Essays on Human Capital Development, International Trade and Robotization

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Abstract

This dissertation consists of three related essays on trade, industrial robots and human capital. In Chapter 1, we investigate the importance of a country's exports and imports for human capital development. In order to analyze this relationship, measures of the educational intensity of exports and imports are developed for a sample of 137 countries from 1962 to 2010. We find that the educational intensity of exports has a positive and statistically significant impact on human capital development while the educational intensity of imports has a negative and statistically significant impact on educational attainment.

In Chapter 2, we investigate the importance of regional exports and imports of the U.S. for human capital development. In order to analyze this relationship, measures of the educational intensity of exports and imports are developed for a sample of commuting zones (CZs) from a single country (U.S.) for a study period from 1980 to 2010. We find that the educational intensity of exports has a positive and statistically significant impact on human capital development. On the other hand, the educational intensity of imports, as a whole, has a positive but insignificant effect on educational attainment but educationally-intensive imported intermediate inputs, when separated out, have a positive and significant effect on human capital development.

In Chapter 3, we study the effect of robot adoption exposure in the labor market to identify the effect of technological-induced changes on educational attainment in the U.S. from 1993 to 2007. A closer look is taken by looking at educational attainment for the overall sample (ages 15 to 65), age group, educational share, and gender. We document exposure to robots having a positive impact on the educational attainment of middle-age groups across U.S. commuting zones, providing indication that the opportunity cost of schooling is less for middle-aged groups. We find a significant and positive relationship between robot adoption and an increase in educational level of those with a high school education but not a college degree. We did not find any significant relationship for the overall sample (ages 15 to 65) and gender with robot adoption.

Dedication

To my loving parents and my husband, without whose encouragement, all of this would not have been possible

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Chapter 1

Trade Composition Drives Educational Attainment: The Global Perspective

1.1 Introduction

Education is a vital component in human capital accumulation. It is an important element in the long-run sustainable economic growth that allows for the proper and necessary development of an economy through increasing human productivity. Since human capital is a main factor of production when combined with physical capital in an aggregate production function and therefore, economic growth, trade can be one of the potential channels for stimulating educational attainment.

Over the past few decades, world trade integration has resulted in the rapid growth of the global economy. Falling trade barriers have facilitated the growth of export competition which has had an impact on human capital formation. Two stylized facts appear in the existing trade literature (Bernard et al., 1995; Goldberg and Pavcnik, 2007; Verhoogen, 2008): first of all, export firms offer higher wage premiums; and secondly, there is a positive relationship between export growth and return to skills. However, according to Atkin (2016), these facts can be misleading, because they allow one to infer that export growth increases the number of years of schooling. His study argues that this conclusion overlooks the opportunity cost of schooling. Using Mexican census data from 1986 to 2000, a period of rapid trade liberalization, he finds evidence that high school drop-out rates increase when there is a high rate of low-skill manufacturing export job creation. He points out that some youths drop out of school at younger ages because the opportunity cost of schooling is higher than the return to schooling. This gives the insight that export job creation does not always lead to an improvement in educational attainment.

Blanchard and Olney (2017) find that integration into the world market based on skill-intensity sectoral growth has either a positive or a negative effect on human capital formation. Growth in the number of low-skill jobs in the agriculture and low-skill manufacturing sectors has a negative effect on educational attainment. This supports the notion that low-skill job creation decreases educational attainment. On the other hand, high-skill sectoral growth increases educational attainment. They conclude that demand-side mechanisms play a crucial role in determining educational attainment.

Country specific data also support this finding. For example, Li (2018) finds compelling evidence regarding the nuanced relationship between export growth and educational attainment. Using Chinese data from 1990 to 2005, she examines regional exposure to high-skill and low-skill export demand shocks in China. Her findings suggest that a positive shock to high-skill export demand increases both high school and college enrollments while in contrast, a positive shock to low-skill export demand decreases both. Similarly, Shastry (2012) finds that more export-oriented skilled job opportunities across Indian districts mainly in the information technology (IT) sector resulted in pronounced growth in school enrollment.

Demand factors can be more powerful than supply factors in shaping human capital attainment. One study by Heath and Mobarak (2015) found that attractive jobs in the export-oriented garment manufacturing sector, which required basic literacy and numeracy skills, increased educational attainment for a large percentage of Bangladeshi women. Traditionally, women had been mostly preoccupied with early marriage and childbearing and usually did not work outside the home. The job opportunities resulted in a vast demand for female education. Furthermore, the demand for skilled workers had an even greater impact upon female educational attainment than large-scale government cash transfer programs that were conditional upon school attendance. This highlights the importance of the demand mechanism in shaping an individual's decision to invest in their human capital.

The research reviewed above indicates the complex relationship between trade and educational attainment. In general, trade has been thought to drive increased educational attainment. However, high-skill and low-skill exports have distinct impacts on educational attainment. This paper further investigates this relationship by analyzing the effects of trade composition on educational attainment. The current paper is closely related to that of Blan-

chard and Olney (2017) with significant differences. In their study, the authors categorize the labour market into three sectors where the sectors are defined by skill-intensity. The three sectors are low-skill intensive agriculture, low-skill intensive manufacturing and high-skill intensive manufacturing where the sectors' level of skill-intensity is assumed. In this study, we take a skill-intensity measurement approach to defining exports as opposed to a sector-based categorization. This allows for skill heterogeneity both across and within sectors and the construction of a measure of education intensity for each sector. This approach is more reliable than Blanchard and Olney′s since it clarifies skill-intensity and allows it to vary across the sectors over time. This skill-intensity variable is referred to as ″educational intensity″ in our paper.

Using a panel of 137 countries from 1962 to 2010, we investigate how the growth in educationally-intensive exports affects educational attainment overall and by age group. A second analysis is performed to examine the effect of the change in imports on educational attainment. The panel data set has the advantage of allowing us to analyze both time and inter-country effects of imports and exports on educational attainment.

The methodology employed is divided into several steps. An OLS baseline specification for educational attainment is estimated. However, as pointed out by Feyrer (2009), this approach does not correct for the reverse causality problem and, as a result we cannot infer any causal relationships. We correct for this problem by using an instrumental variable approach. The exogenously driven variables are constructed using a variation of the gravity model which allows us to make inferences about the nature of the causal relationship between educational attainment and the educational intensity of exports and imports.

Here, educational intensity is defined as the average years of schooling needed by workers in a particular industry. Educational intensity of exports/imports is composed of two components: (i) trade shares, and (ii) educational intensity of a particular industry. (i) and (ii) are multiplied and summed over all industries to obtain educational intensity of exports and imports by country and time. In this study, (ii) is fixed at 2007 and does not change over time. Thus, an increase in educational intensity exports and imports over time is caused by (i).

The results of a panel estimation suggest that an increase in the trade share component

(exports) of educational intensity of exports has a positive impact on educational attainment. This supports our hypothesis that educational intensity of exports encourages educational attainment. An increase in the trade share component (imports) of educational intensity of imports has a negative effect on educational attainment. This also supports our hypothesis that an increase in educational intensity of imports discourages education attainment. While this result is applicable to the overall sample, it is most pronounced for the age group 15 – 29.

The paper is organized as follows: there is a brief discussion of the relationship between human capital and economic growth, then we cover the theoretical framework, the construction of educational intensity variables, the empirical methodology, the data and some summary statistics, the results, various extensions and concluding remarks.

1.2 Human Capital and Economic Growth

Solow (1956), Romer (1989) and Lucas Jr (1988) present the major role innovation, to which human capital contributes to, plays in economic development. Blundell et al. (1999) defines human capital through three main components: innate ability, knowledge from formal education, and skills and expertise gained through job training. The development of an economy is generated from productivity growth Krugman (1997). Human productivity is essential to production and is, in large measure, determined by the level of education. Better education of workers leads to more productive workers and therefore economic development. If we better understand the factors that influence the growth of human capital, we can increase it and enhance the lives of people around the world. It is a vital component in the links between skill development, employment and innovation and, as such, is an essential element in the establishment of long-run sustainable economic growth.[1]

Specifically, an increase in human capital leads to greater innovation in an economy because if there is an increase in the stock of knowledge and its diffusion, more people will have the opportunity to become innovators. Pelinescu (2015) shows that human capital affects economic development. She references the work of Blundell et al. (1999) who recognise

[1] see De la Fuente and Doménech (2006), Goldin and Katz (2008), Ciccone and Papaioannou (2009)

that human capital accumulation affects labour productivity growth which in turn affects GDP per capita and the level of economic development. An increase of human capital like an increase in the number of school years, leads to an increase in labour productivity since workers will be able to do a much greater variety of tasks more efficiently. Indeed, an increase in labour productivity usually leads to an increase in GDP per capita. This is because workers are paid according to the different degrees of task complexity and are paid more if tasks become more complex and are to be done more efficiently than previously. An increase in human capital may also increase total factor productivity. Pelinescu (2015) refers to a paper by Nelson and Phelps (1966) that shows the positive effect of an increase in human capital on technology diffusion and innovation. For example, an individual who has completed high school should be capable of using information technology while someone who has not completed high school will, in all likelihood, be unable to use it.

A case study conducted by Chuang (2000) displays an instance of human capital affecting economic growth of an Asian Tiger.[2] Chuang (2000) considers the case of an Asian tiger economy, Taiwan, which has seen very high rates of economic growth and development. He examines the causal relationships between human capital accumulation and export demand on the one hand and economic growth on the other, using Taiwan's real GDP, real exports and high educational attainment data from the period 1952 to 1995. He finds that endogenous variables like human capital accumulation and exogenous factors like an export demand shock affect economic growth and international trade performance. Thus, an increase in export demand and human capital formation increase economic growth which further stimulates export demand and economic growth creating a vicious circle of increasing human capital formation, export demand and economic growth. Chuang (2000) findings strongly support the endogenous human capital growth theory and the export-led growth hypothesis, leading him to argue that both the theory and hypothesis together explain changes in Taiwan's economic growth, human capital and export demand in the post-World War II period.

Moving forward, a major aspect of the literature on human capital is the extent of its

[2]The Four Asian Tigers refers to the economies of Hong Kong, Singapore, South Korea and Taiwan. Starting from the 1960s, increase in exports and rapid industrialization led these nations to achieve high levels of economic growth; joining ranks with the world's wealthiest nations (Bloomenthal, 2020).

positive impact depends on the diffusion of knowledge and skills in a community. A person who has a high school diploma and knows how to use a computer can communicate his knowledge and skills to others in his or her community. Thus, the immediate effect of an increase in human capital is likely to be felt at both the local and regional level. Accordingly, in a recent empirical study by Diebolt and Hippe (2022), regional differences in terms of the stock of human capital are just as significant as national ones for determining the rate of economic development. Diebolt and Hippe (2022) use historical data on the stock of human capital to argue that human capital development performance was the major factor behind the present and future economic development at the regional level. It has been demonstrated that regional differences in human capital could be at least as important as national ones in the sense that such differences play a crucial role in regional development (Cipolla, 1969).

