Guinea	3.9	11	71	2
Chile	9.3	84	52	41	Paraguay	7.0	7	83	8
China	7.8	1210	7	85	Peru	8.1	41	50	33
Colombia	6.9	59	44	20	Philippines	8.0	123	24	72
Costa Rica	7.6	21	50	45	Poland	9.4	159	16	64
Cote Divoire	4.0	25	87	7	Portugal	8.2	100	16	73
Croatia	8.7	29	17	62	Romania	10.0	58	13	66
Czech Rep	11.5	269	7	83	Russian Fed	10.5	1281	8	23
D.R. Congo	3.2	19	18	60	Saudi Arabia	8.6	723	1	3
Denmark	9.6	237	31	48	Senegal	4.4	5	76	9
Dominican Rep.	6.8	20	33	60	Singapore	9.0	359	5	69
Ecuador	7.7	31	49	5	Slovakia	9.8	113	7	78
Egypt	5.7	43	20	22	Slovenia	11.1	69	5	80
El Salvador	6.5	10	49	46	South Africa	7.2	161	28	45
Estonia	10.8	33	16	60	Spain	9.4	415	19	67
Finland	9.1	193	14	76	Sri Lanka	10.4	18	38	57
France	8.9	1369	16	66	Sudan	3.2	9	48	3
Germany	9.7	3815	6	73	Sweden	11.0	407	13	75
Greece	10.3	61	34	50	Switzerland	9.8	435	5	64
Haiti	4.2	3	24	71	Syria	4.8	19	19	10
Honduras	5.9	12	58	39	Tajikistan	8.9	3	30	68
Hong Kong	11.3	319	3	91	Tanzania	4.8	6	76	13
Hungary	10.7	106	15	71	Thailand	7.0	225	27	65
India	4.3	138	29	61	Trinidad & Tobago	9.3	26	5	5
Indonesia	5.5	268	22	34	Tunisia	6.3	28	16	54
Iran	7.0	240	3	3	Turkey	6.1	118	24	69
Ireland	11.0	228	19	44	U Arab Emirates	9.3	333	3	18
Israel	10.7	102	11	70	UK	9.4	1258	8	65
Italy	9.4	1071	9	78	USA	12.2	3071	17	66
Japan	11.4	2056	2	90	Uganda	4.2	4	92	6
Jordan	8.2	7	38	33	Ukraine	10.4	128	21	63
Kazakhstan	10.1	106	12	21	Uruguay	8.4	13	52	35
Kenya	6.0	11	68	13	Venezuela	6.5	170	4	8
Korea Rep.	11.3	543	4	86	Vietnam	6.3	45	26	48
Kuwait	6.5	134	1	1	Yemen	4.2	21	5	1
Kyrgyzstan	8.0	3	35	26	Zambia	5.7	14	8	91
Latvia	10.3	21	29	45	Yemen	2.3	10	6	2
Libya	9.3	93	0	1	Zambia	5.7	14	8	91

Average years of schooling of 15-29 year olds, average real exports (in millions of real US $), and the share of agricultural and 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 Gravity Model

	ln (Exports)	ln (Exports)	ln (Exports)	ln (Agr. Exports)	ln (Man. Exports)	ln (Unskilled Man. Exports)	ln (Skilled Man. Exports)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ln (Importer GDP)	1.250***	1.358***	1.373***	1.272***	1.263***	1.198***	1.058***
	[0.039]	[0.034]	[0.034]	[0.037]	[0.039]	[0.041]	[0.044]
ln (Exporter GDP)	1.330***	1.386***					
	[0.037]	[0.033]					
ln (Distance)	-1.213***						
	[0.013]						
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer FE	Yes	No	No	No	No	No	No
Exporter FE	Yes	No	No	No	No	No	No
Bilateral Pair FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,718	51,718	53,433	45,983	46,426	42,232	40,601
R-squared	0.722	0.873	0.857	0.829	0.87	0.854	0.868