International trade plays a major role in human capital formation. Blanchard and Olney (2017) discuss the relationship between skill-intensive export industries and educational attainment across 138 countries. They show that, specifically, doubling agriculture exports, which is a low-skill labour sector, is negatively correlated to the average years of schooling. In addition, low-skill workers in the manufacturing sector displayed a similar pattern of decreased investment in human capital. They find that an increase in exports from low-skill industries depresses educational attainment, while exports from high-skill industries increase educational attainment. Blanchard and Olney (2017) found that if there is an increase in jobs for skilled labour in high-skill export-oriented industries in an economy, there will be a positive effect on human capital since it will encourage people to increase their educational attainment level and thus the stock of human capital.

The Heckscher-Ohlin model contains a number of results about the effect of international trade on initial factor endowment. The first result concerns the quantities of these factor endowments. The model links a country's trade pattern to its relative abundance of the factors capital and labour. It shows that capital-abundant countries will specialize in the production of capital-intensive goods, while labour-abundant countries will specialize in the production of labour-intensive goods, after which they will initiate trade with one another. After trade, the respective factor prices for capital and labour in the countries that had initial factor endowments in one of them will reach an equilibrium price. This implies

relative abundance of a factor, for instance capital, will allow a capital-abundant country to produce capital-intensive goods at a cheaper expense compared to the labour-abundant country. Thus, capital-abundant countries will export capital-intensive goods and import labour-intensive goods and vice versa for labour-abundant countries.

A number of studies use the Heckscher-Ohlin model to study the effects of international trade on endogenous education in developed and developing countries. For instance, Findlay and Kierzkowski (1983) build on the Heckscher-Ohlin model using endogenous skill acquisition to study trade patterns. They provide a theoretical framework to link the skill-intensity of a country's exports to endogenous human capital investment. The framework bridges trade to education by relating how trade affects the relative prices of goods, thus shaping relative wages through the Stolper-Samuelson effect.[3]. This, then, impacts the returns to education which shapes one's school choices. For example, consider a country holding a comparative advantage in high-skill intensive goods. Once it opens to trade, the relative prices of its high-skill intensive goods shall increase. As a result, there will be a growth in the relative demand for higher skilled workers, creating the skilled wage premium. The increase in return to education will influence a greater number of workers to invest in schooling.

Furthermore, the Heckscher-Ohlin model relates the importance of comparative advantage. Using the two-country setting, opening to trade will create a positive effect on education for the more skill-abundant country and create a negative effect for the less skill-abundant country. In general, the Heckscher-Ohlin model shows that a country's export skill composition reflects its trade effects on educational attainment (Blanchard and Olney, 2017).

However, the Heckscher-Ohlin model has received criticism due to the Leontief Paradox. The Leontief paradox (Leontief, 1953) is a recognition of a surprising empirical fact that seems to contradict the conclusion of the Heckscher-Ohlin model; despite being a capital-abundant country, the U.S. was importing capital-intensive goods and exporting labour-intensive goods, contradicting the Heckscher-Ohlin model. Following the Heckscher-Ohlin model, the U.S. should have been exporting capital-intensive goods and importing labour-

[3]The Stolper-Samuelson theorem predicts that given trade liberalization; the relative wages of skilled workers exports shall increase due to increases in skill-intensive exports. Ceteris paribus, following this theorem, the skill premium increases, resulting in a rise in inequality in developed countries with a comparative advantage in skill-intensive goods (Blanchard and Olney, 2017).

intensive goods. However, Leontief (1956) attempted to solve the paradox through the Heckscher-Ohlin model.[4] He argued that U.S. workers had greater productivity levels compared to foreign workers; thus, "it was legitimate to reduce the U.S. capital-to-labour ratio before assessing their comparative advantage". Further studies conducted by economists point out that the U.S. was exporting human capital-intensive goods, which were goods that required workers to possess a high degree of skill and education to produce and therefore, were also capital-intensive goods. The paradox was explained to the extent that the U.S. which had a large supply of highly educated skilled individuals and was exporting goods that used their skilled labour. The U.S. specializes in the production of skill-intensive goods that requires the use of skilled labour.

The resolution of the Leontief paradox emphasizes the importance of human capital for determining the degree of U.S. comparative advantage regarding its labour endowments with different countries. This comparative advantage can increase according to a feedback loop whereby an increased demand for skilled labour leads to further increase in human capital and production of skilled labour-intensive goods.

Michaels (2008) looks at the effect of reduced trade barriers on skilled labour demand in different regions of the U.S. He looks at the Interstate Highway System as a source of trade variation and its effect on the demand for skill in rural areas. On average, highways showed to have no significant effect on the relative demand for high-skill to low-skill workers in the manufacturing sector. Though, he finds some evidence that supports the Heckscher-Ohlin model: highways increase the wage level in counties where skill is an abundant factor of production and decrease the wage level in counties where it is a scarce factor, which is what we expect from the model. However, in contrast to the Heckscher-Ohlin model, he finds that trade does not significantly shift the labour demand towards industries intensive and abundant in skill. These contradictory findings with the Heckscher-Ohlin model show that it is not a complete model of international trade when applied to the real world, at least at the regional level (within the U.S.). It is still well-worth reviewing as it is still the most used

[4]Additional proposed solutions by economists to the Leontief paradox include the Linder Hypothesis and the New Trade Theory. The Linder Hypothesis argues for demand as a greater determinant of trade between countries than comparative advantage. The New Trade Theory (like the House Market Effect) turns to economies of scale and network effects, instead of comparative advantage to model international trade.

model in this area despite its lack of empirical verification.

1.3 Theoretical Framework

To understand the conceptual framework of how trade composition drives educational attainment, we use relative demand and relative supply analysis.

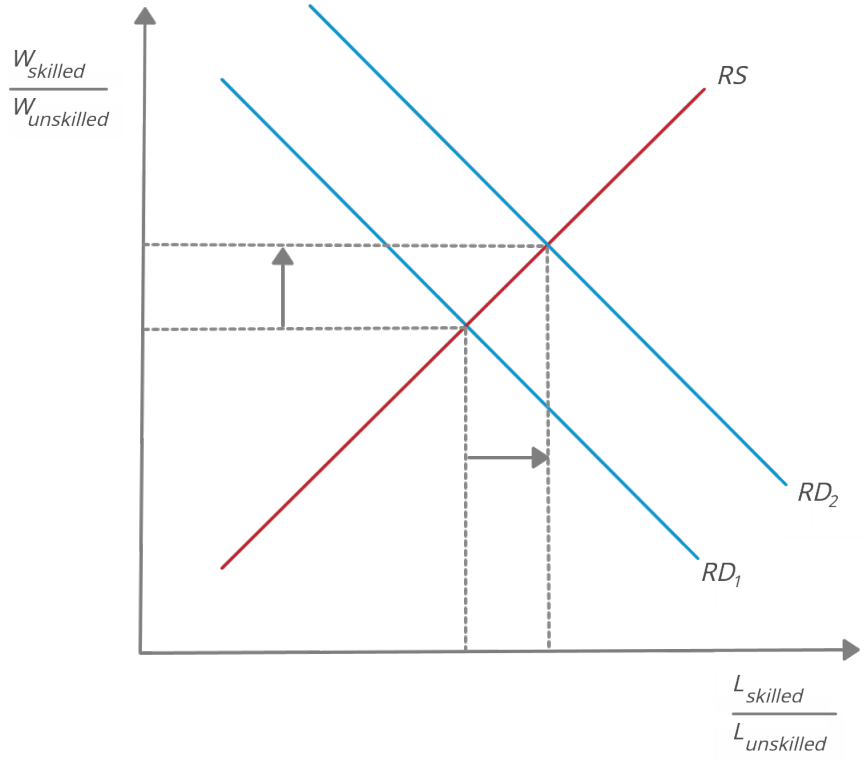

Figure 1.1: Demand and Supply of Educated Workers

Figure 1.1 depicts a country's relative demand (RD) and relative supply (RS) of educated workers. The horizontal axis is the ratio of skilled to unskilled workers ($L_{skilled}/L_{unskilled}$) and the vertical axis measures the relative wage ($W_{skilled}/W_{unskilled}$), that is, the skill premium for educated workers. Changes in a country's imports and exports can both affect relative demand.

According to the Heckscher-Ohlin model, when a country with a comparative advantage in high-skill intensive goods opens to trade, the relative price of skill-intensive goods will increase. As the relative price of skill-intensive goods increases, so too will the relative

demand for higher skill workers, and therefore, the skilled wage premium. The greater numbers of workers returning to education will then encourage more workers to invest in schooling. As well, the Heckscher-Ohlin model also shows the critical role of comparative advantage. In a two-country setting, opening to trade will have a positive effect on education in the initially skill abundant country and a negative effect on its initially skill deficient counterpart. In general, the effect of trade on educational attainment is determined by the skill-composition of a country's exports.

If a country experiences a relative demand shock for educationally-intensive exports and an increase in its exports of educationally-intensive products, it will need more educated workers to produce the exported goods. In this case, the relative demand for educated workers will go up. As the skill premium increases, workers are motivated to become more educated, ceteris paribus.

In contrast, if the country experiences an increase in imports of educationally-intensive products, there are two potential outcomes. The country will either stop producing these educationally-intensive products altogether or reduce the quantity produced. In either case, firms do not need many educated workers and therefore, the relative demand for educated workers will go down reducing the quantity of educated workers in the future.

In conclusion, the idea is twofold: trade will positively affect the relative demand for educated workers when a country increases the amount of educationally-intensive exports, which will increase the number of educated workers in the population; similarly, an increase in the demand for educationally-intensive imports will decrease the share of educated workers in the population. The relative demand and supply analysis above lead to the following two hypotheses:

Hypothesis 1: An increase in exports of educational intensity industries will increase demand for educated workers and increase educational attainment.

Hypothesis 2: An increase in imports of educational intensity products will decrease demand for educated workers and decrease educational attainment.

1.4 Construction of the Intensity Variables

In this section, we describe the construction of the educational intensity variables. First, the educational intensity of exports is derived in the following fashion:

$$EI\_exp_{c,t} = \sum_{i=1}^{I} share\_exp_{i,c,t} * I_i \tag{1.1}$$

where I_i is educational intensity of industry i which is measured by the average years of schooling of workers in that industry in the U.S. based on the U.S. census data for 2007. It is used as a reference variable across other countries due to data limitation and it is taken at its 2007 values only. For example, in the automobile industry, American workers have an average number of years of schooling of 13 years which proxies for the average number of years of schooling for workers in the automobile industry in other countries. $share\_exp_{i,c,t}$ is the export share, the proportion of the total exports for a particular industry i in a given country c at year t. Note the sum of the export shares over all industries for a given country and year is one. Educational intensity of exports $EI\_exp_{c,t}$ is educational intensity I_i weighted by aggregate export shares by country c at time t which is given by $\sum_{i=1}^{I} share\_exp_{i,c,t} * I_i$. In other words, education intensity of exports is the weighted average of educational intensity where the weights are industry shares of exports.

The educational intensity variable for imports is constructed as follows:

$$EI\_imp_{c,t} = \sum_{i=1}^{I} share\_imp_{i,c,t} * I_i \tag{1.2}$$

Similarly, educational intensity of imports $EI\_imp_{c,t}$ is educational intensity I_i weighted by aggregate imports share by country c at time t which is given by $\sum_{i=1}^{I} share\_imp_{ic,t} * I_i$

1.5 Empirical Specification

The following specification estimates how the composition of a country's exports and imports affects educational attainment:

$$edu_{c,t} = \alpha + \beta_1 EI\_exp_{c,t-5} + \beta_2 EI\_imp_{c,t-5} + \gamma_c + v_t + \epsilon_{c,t} \tag{1.3}$$

where the dependent variable $edu_{c,t}$ denotes the educational attainment of country c at time t and is measured as the average years of schooling. The independent variable EI_exp_{t-5}

is the educational intensity of exports and EI_imp_{t-5} is the educational intensity of imports. The educational intensity of exports and imports are lagged five years to account for the economic factors that impact the average number of years of schooling. γ_c is the country fixed effect, v_t is the time fixed effect, and $\epsilon_{c,t}$ is an error term. Standard errors are clustered by year. The signs of β_1 and β_2 are determined by hypotheses 1 and 2, respectively.

1.6 Data & Descriptive Statistics

Several data sources are combined in order to explore the relationship between the composition of trade and educational attainment. Data on the average years of schooling of workers across industries is taken from IPUMS-CPS, which is an integrated set of data that combines U.S. Census data for 2007 with data from the Current Population Survey (CPS). The data is a 5% sample of the U.S. population.

Educational attainment data across countries at five-year intervals is taken from Barro and Lee (2013) for the period 1960 to 2010. This data contains information on the average number of years of schooling and the completion rates at the primary, secondary, and tertiary levels by age group and gender.

The data provided by Barro and Lee (2013) is quantitative in nature and Blanchard and Olney (2017) use Barro's data. Thus, Blanchard and Olney's study, as they themselves note, presents limitations: to the extent that it is only quantitative, the study omits important qualitative data (e.g. test scores). This means that we cannot conclude that increased educational attainment automatically leads to greater skill acquisition and greater stock of human capital. Blanchard and Olney (2017) point out that the work that Hanushek and Woessmann (2011) have done regarding the lack of comparability of international test scores over time shows the limits of a qualitative study of human capital. Therefore, a more quantitative analysis of human capital formation is unavoidable. What we need to consider regarding educational attainment data is the educational decision to use the term coined by Atkin (2016). In other words, a quantitative-based study will focus on the degree to which trade composition increases or decreases the opportunity cost of more years of education. For example, a decrease in the skill-intensity export-oriented manufacturing industries will

lead to a decrease in educational attainment, since many young people who have completed their compulsory education at 15 will choose to leave school in order to start working. Their opportunity cost of staying in school has increased while the opportunity cost of working has decreased. However, due to data limitations of a qualitative measure of educational attainment, the exact nature of the link between trade composition and educational attainment is only going to be partially captured by a quantitative measure (Blanchard and Olney, 2017).

Supply and demand sides both have an effect on educational attainment. Yet, much of the existing literature on the drivers of educational attainment has focused on the supply-side, that is, on the determinants of skill acquisition like access to schools and educational expenditure. While supply-side drivers of educational attainment are very significant, they need to be balanced by a thorough analysis of demand-side drivers, so as to give a more complete picture of the drivers of educational attainment. Hence, in order to better understand the relative contribution of demand-side drivers of educational attainment, we have taken trade data for the period 1962 - 2000 from the World Trade Flows data set which was constructed by Feenstra et al. (2005).

This data consists of bilateral trade flows for pairs of countries based on export and import values by industry. The industry classification is the 4-digit SITC (revision 2) which was converted into the 4-digit North American Industry Classification System (NAICS) using NBER concordance tables. The period from 2000 until 2010, the industry-level bilateral trade flow data is from the UN-TRAINS database at the 6-digit Harmonized System Classification and subsequently aggregated into the 4-digit NAICS using the concordance from Feenstra et al. (2002).

Table 1.1: **Summary Statistics**

Variable	Obs	Mean	Std. Dev.
Average Years of Schooling	1117	6.654	3.465
Young Avg. Years of Schooling	1117	6.364	3.422
Mid Avg. Years of Schooling	1117	5.344	3.455
Old Avg. Years of Schooling	1117	4.012	3.120
Educational Intensity of Exports	1117	12.643	0.610
Educational Intensity of Imports	1117	13.086	0.195

Table 1.1 reports the summary statistics of the educational attainment for each of the

three age groups from 1962 - 2010 for 137 countries. The results show that young individuals aged 15 - 29 are better educated than the other two age groups. The large magnitude of the standard deviation indicates a wide dispersion in educational attainment. Analysis of the primary results indicates that there is heterogeneity in educational attainment within groups and across groups.

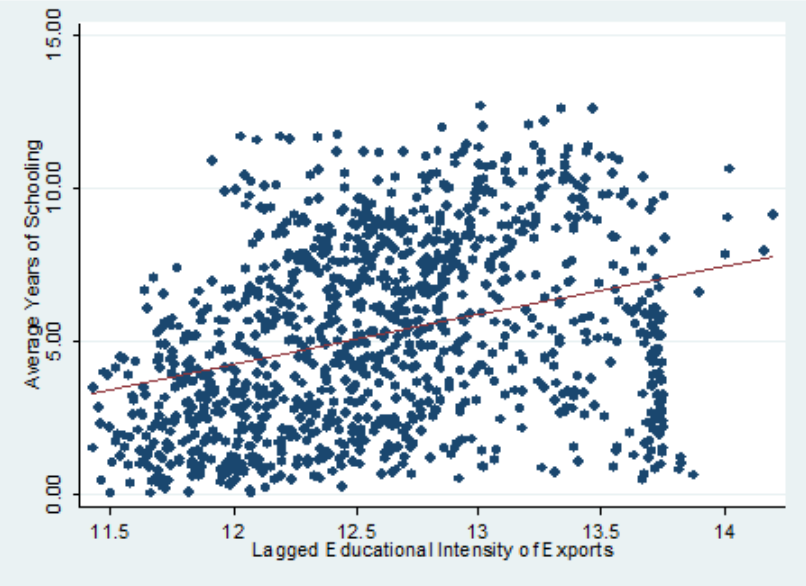

Figure 1.2: Average Years of Schooling vs Lagged Educational Intensity of Exports

Figure 1.2 gives an insight into the data by plotting the average years of schooling against the lagged 5 years educational intensity of exports. It would appear that a clear and positive relationship exists.

1.7 Results

1.7.1 Benchmark Results

Table 1.2: **Impact of Exports and Imports on Average Years of Schooling**

VARIABLES	(1) Years of Schooling	(2) Years of Schooling
Educational Intensity Export	0.161***	0.155***
	(0.034)	(0.027)
Educational Intensity Import	-0.561***	-0.760***
	(0.121)	(0.180)
ln (GDP)		0.496***
		(0.114)
Observations	935	916
R-squared	0.974	0.977
Country FE	YES	YES
Year FE	YES	YES

Notes: The dependent variable is average years of schooling. Controlled are the lagged educational intensity of exports and imports and log of per capita GDP. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.2 presents the results from running the regressions using the ordinary least squares (OLS). Column 1 contains the results for the entire sample (15 - 65+ years old). Country and year fixed effects are included in all regressions. Standard errors are clustered by year and reported in brackets. Examination of Column 1 reveals that a one year increase in the educational intensity of exports would result in the average years of schooling increasing by .16. Education intensity of imports have a negative relationship which indicates that increased educational intensity of imports would decrease the average years of schooling by .56 which is also statistically significant at 1% level. These results can be interpreted as indicating that if a country exports a lot of educationally-intensive goods for the next five years, the country will have a more educated population. On the other hand, if a country imports a lot of educationally-intensive goods for the next five years, the country will have a less educated population.

In Column 2, we control the level of development by including the log of per capita GDP. Inclusion of the level of development is important since it accounts for the quality of education available through government funding. Also, higher per capita household income allows a family to invest more in their children's education. This variable is expected to have a positive effect on educational attainment. Examination of the estimated coefficients in Column 2 reveals that all variables have their expected signs and are statistically significant. Controlling for the level of economic development does not change the result reported in Column 1. Thus, the empirical result listed in Columns 1 - 2 clearly support the hypotheses discussed in the theoretical framework.

1.7.2 IV Results

The major empirical issue facing a study of this nature is causality. Namely, countries which are endowed with an educated workforce will export an educationally-intensive product. On the other hand, countries which export an educationally-intensive product will develop a highly educated workforce. To solve this endogeneity problem, we use some instrument which has a relationship to the endogenous variable (educational intensity of exports and imports). Thus, we construct two instrumental variables which have a relationship to a country's exports or imports but are independent of the domestic education level.

We use the bilateral trade flows to resolve the endogeneity concerns of reverse causality where skill-abundant countries have a comparative advantage in skill-intensive sectors and skill-deficit countries have a disadvantage. Certain omitted variables such as locally-based changes in policy, technological advancement, or institutional change may influence both education and the structure of production. We use a gravity model to construct instruments which make use of exogenous changes in trading partner conditions or bilateral trade frictions for the composition of a country's exports and imports. The instruments for educational intensity of exports and imports are correlated with the bilateral trade flows, but are by construction independent of conditions in the exporting/importing country, which mitigates any of the aforementioned issues of reverse causality or omitted variables.

The gravity model seeks to explain bilateral trade flows in term of distance, resistance and other macroeconometric variables (Anderson, 2011). The gravity model in the log trans-

formation is as follows:

$$lnx_{ijt} = lny_{it} + lny_{jt} - lny_{wt} + (1-\sigma)ln\tau_{ijt} - lnP_{it} - lnP_{jt} \tag{1.4}$$

where the log bilateral export flows between countries i and j (lnx_{ijt}) is a function of the log GDP (lny_{it}) of the exporting country, log of GDP (lny_{jt}) of the importing country, log of world GDP (lny_{wt}), log of bilateral trade friction ($ln\tau_{ijt}$), log of the resistance term (lnP_{it}) and multilateral resistance terms (lnP_{jt}) in country i and j.

This model has been used successfully in several studies. Feyrer (2009) obtained predicted bilateral trade flows as a function of several exogenously driven factors. Predicted values of trade flows were subsequently used as variable in his income equation. A similar approach was developed by Blanchard and Olney (2017) to model educational attainment. In their paper, they used the log of real GDP of importing countries and a pair of fixed effects as instruments in 2SLS model of educational attainment.

In our study, we use a similar instrumental variable approach. We eliminate exporter GDP from the following regression equation since it is correlated with educational attainment and have included only importer GDP and used exporter fixed effect, importer fixed effect, and year fixed effect to control factors such as, change in world GDP and variance resistance terms to identify exogenous factors with which to explain trade flows. The equation used is as follows:

$$lnexp_{ijt} = \beta_1 lngdp_{jt} + \beta_2 lndist_{ij} + \gamma_{it} + \gamma_{jt} + \epsilon \tag{1.5}$$

Where the dependent variable is the log of bilateral flow of exports from exporter i to importer j in year t. Independent variables are: the log of importer GDP ($lngdp_{jt}$), the log of bilateral distance ($lndist_{ij}$) between exporter i to importer j. γ_{it} is the exporter-year fixed effect and γ_{jt} is the importer-year fixed effect.