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)
ln (Agr. Exports)$_{t-5}$	-0.305**	-0.338***	-0.374***	-0.336***
	[0.123]	[0.117]	[0.124]	[0.110]
ln (Man. Exports)$_{t-5}$	0.047			
	[0.065]			
ln (Unskilled Man. Exports)$_{t-5}$		-0.135**	-0.145**	-0.158***
		[0.059]	[0.061]	[0.054]
ln (Skilled Man. Exports)$_{t-5}$		0.204***	0.193***	0.169***
		[0.065]	[0.064]	[0.058]
ln (Imports)$_{t-5}$	0.248*	0.213*	0.169	0.052
	[0.142]	[0.126]	[0.143]	[0.125]
ln (Population)$_{t-5}$	0.913*	0.820*	0.849*	0.456
	[0.489]	[0.477]	[0.490]	[0.471]
ln (Death Rate)$_{t-5}$	-1.419***	-1.487***	-1.468***	-1.469***
	[0.416]	[0.393]	[0.402]	[0.386]
ln (Migrant Share)$_{t-5}$	0.016	0.059	0.050	0.044
	[0.131]	[0.126]	[0.129]	[0.133]
ln (Total Exports)$_{t-5}$			0.105	
			[0.156]	
ln (GDP)$_{t-5}$				0.739***
				[0.237]
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	787	787	787	787
R-squared	0.953	0.955	0.955	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

	Agr. Exports	Unskilled Man. Exports	Skilled Man. Exports
	(1)	(2)	(3)
ln (Agr. Exports IV)$_{t-5}$	0.772***	-0.649***	-0.517**
	[0.125]	[0.244]	[0.235]
ln (Unskilled Man. Exports IV)$_{t-5}$	0.017	0.978***	-0.146
	[0.103]	[0.147]	[0.162]
ln (Skilled Man. Exports IV)$_{t-5}$	0.020	0.304*	1.304***
	[0.087]	[0.162]	[0.119]
ln (Imports)$_{t-5}$	0.290***	0.427***	0.481***
	[0.070]	[0.107]	[0.126]
ln (Population)$_{t-5}$	-0.552**	-0.882**	-0.021
	[0.263]	[0.417]	[0.477]
ln (Death Rate)$_{t-5}$	-0.109	-1.098***	-0.391
	[0.250]	[0.349]	[0.290]
ln (Migrant Share)$_{t-5}$	0.134**	-0.047	-0.178*
	[0.066]	[0.113]	[0.098]
ln (GDP)$_{t-5}$	0.086	0.755**	0.897***
	[0.168]	[0.294]	[0.219]
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	787	787	787
R-squared	0.958	0.951	0.971
F-Stat, Instrument	13.6	20.4	52.4

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. These are the first stage IV results from the specification listed in Column 4 of Table 6.

TABLE 6

Impact of Exports on Average Years of Schooling (IV)

	Average Years of Schooling			
	(1)	(2)	(3)	(4)
ln (Agr. Exports)$_{t-5}$	-0.620**	-0.659***	-0.816**	-0.666***
	[0.287]	[0.218]	[0.320]	[0.199]
ln (Man. Exports)$_{t-5}$	-0.183			
	[0.203]			
ln (Unskilled Man. Exports)$_{t-5}$		-0.321***	-0.407***	-0.300***
		[0.120]	[0.141]	[0.110]
ln (Skilled Man. Exports)$_{t-5}$		0.332***	0.316***	0.299***
		[0.104]	[0.109]	[0.105]
ln (Imports)$_{t-5}$	0.615**	0.391**	0.222*	0.195
	[0.278]	[0.165]	[0.128]	[0.148]
ln (Population)$_{t-5}$	0.729	0.623	0.721	0.275
	[0.476]	[0.465]	[0.482]	[0.456]
ln (Death Rate)$_{t-5}$	-1.704***	-1.674***	-1.626***	-1.603***
	[0.433]	[0.367]	[0.383]	[0.360]
ln (Migrant Share)$_{t-5}$	0.033	0.119	0.087	0.109
	[0.110]	[0.104]	[0.112]	[0.108]
ln (Total Exports)$_{t-5}$			0.439	
			[0.318]	
ln (GDP)$_{t-5}$				0.747***
				[0.216]
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	787	787	787	787
R-squared	0.949	0.952	0.951	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.

TABLE 7
Impact of Exports on Average Years of Schooling by Education Level (IV)

	Primary	Secondary	Tertiary
	(1)	(2)	(3)
ln (Agr. Exports)$_{t-5}$	-0.608***	-0.108	0.05
	[0.142]	[0.186]	[0.044]
ln (Unskilled Man. Exports)$_{t-5}$	-0.226**	-0.06	-0.014
	[0.115]	[0.102]	[0.022]
ln (Skilled Man. Exports)$_{t-5}$	0.117	0.167*	0.014
	[0.089]	[0.095]	[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	0.84