To construct the instrument variable (IV), we proceed in the following steps: first, we estimate the above equation; second, the estimated predicted values are transformed to the level form by taking the antilog and adjusting the result by multiplying by a factor which is given by exp $(0.5\hat{\sigma})$ where $\hat{\sigma}$ is the estimated variance of the error term; third, the adjusted

predicted export values are used to construct the educational intensity of export instrument variable which was discussed earlier in detail.

$$EI\_ivexp_{c,t} = \sum_{i=1}^{I} share\_exp\_adj\_pre_{i,c,t} * I_i \tag{1.6}$$

We construct an instrument for imports in a similar fashion to that for exports.

$$lnimp_{ijt} = \beta_1 lngdp_{it} + \beta_2 lndist_{ij} + \gamma_{it} + \gamma_{jt} + \epsilon \tag{1.7}$$

where dependent variable is the log of imports values of importer j to exporter i in year t. Independent variables are the log of exporter GDP ($lngdp_{i,t}$) and the log of bilateral distance ($lndist_{ij}$) between exporter i to importer j. γ_{it} is the exporter-year fixed effect and γ_{jt} is the importer-year fixed effect.

The educational intensity of import instrument variable, $EI\_ivimp_{c,t}$, given in Equation 1.8, is constructed in a fashion similar to that used for the development of the educational intensity of export instrumental variable which is discussed above.

$$EI\_ivimp_{c,t} = \sum_{i=1}^{I} share\_imp\_adj\_pre_{ic,t} * I_i \tag{1.8}$$

These instrumental variables are subsequently used in our main specification and enables us to form causal inferences about the effect of trade composition on educational attainment.

Table 1.3: **IV Estimation of Overall Sample**

VARIABLES	(1) Years of Schooling	(2) Years of Schooling
Predicted Educational Intensity Exports	0.272*	0.216**
	(0.130)	(0.086)
Predicated Educational Intensity Imports	-0.589**	-0.375*
	(0.182)	(0.178)
Log GDP		0.440***
		(0.119)
Observations	935	916
R-squared	0.973	0.976
Country FE	YES	YES
Year FE	YES	YES

Note: The dependent variable is average years of schooling. Controlled are the lagged predicted educational intensity of exports, imports, and log of per capita GDP. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.3 shows the result using the exogenous instruments in the educational intensity of exports and imports. Column 1 of Table 1.3 reports the 2SLS estimates over the entire sample (age range from 15 to 65). Comparison of estimated 2SLS results to the OLS baseline specification findings presented in Table 1.2 reveal that the two sets of results are similar but the 2SLS results have a causal interpretation. The educational intensity of exports has the effect of increasing the average years of schooling and the educational intensity of imports has a negative causal impact on the average years of schooling.

Table 1.4: **Impact of Exports and Imports on Average Years of Schooling by Age Groups (IV Estimation)**

VARIABLES	(1) Young	(2) Mid-age	(3) Old
Predicted Educational Intensity Exports	0.336**	0.359	0.466
	(0.106)	(0.254)	(0.298)
Predicted Educational Intensity Imports	-0.144	-1.005**	-1.739**
	(0.247)	(0.360)	(0.604)
Observations	935	935	935
R-squared	0.955	0.964	0.969
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Note: The dependent variables are average years of schooling for each of the three age groups. Controlled are the lagged predicted educational intensity of exports and imports. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.4 shows the 2SLS estimated results for the three different age groups.

1.8 Extensions

Various studies have indicated that educational attainment has different effects upon various age cohorts. An empirical study was conducted to analyze the effect of imports and exports on the educational attainment of the following three age groups: individuals 15 - 29 years old, individuals 30 - 44 years old, and individuals 45 - 65 years old. In addition, within age groups, educational attainment is tracked over the sample periods (for example, the educational attainment of an age cohort that is 15 - 19 in 1960 and 20 - 24 in 1965 and so forth). Educational attainment is also examined by gender and level of education.

1.8.1 Age

Table 1.5: **Impact of Exports and Imports on Average Years of Schooling by Age Groups**

	(1)	(2)	(3)
VARIABLES	Schooling Young	Schooling Mid-age	Schooling Old
Educational Intensity Exports	0.212***	0.133	0.044
	(0.032)	(0.071)	(0.037)
Educational Intensity Imports	-0.849***	-0.060	0.218
	(0.240)	(0.105)	(0.175)
Observations	935	935	935
R-squared	0.956	0.964	0.967
Country FE	YES	YES	YES
Year FE	YES	YES	YES

Note: The dependent variables are average years of schooling for each of the three age groups. Controlled are the lagged educational intensity of exports and imports. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.5 shows the results of rerunning the main specification for each of the three age groups. In all three specifications, the dependent variable, educational attainment, is measured based on the respective age cohort. The result for age group 15 - 29 in Column 1 shows that the educational intensity of exports has positive effect on educational attainment, the educational intensity of imports has negative effect on educational attainment, and both variables are statistically significant, which is in line with our theoretical predictions. Columns 2 - 3 present the results for the other two age groups, 30 - 44 years old, and individuals 45 - 65 years old, respectively, which are found to not have an effect on educational attainment.

These results reflect the fact that individuals in the age bracket 15 - 29 are more likely to enter formal education. This is predominately the common and more ideal time to invest in education. We can, then, interpret that the younger cohort is most sensitive to change in the composition in the country's exports and imports due to the fact that these individuals have a low opportunity cost of changing their educational level. Thus, trade composition

has a greater impact on this age group. The older cohort is less responsive to changes in the pattern of trade composition.

1.8.2 Within Groups

Table 1.6: **Within Groups**

VARIABLES	(1) Schooling (15 - 20)	(2) Schooling (20 - 25)
Educational Intensity Exports	0.008	-0.011
	(0.025)	(0.064)
Educational Intensity Imports	-0.186	-0.179***
	(0.099)	(0.047)
Observations	825	825
R-squared	0.987	0.985
Country FE	YES	YES
Year FE	YES	YES

Note: Dependent variables are average years of schooling for fixed groups and controlled are lagged educational intensity of exports and imports. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.6 shows the results rerunning the basic specification for within group. The result becomes non-significant. We can conclude that the educational attainment is achieved with the age range of 15 - 29 as most relevant for formal education and there after remains unchanged.

1.8.3 Gender

Table 1.7: **Impact of Exports on Average Years of Schooling by Gender**

	(1)	(2)
VARIABLES	Years of Schooling (Female)	Years of Schooling (Male)
Educational Intensity Exports	0.134**	0.228***
	(0.047)	(0.028)
Educational Intensity Imports	-0.346**	-0.753***
	(0.122)	(0.139)
Observations	935	935
R-squared	0.970	0.971
Country FE	YES	YES
Year FE	YES	YES

Note: Dependent variables are average years of female and male schooling. Controlled are lagged educational intensity of exports and imports. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 1.7 represents the result of the main specification for females and males. Columns 1 - 2 shows that the educational intensity of exports has a positive and significant impact on female and male average years of schooling. The educational intensity of imports has a negative and significant impact on female and male average years of schooling. Depending on the gender, there is some variation on the level of significance. The female results are significant at the 5% level and the male results have a greater significance at the 1% level. While the educational intensity of exports increased the average years of schooling for males and females, it had much more influence on male (0.228 for male and 0.134 for female). The educational intensity of imports influenced years of schooling much more (-0.753 and -0.346 respectively). Blanchard and Olney (2017), however, found that males were a little more affected by less intensive agricultural and manufacturing exports and the results were significant at the 5% level and educational intensive manufacturing exports influence both genders to a similar extent. Our findings show that the educational intensity of imports and exports have a differential effect on educational attainment.

1.8.4 Level of Education

Table 1.8: **Impact of Different Levels of Educational Intensity of Exports and Imports on Average Years of Schooling**

VARIABLES	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling
Educational Intensity Exports (Group 1)	-0.770*			
	(0.330)			
Educational Intensity Imports (Group 1)	5.004***			
	(0.947)			
Educational Intensity Exports (Group 2)		-3.210***		
		(0.770)		
Educational Intensity Imports (Group 2)		5.654**		
		(2.248)		
Educational Intensity Exports (Group 3)			0.038	
			(0.955)	
Educational Intensity Imports (Group 3)			-4.212*	
			(2.096)	
Educational Intensity Exports (Group 4)				2.616***
				(0.410)
Educational Intensity Imports (Group 4)				-4.633**
				(1.371)
Observations	935	935	935	935
R-squared	0.973	0.974	0.973	0.974
Country FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes: Dependent variable is the average years of schooling. Controlled are the share of educational intensity of exports and imports at different educational levels. Standard errors are clustered by year and reported in parentheses.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

In Table 1.8, the levels of schooling are divided into four categories within each industry: Group 1 - the proportion of those who have no schooling to Grade 11; Group 2 - the proportion of those who have Grade 12 to less than one year of college; Group 3 - the proportion of those who have from one to three years of college education; and Group 4 - the proportion of those who have four years and higher of college education. Using these four groups, we reconstruct the educational intensity of exports and imports variables. We rerun the regression using ordinary least squares (OLS) and report the estimates of Equation 1.1 according to the educational intensity of exports and imports by share of the educational group. Column 1 - 2 show that low educational-intensive exports have a negative effect on educational attainment while low educational-intensive imports have a positive effect. However, in Columns 3 and 4, high educational-intensive exports have a positive effect and high educational-intensive imports have a negative effect on educational attainment. Therefore, we see that people may change their educational decisions based on the demand for educational-intensive exports and imports.

1.9 Conclusion

The theoretical framework indicates how the educational intensity of both exports and imports affect the development of human capital. One hypothesis is that countries with higher exports in industries that require an educated workforce will witness an increased level of human capital development in the future because exporting educationally-intense goods may carry important long-run benefits through an increase in human capital. A second hypothesis is that countries that import a high amount of educationally intensive goods will witness a decrease in the average number of years of schooling in the future, since there is a high opportunity cost of education for less educated workers. The current research reveals that: one, the educational intensity of exports generally has a positive impact on educational attainment; and two, the educational intensity of imports has a negative effect on years of schooling attained. Thus, both hypotheses would appear to hold in most cases.

The results are in line with the seminal work of Findlay and Kierzkowski (1983) which suggests that trade may exacerbate income differences across countries through its effect

on educational attainment. An implication is that countries that are heavily dependent on low-skill intensive exports are likely to remain less developed nations.

Our results imply that the demand-side mechanisms are empirically important in shaping the level of aggregate educational attainment over the period 1962 - 2010. These findings have important implications for the industrial and trade policies a country adopts. Should existing export industries that produce educationally-intensive goods be encouraged? Furthermore, in developing countries, should new export industries emphasize the production of educationally-intensive goods since they provide high-skill job opportunities for the domestic workforce? If so, individuals will seek to become highly educated, increasing their human capital. However, the government and policy makers should perhaps discourage import opportunities since there appears to be a negative correlation between the educational intensity of imports and the number of years of schooling attained. These strategic decisions incorporating the relationship between trade and educational attainment can promote human capital and overall economic development/progress.

Chapter 2

The Impact of Trade Composition on Educational Attainment: Evidence from the U.S.

2.1 Introduction

This paper critically analyzes the extent to which demand-side factors influence human capital formation. There is general consensus that supply-side factors influence educational attainment. But what is less understood is how demand-side factors affect educational attainment. Unlike major trade research which analyzes the impact of trade on U.S. local labour market conditions such as unemployment and wages, our research question addresses how trade composition affects educational attainment at the regional level which is in line with the work done by Blanchard and Olney (2017) and Greenland and Lopresti (2016). The paper analyzes the American experience using data from the following censuses: 1980, 1990, 2000 and 2010. We use the census to obtain education, wage, employment and population data. As the census does not use commuting zones as a measurement, we apply the matching strategy created by Dorn (2009), subsequently used by Dorn et al. (2009), Acemoglu and Autor (2011) and Smith (2010), among others.

Differences in the regional experience are accounted for by using commuting zones as the unit of analysis. This is a beneficial approach since it includes both metropolitan and non-metropolitan areas and, as such, captures the effect of U.S. local labor markets on educational attainment. This is an insightful exercise since examining such a diverse economy as the U.S. by commuting zones (CZs), at the regional level, will provide a sound comparison of the magnitude of imports/exports effects on educational attainment. Due to the fact that exports and imports data are not available at the CZs level, a proxy has to be estimated. The approach that is taken is that for each commuting zone, the industry employment share

is multiplied by the national level industry specific exports and imports data.

Specifically, in this research, we develop two hypotheses that focus on the effects of two main variables, educational intensity of exports and imports by CZs, to examine their impact on educational attainment. Following the existing literature (David et al., 2013; Greenland and Lopresti, 2016; Li, 2018), we constructed these variables with some modification which is the incorporation of educational intensity. We predict that an increase in exports of educational-intensive industries will increase demand for educated workers and increase educational attainment. As well, we suggest that an increase in imports of educational-intensive products will decrease demand for educated workers and decrease educational attainment.

Results in Chapter 2 are only partially consistent with our study of the global perspective conducted in Chapter 1: the educational intensity of exports has a positive relationship with educational attainment and the educational intensity of imports also has a positive relationship with educational attainment. However, the relationship between import shocks and educational enrollment is positive (Greenland and Lopresti, 2016). The other contribution of this paper is to deepen our knowledge about the causes behind this differential effect of import shocks. Namely, industries using educationally-intensive imported intermediate inputs might increase the demand for high-skilled workers which would, as a result, increase the demand for higher education. We predicted that population consumption of final educationally-intensive imported goods would decrease demand for high-skilled workers thereby reducing educational attainment. Our study, however, shows a positive relationship for intermediate educationally-intensive imported goods while the results for final imported goods is negative but not significant. We suggest some possible reasons for these effects in the Further Exploration section of this paper.

In this study, the employed methodology is divided into several steps. An OLS baseline specification for educational attainment is performed for the overall sample (15 to 65), age group, and gender. An OLS will be biased due to the endogeneity problem. To ensure any potential endogeneity problem is controlled by using an instrument variable approach, we construct an exogenously-driven component of trade flows using a variation of the gravity model the methodology of David et al. (2013).

The overall results reveal that educationally-intensive exports have a significant positive

relationship, while for educationally-intensive imports there is a positive relationship on educational attainment. In our study, educationally-intensive intermediate imported inputs have a positive and significant relationship on educational attainment. This impact can be seen because high-skilled workers are complementary to intermediate imported inputs. In contrast, final educationally-intensive imported goods have a negative but insignificant relationship with educational attainment.

This paper is divided into the following sections: literature review, the conceptual framework needed to understand the hypotheses; the construction of the variables; the data, empirical strategy and construction of the instrument variables; the results; further explorations; robustness check; and conclusions.

2.2 Literature Review

Education is one of the key factors that contributes to change in a country's human capital formation which in turn helps determine a country's trajectory of economic growth. The objective of this paper is to demonstrate how a country's trade can be one of the important channels in human capital accumulation. Therefore, it is important to understand the linkages between human capital accumulation and a country's exports. A country's exports are found to be a key demand-side driver of education and shifting production patterns and skill intensity of a country's exports are responsible for the reallocation of labor across sectors and thus can affect the opportunity cost of continued education (Blanchard and Olney, 2017; Duncan, 1965). The trade policies can support the country's need for strengthening its complex skills and capabilities. For example, in many developing countries, export-oriented policies in the past decades have promoted industrialization and economic growth (Li, 2018). While export-led growth strategies lead to growth in the short-run, the long-term effects are worth analyzing to see if economic growth is sustained. For instance, Waithe et al. (2010) performed a case study in Mexico that found that the Export-led Growth Hypothesis held in the short-run but not in the long-run. In the long-run, exports and economic growth were found to have an inverse relationship. Waithe et al. (2010) provide a possible explanation for this result - this result was due to Mexican exports containing high

import content which may have significantly reduced spillover or multiplier effects.[5]

There are a number of studies on the subject of educational attainment and globalization. For example, Blanchard and Olney (2017) conducted a study of 100 countries, both developing and developed, and questioned how exports drive human capital development. Their results show that, specifically, an increase in agriculture exports, which is a low-skilled labor sector, is negatively correlated to the average years of schooling. In addition, low-skilled workers in the manufacturing sector display a similar pattern of decreased investment in human capital. On the other hand, there appears to be a positive relationship between the educational attainment of the high-skilled manufacturing labor sector and export growth. Our analysis will provide insight into the relationship between average years of schooling and skill-intensity of imports and exports.

A seminal paper by Findlay and Kierzkowski (1983) provides the link between returns to labour driven by trade and investment in human capital. It is a general equilibrium model which is based upon Heckscher-Ohlin theory and the Stolper-Samuelson theorem. An increase in relative wages as predicted by the Stolper-Samuelson theorem serves to encourage people to invest more in their human capital formation. Our study examines the connection between demand-side factors, skill intensity and human capital. In addition to papers which examine the relationship between trade liberalization and human capital formation on a global scale, there is a wealth of literature on individual countries, primarily among the developing nations. Two of these studies consider the cases of Mexico and Bangladesh. Atkin (2016) examines the case of Mexico, a country which he contends is an ideal setting to study the effect of globalization on the labor market. His results indicate that the huge expansion of export manufacturing which occurred during the period 1986 - 2000 altered the distribution of education. Specifically, the boom in low-skilled, relatively high paying jobs in the export manufacturing sector resulted in a high opportunity cost in progressing to the secondary level.

To summarize, these papers indicate that school enrollment is closely linked to the arrival

[5]The argument "through dynamic spillover effects on an economy, export growth can affect total factor productivity" is one of the key arguments in support of Export-led Growth Hypothesis (Feder, 1983). Spillover effect has been defined as "learning by doing" or more specifically, "learning by exporting" (Lucas Jr, 1988; Tyler, 1981).

of jobs which reward education. Furthermore, in countries such as Bangladesh, the increased school enrollment among women has the added benefit of increasing female social welfare due to their ability to avoid early marriage and childbirth.

This analysis is based upon the notion that human capital ranks among the most important determinants of growth and income. Human capital can be determined by both demand and supply factors. There is a double mechanism for influencing educational attainment. First, the supply-side mechanism of human capital development includes policies such as government funding for education and those that ensure each person has access to a minimum amount of schooling. Second, the demand-side consists of macroeconomic conditions such as wages and changes in the skill composition of different job opportunities, which shape individuals' decisions to invest in human capital. For example, David and Dorn (2013) and David et al. (2013) find that Chinese import competition not only causes job losses, especially in CZs that have a large exposure to manufacturing, but wages are depressed in CZs with large exposure. As well, transfer payments such as retirement, Social Security Disability Insurance (SSDI), and Trade Adjustment Assistance (TAA), increase dramatically. The cost of these programs are high, partly because the numbers of workers accessing TAA (which is a temporary benefit) is much fewer than those who retire or access disability benefits which are long term. Yet, in this analysis, we are focusing only on the demand-side by examining how demand-side conditions can shape the human capital decisions of individuals.

2.3 Conceptual Framework

We use relative demand and relative supply analysis to understand the conceptual framework of how trade composition drives educational attainment.

Figure 2.1 depicts a commuting zone's relative demand (RD) and relative supply (RS) of educated workers. The horizontal axis is the ratio of skilled to unskilled workers ($L_{skilled}/L_{unskilled}$) and the vertical axis measures the relative wage ($W_{skilled}/W_{unskilled}$), (i.e. the skill premium for educated workers). Changes in a commuting zone's imports and exports can both affect relative demand.

Consider a commuting zone (CZ) which experiences a relative demand shock for educa-

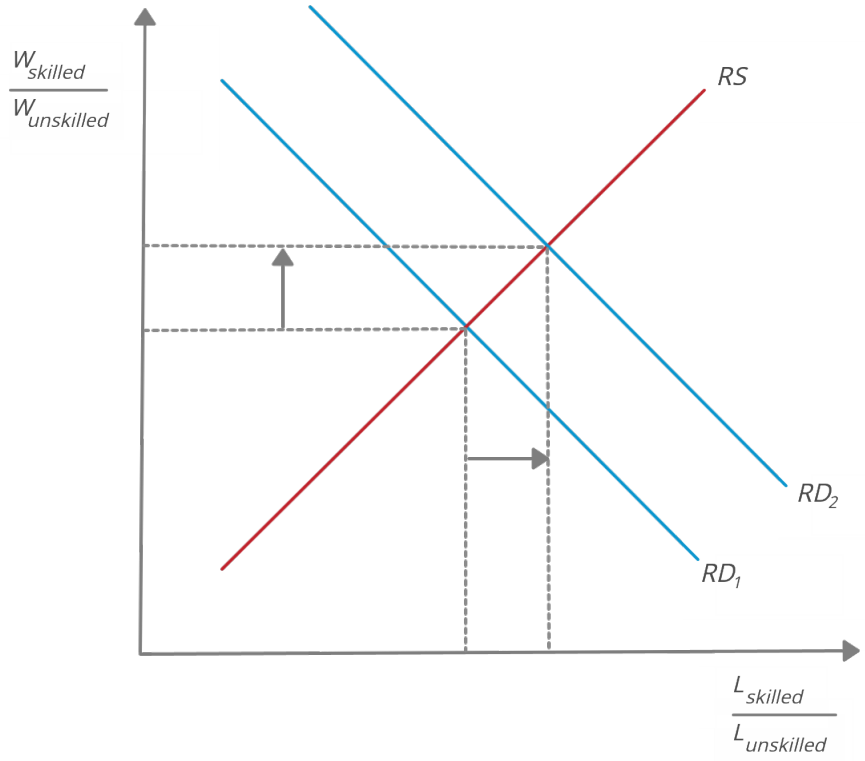

Figure 2.1: Demand and Supply of Educated Workers

tionally intensive imports. An increase in imports of educationally intensive products would create one of two potential results: the CZ will either stop producing these educationally intensive products altogether or the commuting zone will reduce the quantity produced. In either case, firms do not need many educated workers and therefore, the relative demand for educated workers will go down reducing the quantity of educated workers in the future.

In contrast, if the CZ experiences an increase in its exports of educationally intensive products, it will need more educated workers to produce the exported goods. In this case, the relative demand for educated workers will go up (see Figure 2.1). As the skill-premium increases, workers are motivated to become more educated, ceteris paribus. To summarize, the effect of trade will positively affect the relative demand for educated workers when a CZ increases the amount of educationally-intensive exports, which will increase the number of educated workers in the population; similarly, an increase in the demand for educationally-intensive imports will decrease the share of educated workers in the population. The relative demand and supply analysis above leads to the following two hypotheses:

Hypothesis 1: An increase in exports of educationally intensive industries will increase the demand for educated workers and increase educational attainment.

Hypothesis 2: An increase in imports of educationally intensive products will decrease the demand for educated workers and decrease educational attainment.