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)$_{t-5}$	3.357*	-3.343*	-7.446***	-10.975***	-3.819	1.862	0.614
	[1.813]	[1.815]	[1.992]	[2.928]	[2.428]	[1.480]	[0.753]
ln (Unskilled Man. Exports)$_{t-5}$	2.545**	-2.532**	-2.624*	-1.62	-0.375	-0.337	-0.387
	[1.159]	[1.158]	[1.376]	[1.485]	[1.449]	[0.756]	[0.386]
ln (Skilled Man. Exports)$_{t-5}$	-1.086	1.091	2.756**	3.477**	1.518	0.277	0.446
	[0.935]	[0.933]	[1.167]	[1.574]	[0.987]	[0.657]	[0.305]
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	0.838

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)$_{t-5}$	-0.666***	-0.453
	[0.199]	[0.282]
ln (Unskilled Man. Exports)$_{t-5}$	-0.300***	0.219
	[0.110]	[0.149]
ln (Skilled Man. Exports)$_{t-5}$	0.299***	-0.06
	[0.105]	[0.118]
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	787	787
R-squared	0.954	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)$_{t-5}$	-0.715***	-0.613***
	[0.205]	[0.231]
ln (Unskilled Man. Exports)$_{t-5}$	-0.427***	-0.165
	[0.118]	[0.127]
ln (Skilled Man. Exports)$_{t-5}$	0.307**	0.290***
	[0.124]	[0.107]
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	Educ. Expenditures	FDI	NR Exports	Import Components
	(1)	(2)	(3)	(4)	(5)
ln (Agr. Exports)	-0.550***	-0.518**	-0.609**	-0.666***	-0.653***
	[0.205]	[0.222]	[0.264]	[0.203]	[0.195]
ln (Unskilled Man. Exports)	-0.360***	-0.389***	-0.327**	-0.300***	-0.302***
	[0.125]	[0.146]	[0.146]	[0.107]	[0.113]
ln (Skilled Man. Exports)	0.383***	0.307***	0.267**	0.299***	0.275***
	[0.137]	[0.107]	[0.114]	[0.108]	[0.101]
ln (Educ. Expenditures)		0.491***			
		[0.139]			
ln (Inward FDI)			-0.029		
			[0.033]		
ln (Coal, Oil, Gas Exports)				0.000	
				[0.031]	
ln (Agr. Imports)					-0.029
					[0.127]
ln (Unskilled Man. Imports)					0.329**
					[0.137]
ln (Skilled Man. Imports)					-0.154
					[0.177]
Controls	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	682	660	591	787	787
R-squared	0.954	0.957	0.954	0.954	0.955

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 (like the rest of the columns). Column 2 controls for educational expenditures, Column 3 controls for inward FDI, Column 4 controls for coal, oil, and gas exports (SITC 3), and finally Column 5 controls for the type of imports.

TABLE 13
Construction of Alternate Instruments using Gravity Model

	Baseline	Importer Death Rate	Trade Agreement	All
	(1)	(2)	(3)	(4)
ln (Importer GDP)	1.373***			1.302***
	[0.034]			[0.037]
ln (Importer Death Rate)		-0.694***		-0.365***
		[0.041]		[0.046]
Both in WTO Dummy			0.270***	0.136***
			[0.025]	[0.030]
Both in NAFTA Dummy			0.515***	0.452***
			[0.133]	[0.065]
Both in EU Dummy			0.287***	0.063*
			[0.027]	[0.034]
Year FE	Yes	Yes	Yes	Yes
Importer FE	No	No	No	No
Exporter FE	No	No	No	No
Bilateral Pair FE	Yes	Yes	Yes	Yes
Observations	53,433	54,949	55,491	52,891
R-squared	0.857	0.846	0.845	0.858

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. The dependent variable is the ln of exports. Column 1 reports the baseline specification and columns 2-4 report results from three alternate specifications.

TABLE 14
Impact of Exports on Average Years of Schooling using Alternate Instruments (IV)

	Baseline	Importer Death Rate	Trade Agreements	All
	(1)	(2)	(3)	(4)
ln (Agr. Exports)$_{t-5}$	-0.666***	-0.662***	-0.575***	-0.622***
	[0.199]	[0.169]	[0.157]	[0.214]
ln (Unskilled Man. Exports)$_{t-5}$	-0.300***	-0.267**	-0.259**	-0.256**
	[0.110]	[0.124]	[0.123]	[0.110]
ln (Skilled Man. Exports)$_{t-5}$	0.299***	0.254**	0.268***	0.281***
	[0.105]	[0.100]	[0.103]	[0.104]
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	787	787	787	787
R-squared	0.954	0.955	0.956	0.955

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 uses the baseline method to construct the instruments while columns 2-4 use alternate methods to construct the instruments.