2.4 Empirical Specification

To identify the effect of trade composition on educational attainment in the U.S., we estimate the following empirical specification:

$$\Delta edu_{c,t} = \alpha + \beta_1 \Delta EI\_exp_{c,t} + \beta_2 \Delta EI\_imp_{c,t} + \gamma_c + \epsilon_{c,t} \tag{2.1}$$

where the dependent variable $\Delta edu_{c,t}$ denotes the change in the average years of schooling of commuting zone c at time t. The independent variables, $\Delta EI\_exp_{c,t}$ and $\Delta EI\_imp_{c,t}$, are respectively change in the educational intensity of exports and the educational intensity of imports, γ_c is the commuting zone fixed effect and $\epsilon_{c,t}$ is an error term. The independent variables, educational intensity of exports and imports, represent the change of the past ten years. We use a first difference approach to remove any time invariant effects within CZs. This approach does not control for long term c-zone specific effects, like the economic decline seen in the Detroit area starting in the 1950's. This started before Chinese import competition so Chinese import competition did not cause all of the economic decline as noted by Greenland and Lopresti (2016). In our study, we need to eliminate similar long term localized effects that are not from export or import shock. Standard errors are clustered by state level to adjust for the effect of state level policies as they relate to trade adjustment assistance or other changing labour market polices which could have affected our sample (Greenland and Lopresti, 2016). β_1 and β_2 represent respectively the effect of a change in educationally-intensive exports and imports. The expected signs of β_1 and β_2 are positive and negative as determined by hypotheses 1 and 2, respectively.

2.5 Construction of the Intensity Variables

In this section, we describe the construction of the educational intensity variables. First, the educational intensity of exports is derived in the following fashion:

$$export_{c,i,t} = \sum_i \frac{L_{c,i,t}}{L_{i,t}} * export_{i,t} \tag{2.2}$$

$$share\_export_{c,i,t} = export_{c,i,t} / \sum_c export_{c,i,t} \tag{2.3}$$

$$EI\_exp_{c,t} = \sum_i share\_export_{c,i,t} * I_{i,t} \tag{2.4}$$

where $I_{i,t}$ is educational intensity of industry i which is measured by the average years of schooling of workers in that industry. For example, in the automobile industry, if 13 years is the average number of years of schooling for American workers, this represents educational intensity of the automobile industry. $export_{c,i,t}$ gives us the estimation of the contribution of each commuting zone by industry to national exports. $share\_export_{c,i,t}$ is the export share for a particular industry i in a given commuting zone c at time t. Note the sum of the export shares over all industries for a given commuting zone and a particular year is one. Educational intensity of exports $EI\_exp_{c,t}$ is educational intensity $I_{i,t}$ weighted by aggregate exports share for a commuting zone c at time t which is given by: $\sum_i share\_export_{c,i,t} * I_{i,t}$. In other words, educational intensity of exports is the weighted average of educational intensity weighted by the share of exports. Secondly, the educational intensity variable for imports is constructed as follows:

$$import_{c,i,t} = \sum_i \frac{L_{c,i,t}}{L_{i,t}} * import_{i,t} \tag{2.5}$$

$$share\_import_{c,i,t} = import_{c,i,t} / \sum_c import_{c,i,t} \tag{2.6}$$

$$EI\_imp_{c,t} = \sum_i share\_import_{c,i,t} * I_{i,t} \tag{2.7}$$

Similarly, educational intensity of imports ($EI\_imp_{c,t}$) is educational intensity ($I_{i,t}$) weighted by imports share in a commuting zone c at time t which is given by: $\sum_i share\_import_{c,i,t} * I_{i,t}$.

2.6 Data and Summary Statistics

Our empirical analysis draws on the Census Integrated Public Use Micro Samples for 1980, 1990, 2000 and 2010 which each includes 5% of the U.S. population. To evaluate the effect on educational attainment of a change in exports and imports, the local labor market definition employed is the CZ[6] as developed by Tolbert and Sizer (1996). They used commuting data from the 1990 census at the county-level to create 741 clusters of counties. They are characterized by strong commuting ties within CZs, and weak commuting ties across CZs. We, however, use 722 commuting zones which form the U.S. mainland and exclude Alaska and Hawaii.

The commuting zone measure is more reliable than other geographic units used to analyze the labour market. Here are two advantages of using commuting zones as a definition of a regional economy: first, they cover the entire U.S., thereby, allowing researchers to analyze the entire country as opposed to just census metropolitan areas; second, the grouping of counties together based upon commuting flows (who lives in one county and works in another; in addition, those who live in that county but work in another county) implies a certain level of economic integration.

The data on educational attainment is obtained across regional variables from the U.S. census for the period 1980 to 2010 at ten-year intervals. Trade data for the period 1962 - 2010 are taken from the World Trade Flows data set which was constructed by Feenstra et al. (2005). This data consist of bilateral trade flows for pairs of countries based on export and import values by industry. The industry classification is the 4-digit SITC (revision 2) which was converted into the 4-digit North American Industry Classification System (NAICS) using NBER concordance tables. For the period from 2000 until 2010, the industry-level bilateral trade flow data is from the UN-TRAINS database at the 6-digit Harmonized System Classification and subsequently aggregated into the 4-digit NAICS using the concordance from Feenstra et al. (2002). The input-output table is from Bureau of Economic Analysis Database (BEA).[7] To test hypotheses 3 and 4 under Further Exploration in the input-output

[6]Because the census data uses counties and not commuting zones, we follow the method of David Dorn which can be found at his website: http://www.ddorn.net/data.htm to match counties to c-zones.

[7]The U.S. Department of Commerce Bureau of Economic Analysis (BEA) publishes annual

section, we constructed two new variables: the educational intensity of intermediate imports and the educational intensity of final imports.

Table 2.1: **Summary Statistics**

Variables	Obs.	Mean	Std. Dev.
Average Years of Schooling	2902	12.42	1.69
Educational Intensity of Exports	2077	12.06	2.45
Educational Intensity of Imports	2077	12.45	0.78

Table 2.1 reports the summary statistics for our main variables of interest from 1980 to 2010. Variables are measured at the commuting zones level. The standard division of educational intensity of exports is much greater at 2.45 than educational intensity of imports at 0.78. It shows that there is more variation across commuting zones for the educational intensity of exports.

Figure 2.2 (below) gives an insight into the data by plotting the change in average years of schooling against the educational intensity of exports. It shows that a positive relationship does exist between these two variables. This relationship is consistent with the theory that the educational intensity of exports decreases the opportunity cost of education. This encourages students to remain in school and increase their skills.

The map in Figure 2.3 (below) shows the geographical distribution by commuting zones of the predicted educational intensity of exports. We see there is a reasonably even geographical distribution for those commuting zones where the educational intensity of exports can be expected to have a medium to large effect upon educational attainment. The number of years of schooling is shown by how dark the colour of the commuting zone is: namely, the darker the colour, the greater the average numbers of years of education possessed by the commuting zone. Areas that have large manufacturing sectors like the rust belt and parts of California show a relatively high effect on years of schooling as is expected.

data on sales of commodities used by industries in input-output table which can be found at http://www.bea.gov/industry/input-output-accounts-data

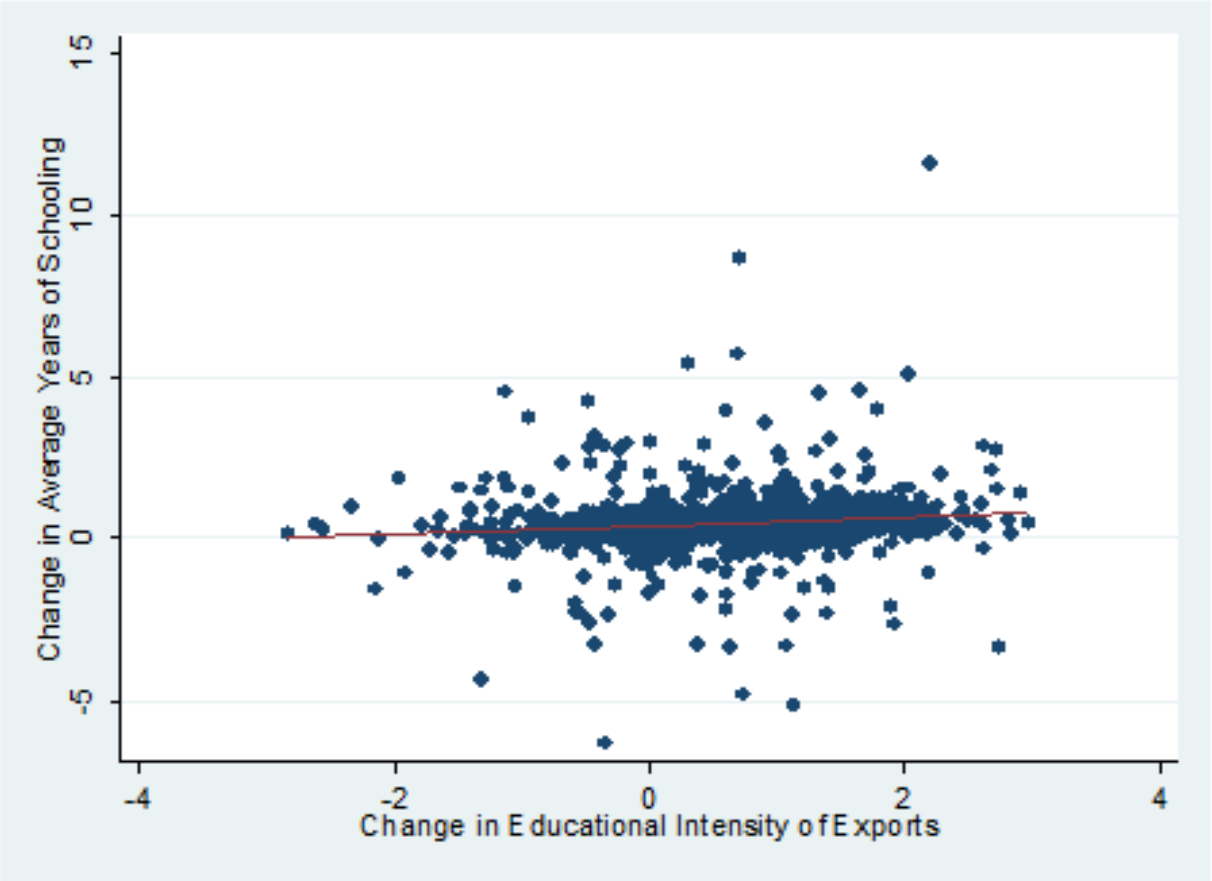

Figure 2.2: Change in Average Years of Schooling vs Change in Educational Intensity of Exports

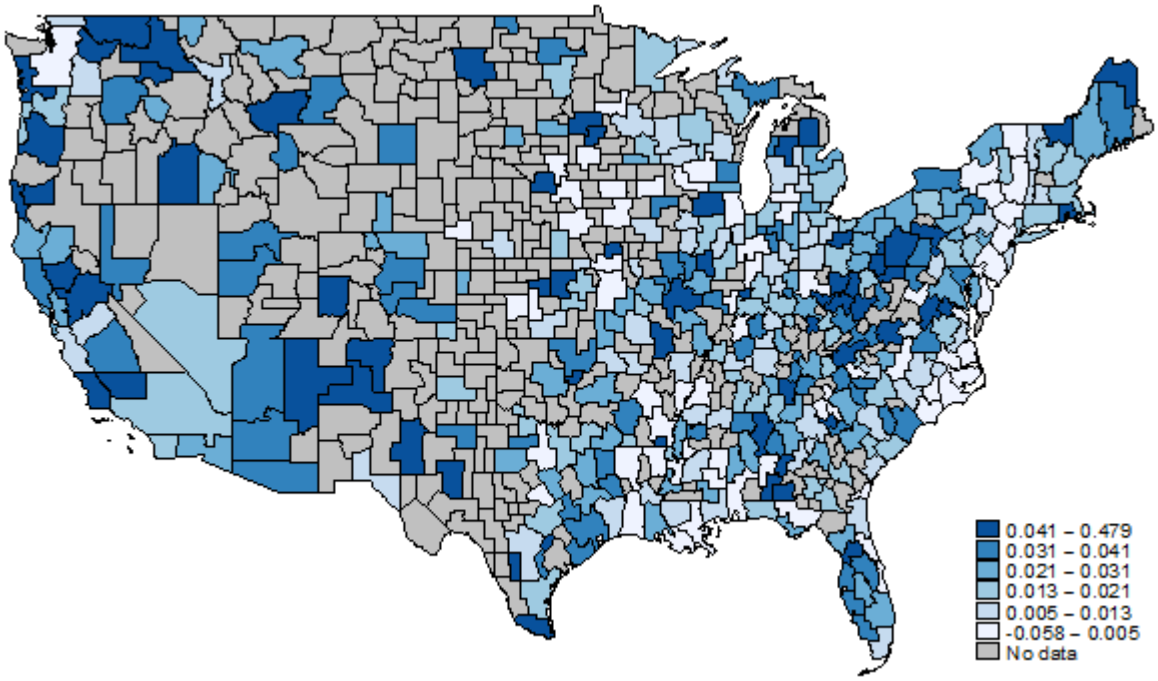

Figure 2.3: Predicted Educational Intensity of Exports of CZs

2.7 Results

2.7.1 Benchmark Results (OLS)

Table 2.2: **Impact of Exports and Imports on Average Years of Schooling**

	(1)	(2)
VARIABLES	Years of Schooling	Years of Schooling
Δ Educational Intensity Exports	0.127**	0.0864**
	(0.0475)	(0.0405)
Δ Educational Intensity Imports	0.149	0.108
	(0.101)	(0.105)
Δ Wage		0.0271**
		(0.012)
Observations	1,188	1,161
R-squared	0.536	0.517
Czone FE	YES	YES

Notes: Dependent variable is the change in the average years of schooling. Controlled are the change in educational intensity of exports and imports and average wage. Wage is normalized by dividing it by 1000. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.2 presents the results from running the regressions using the ordinary least squares (OLS). Column 1 contains the results for the entire sample (15 - 65+ years old). The dependent variable is the change in average years of schooling and the independent variables are the change in educational intensity of exports and the change in the educational intensity of imports. Standard errors are clustered by state level and those are reported in brackets. Examination of Column 1 reveals that a one year change in the educational intensity of exports would result in the average years of schooling increasing by .127 which is also statistically significant at the 5% level. This finding is consistent with the idea that there is a positive relationship between the demand of educational intensity of exports and educational attainment. This result is in line with work done by Blanchard and Olney (2017) who find that both high skill-intensive manufacturing exports and low skill-intensive manufacturing exports and agriculture exports have opposite effects on educational attainment. In other words, an increase in the demand for high skill-intensive manufacturing exports leads to increase educational attainment. Additionally, an increase in the demand for low-skill intensive manufacturing and agriculture exports lead to decrease in educational attainment.

Having considered the effect of change in educational intensity of exports, we now move to examine the change in educational intensity of imports, which does not have the expected negative effect on educational attainment. It shows that an increase in the educational intensity of imports actually increases the amount of average years of schooling by .149, which is not statistically significant. In Column 2, we control for the change in the average wage. Inclusion of this variable is important since it accounts for the potential effect of changes in income that allows families to invest more in their children's education. The variable is expected to have a positive effect on educational attainment. Examination of the estimated coefficients in Column 2 reveals that adding this variable does not change the results from those in Column 1. Thus, the empirical results listed in Columns 1 and 2 partially support the hypotheses discussed in the theoretical framework.

2.7.2 IV Results

If endogeneity is present, the estimate of the regression coefficient in the OLS will be biased. By using an instrument variable approach, we ensure that any potential endogeneity

problem is controlled for.

The endogeneity problem arises from a concern about reverse causality, omitted variables and measurement errors. Reverse causality stands as a primary concern – whether education drives the educational intensity of exports or if educational-intensive exports drive educational attainment. The educational intensity of exports and educational intensity of imports could be correlated with the error terms, causing biased estimates in Equation 2.1. For example, a firm may choose to locate in an area with low education levels or the local education level may be driven downward due to the establishment of new low-skill factories. In this situation, the coefficient will be biased in an ambiguous direction. Consequently, we accept that the control of the exogenously-driven component of trade flows will depend on the demand-side shock.

Greenland and Lopresti (2016) gives an example of an exogenous increase in the demand for tennis shoes in the U.S. which we would expect to lead to rising employment in areas specializing in the production of tennis shoes. However, Greenland's example is also likely to contribute to increasing tennis shoe imports from China. He is concerned that a failure to control for the change in demand for tennis shoes imports will lead to a biased estimate of their effect on domestic employment. In this context, Greenland mentions how a deteriorating labour market situation could affect the educational decision and lead to a biased estimate for import competition on graduation rates.

In order to control for the endogenity problem, we use a variation of the gravity model to construct instrument variables. Essentially, the gravity model seeks to explain bilateral trade flows in term of distance resistance and other macroeconometric variables. Anderson (2011), the gravity model in the log transformation as follows:

$$lnx_{ijt} = lny_{it} + lny_{jt} - lny_{wt} + (1-\sigma)ln\tau_{ijt} - lnP_{it} - lnP_{jt} \tag{2.8}$$

where the log bilateral export flows (lnx_{ijt}) is a function of log GDP (lny_{it}) of the exporting country, log of GDP (lny_{jt}) of the importing country, log of world GDP (lny_{wt}), log of bilateral trade friction ($ln\tau_{ijt}$) and log of the resistance term (lnP_{it}) and multilateral resistance terms (lnP_{jt}) in country i and j. This model has been used successfully in several studies. Feyrer (2009) obtained predicted bilateral trade flows as a function of several exoge-

nously driven factors. Predicted values of trade flows were subsequently used as variables in his income equation. A similar approach was developed by Blanchard and Olney (2017) to model educational attainment. In their paper, they used the log of real GDP of importing countries and a pair of fixed effects as instruments in 2SLS model of educational attainment.

In our study, we used a similar instrumental approach. We have eliminated exporter GDP from the following regression equation since it is correlated with educational attainment and have included only importer GDP and used exporter fixed effect, importer fixed effect, and year fixed effect to control the factors such as, change in world GDP and variance resistance terms. In order to identify exogenous factors with which to explain trade flows; the equation used is as follows:

$$lnexp_{ijt} = \beta_1 lngdp_{jt} + \beta_2 lndist_{ij} + \gamma_{it} + \gamma_{jt} + \epsilon \tag{2.9}$$

where the dependent variable is the log of bilateral flow of exports from exporter i to importer j in year t. Independent variables are: the log of importer GDP ($lngdp_{jt}$), the log of distance ($lndist_{ij}$) from exporter to importer, γ_{it} is the exporter-year fixed effect and γ_{jt} is the importer-year fixed effect.

To construct the instrument variable (IV), we proceed in the following steps: first, we estimate Equation 2.9 above; second, the estimated predicted values were transformed to the level form by taking the antilog and adjusting the result by multiplying by a factor which is given by exp $(0.5\hat{\sigma})$ where $\hat{\sigma}$ is the estimated variance of the error term; third, the adjusted predicted export values are used to construct the educational intensity of export instrument variable which was discussed earlier in detail.

$$EI\_ivexp_{c,t} = \sum_{i=1}^{I} share\_exp\_adj\_pre_{i,c,t} * I_i \tag{2.10}$$

We construct an instrument for imports in a similar fashion to that for exports.

$$lnimp_{ijt} = \beta_1 lngdp_{it} + \gamma_{it} + \gamma_{jt} + \epsilon \tag{2.11}$$

Where dependent variable is the log of imports values of importer j to exporter i in year t. Independent variables are the log of exporter GDP ($lngdp_{i,t}$), the log of bilateral distance

($lndist_{ij}$) between exporter i to importer j. γ_{it} is the exporter-year fixed effect and γ_{jt} is the importer-year fixed effect.

The educational intensity of import instrument variable, $EI\_ivimp_{c,t}$, as given in Equation 2.12, is constructed in a similar fashion to that used for the development of the educational intensity of export instrument variable discussed above.

$$EI\_ivimp_{c,t} = \sum_{i=1}^{I} share\_imp\_adj\_pre_{i,c,t} * I_i \tag{2.12}$$

These instrument variables are subsequently used in our main specification, which enables us to form causal inferences about the effect of trade composition on educational attainment.

Table 2.3: **IV Estimation of Overall Sample**

	(1)	(2)
VARIABLES	Years of Schooling	Years of Schooling
Δ Predicted Educational Intensity Exports	0.169**	0.113*
	(0.0653)	(0.0609)
Δ Predicted Educational Intensity Imports	0.201**	0.159**
	(0.0770)	(0.0648)
Δ Wage		0.0314**
		(0.0153)
Observations	1,178	1,150
R-squared	0.539	0.507
Czone FE	YES	YES

Notes: Dependent variable is the change in the average years of schooling. Controlled are the change in predicted educational intensity of exports, imports and wage. Wage is normalized by dividing it by 1000. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.3 shows the result using the exogenous instruments in the educational intensity of exports and imports. Column 1 - 2 of Table 2.3 reports the 2SLS estimates over the entire sample, with age ranging from 15 to 65 years. The results in Column 1 shows that the educational intensity of exports has a positive effect on educational attainment which is statistically significant. The educational intensity of imports has also a significant, positive

effect on educational attainment. Comparison of the estimated 2SLS results to the OLS baseline specification findings reveal that the educational intensity of exports are positive and significant in both the OLS and 2SLS. But educational intensity of imports is positive and significant in the 2SLS but, in the OLS, they are positive but not statistically significant.

2.8 A Further Exploration

2.8.1 Levels of Schooling

While the educational intensity of exports and imports influences educational attainment, the influences change depending on different levels of schooling, age, and gender. The levels of schooling are divided into four categories within each industry: Group 1 - the proportion of those who have no schooling to Grade 11; Group 2 - the proportion of those who have Grade 12 to less than one year of college; Group 3 - the proportion of those who have from one to three years of college education; and Group 4 - the proportion of those who have four years and higher of college education. Using these four groups, we reconstruct the educational intensity of exports and imports variables. We run the regression and report the estimates of Equation 2.1 according to the educational intensity of exports and imports by share of the educational group. We construct this kind of measure to investigate the differential effect of educational intensity of exports and imports on average years of schooling.

Table 2.4: **Impact of Different Levels of Educational Intensity of Exports and Imports on Average Years of Schooling**

VARIABLES	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling
Educational Intensity Exports (Group 1)	-0.618			
	(0.385)			
Educational Intensity Imports (Group 1)	-1.582*			
	(0.874)			
Educational Intensity Exports (Group 2)		-0.711***		
		(0.220)		
Educational Intensity Imports (Group 2)		-1.424**		
		(0.619)		
Educational Intensity Exports (Group 3)			0.686*	
			(0.404)	
Educational Intensity Imports (Group 3)			1.088*	
			(0.647)	
Educational Intensity Exports (Group 4)				1.040***
				(0.384)
Educational Intensity Imports (Group 4)				0.787
				(0.668)
Observations	1,188	1,188	1,188	1,188
R-squared	0.536	0.529	0.535	0.527
Czone FE	YES	YES	YES	YES

Notes: Dependent variable is the change in the average years of schooling. Controlled are the change in share of educational intensity of exports and imports at different educational levels. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.4 represents the results from rerunning the regressions using the ordinary least

squares (OLS). Column 1 - 2 show that low educational-intensive exports and imports have a negative effect on educational attainment. However, in Columns 3 and 4, high educational-intensive exports and imports have a positive effect on educational attainment. Therefore, we see that people change their educational decisions based on the demand for educational-intensive exports and imports. The coefficients of interest remain broadly the same as before for exports in Columns 3 and 4. This means that educational-intensive exports have a substantial effect on educational attainment.

2.8.2 Age

Table 2.5: **Impact of Exports and Imports on Average Years of Schooling by Age Groups**

	(1)	(2)	(3)
VARIABLES	Young Schooling	Mid-age Schooling	Old Schooling
Δ Educational Intensity Exports	0.097**	0.103*	0.124***
	(0.045)	(0.058)	(0.045)
Δ Educational Intensity Imports	-0.075	-0.113	0.353***
	(0.123)	(0.121)	(0.130)
Observations	1,081	1,104	1,107
R-squared	0.409	0.573	0.490
Czone FE	YES	YES	YES

Notes: Dependent variable is the change in the average years of schooling by age groups. Controlled are change in educational intensity of exports and imports. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.5 reruns the main specification for each of the three age groups. In all three specifications, the dependent variable which is educational attainment is measured based on each of three age cohorts. The result for age 15 - 29 in Column 1 shows that the educational intensity of exports has a positive relationship with educational attainment and the educational intensity of imports has a negative but insignificant effect on educational attainment. In Columns 2 and 3, the other two age groups which are 30 - 44 years old and

individuals 45 - 65 years old respectively, do have an effect on educational attainment for exports but only the oldest age category (Column 3) yields a significant result for imports. We can interpret these results as exports influence the educational decision consistently and significantly but imports only influence the decision of the oldest category of workers. Exports seem to influence educational attainment for all three categories but imports only influence the educational decision of the oldest group. Perhaps exports have a more direct and obvious effect on educational decisions because people see the jobs and the education needed which would decrease the opportunity cost of education significantly and obviously. Import competition, on the other hand, is met with transfer benefit payments (disability, retirement, unemployment and healthcare) which would also affect the educational decisions and increase the opportunity cost of education. This seems consistent with the work of Greenland and Lopresti (2016).

2.8.3 Gender

Table 2.6: **Impact of Exports and Imports on Average Years of Schooling by Gender**

	(1)	(2)
VARIABLES	Schooling (Male)	Schooling (Female)
Δ Educational Intensity Exports	0.147**	0.082**
	(0.056)	(0.034)
Δ Educational Intensity Imports	0.194	-0.002
	(0.122)	(0.087)
Observations	1,151	1,106
R-squared	0.564	0.607
Czone FE	YES	YES

Notes: Dependent variable is the change in the average years of schooling. Controlled are change in educational intensity of exports and imports. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.6 represents the result of the main specification for male and female. Columns 1 - 2 shows that the educational intensity of exports has a positive and significant impact on male and female average years of schooling. The educational intensity of imports has a positive but insignificant impact on male and female average years of schooling. Depending on the gender, there is some variation on the level of significance. Again, we suggest further research to determine why exports influence educational attainment consistently but imports do not but again, the triggering of transfer payments by an increase in import competition seem to have affected the results.

Input-Output

We further explore the differential effect of import shocks on educational attainment by using the input-output tables to construct two new variables to test Hypotheses 3 and 4.

Table 2.7: **Industry Input-Output Table**

	Industry 1	Industry 2	Industry 3	Final Demand	Total
Industry 1	30	40	0	30	100
Industry 2	10	200	50	140	400
Industry 3	20	80	200	200	500

Input-output analysis, which is based upon the pioneering work of Leontief (1953), is a widely used economic tool for showing the flow of resources between industries. This tool has a long history in national economic planning and there is a lively body of current work in environmental and resource economics surrounding them. Commonly, input-output data are presented in "use" tables, where the rows show source commodities, the columns show destination industries, and the table industries show resource flows in dollars. The U.S. Department of Commerce Bureau of Economic Analysis (BEA) publishes annual data on sales of commodities used by industries in an input-output table. Based upon the input-output tables, we constructed the two variables and the following two new hypotheses are tested:

Hypothesis 3: Industries using educationally-intensive imported intermediate inputs might increase the demand for high-skilled workers which would, as a result, increase the demand for higher education.

Hypothesis 4: Population consumption of final educationally-intensive imported goods will decrease demand for high-skilled workers, thereby, reducing educational attainment.

Hypothesis 3 implies two things. The first being that workers are *complementary* to the changes occurring in the workplace. If imported intermediate inputs are complementary to high-skilled workers, then one will see an increase in demand for high-skilled workers. The second implication is that the workplace adjustment will prove to be a substitute for high paid workers. If intermediate inputs are a *substitute* for high-skilled workers, then it will decrease demand for educated workers. The variables used in the American specifications were constructed in the following way. First, the educational intensity variable was constructed as follows;

$$E_c = \sum_{j}^{N} I_i * import_{i,c} \tag{2.13}$$

E_c is the educational intensity of imports. $import_{i,c}$ is the imports of industry i in commuting zones c while I_i is the average years of schooling of workers in industry i for commuting zone c. Educational intensity of imports E_c is divided into X_1 and X_2:

$$E_c = X_1 + X_2 \tag{2.14}$$

$$X_1 = (I_i * import_{i,c}) * \left(\sum_{j}^{N} I_i a_{ij} * I_j \right) \tag{2.15}$$

$$X_2 = (I_i * import_{i,c}) * b_i \tag{2.16}$$

$$A_i = \sum_{j}^{N} a_{ij} * I_j = a_{11} I_1 + a_{12} I_2 + a_{13} I_3 \cdot \cdots \cdot a_{1n} I_n \tag{2.17}$$

a_{ij} - share by output from industry i that goes into industry j and is used as intermediate inputs

b_i - the share of output consumed as final demand (private consumption)

New Empirical Specification:

$$\Delta edu_{c,t} = \alpha + \beta_1 \Delta EI\_exp_{c,t} + \beta_2 \Delta EI\_X1_{c,t} + \beta_3 \Delta EI\_X2_{c,t} + \epsilon_{c,t} \tag{2.18}$$

where $\Delta edu_{c,t}$ is the change in the average years of schooling of commuting zone c at time t. $\Delta EI\_exp_{c,t}$ is the change in educational intensity of exports. $\Delta EI\_X1_{c,t}$ is the educational intensity of intermediate imports. $\Delta EI\_X2_{c,t}$ is the educational intensity of final imports.

Table 2.8: **Impact of Exports and Differential Imports on Average Years of Schooling**

	(5)	(6)
VARIABLES	Years of Schooling	Years of Schooling
Δ Educational Intensity Exports	0.0921**	0.0666*
	(0.0384)	(0.0331)
Δ Imported Intermediate Inputs	0.0192**	0.0274***
	(0.00843)	(0.00858)
Δ Imported Final Goods	-0.00469	-0.0101
	(0.0230)	(0.0221)
Δ Wage		0.0525**
		(0.0209)
Observations	884	883
R-squared	0.580	0.617
Czone FE	YES	YES

Notes: Dependent variable is the change in the average years of schooling. Controls are the change in educational intensity of exports, imported intermediate inputs and imported final goods. Wage is normalized by dividing it by 1000. Standard errors are clustered at the state level.
Includes Czone Fixed Effects.
*** p<0.01 indicates significance at 1%.
** p<0.05 indicates significance at 5%.
* p<0.1 indicates significance at 10%.

Table 2.8 explores the two new hypotheses 3 and 4 to identify the causes behind the differential effects of import shocks on educational attainment. Here, the following controls are introduced: a change in educational intensity of exports, a change in imported intermediate inputs and a change in imported final goods. The results show that the educational intensity of exports has a positive effect on educational attainment, statistically significant at the 5% level. This is consistent with our prior results and Hypothesis 1. The two new predictors, imported intermediate inputs and imported final goods, show a positive and negative relationship with educational attainment, respectively. Relating to the new hypotheses 3 and 4, we can conclude that if educationally-intensive imported intermediate inputs are complemen-

tary to high-skilled workers, we will see an increase in the demand for high-skilled workers which will increase the incentive for investing in education. The educationally-intensive final imported goods have a negative effect on educational attainment but it is not statistically significant.

2.8.4 Robustness Check

In our robustness check, we are controlling for any demand shock unrelated to export and import shocks that might bias our results. Our main focus is on trade-induced changes to labor market conditions which result in changes in educational attainment.

In order to test the empirical model for robustness, we use an alternative measure of educational intensity of exports and imports. Robustness is checked by constructing a measure of educational intensity of exports and imports at the commuting zone level.

$$EI\_exp_{c,t} = \sum_i \frac{L_{c,i,t_0}}{L_{i,t_0}} * \frac{export_{i,t}}{L_{i,t_0} * \sum_i export_{i,t}} * I_{i,t} \tag{2.19}$$

In Equation 2.19, the year t_0 is fixed for the national and c-zone labour force, where t_0 indicates the baseline year 1980. The U.S. exports by industry i are scaled by the U.S. labour force in the baseline year t_0. Thus, this gives us the average export share per worker in the U.S., which is weighted by commuting zone employment shares by industry i. This gives us the estimation of the contribution of each commuting zone by industry to national exports. Industries c-zone specific value is summed over all industries. The educational intensity is weighted by each commuting zones specific industry exports. Similarly, the educational intensity of imports is constructed as follows:

$$EI\_imp_{c,t} = \sum_i \frac{L_{c,i,t_0}}{L_{i,t_0}} * \frac{import_{i,t}}{L_{i,t_0} * \sum_i import_{i,t}} * I_{i,t} \tag{2.20}$$

Table 2.9: **Impact of Exports and Imports on Average Years of Schooling**

VARIABLES	(1) Years of Schooling	(2) Years of Schooling
Δ Educational Intensity Exports	0.166***	0.161***
	(0.0447)	(0.0434)
Δ Educational Intensity Imports	0.0752	0.0810
	(0.062)	(0.060)
Δ Wage		0.0493***
		(0.0128)
Observations	1,141	1,121
R-squared	0.560	0.525
Czone FE	YES	YES

Notes: Dependent variable is the change in the average years of schooling. The independent variables are the change in educational intensity of exports and imports and average wage. Standard errors are clustered at the state level.

Includes Czone Fixed Effects.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 2.9 reruns the main specification using an alternative measure of educational intensity of exports and imports. Columns 1 and 2 contain the results for the entire sample (15 - 65+ years old). The results show that educational intensity of exports have a positive and significant relationship on the average years of schooling. While our results are not statistically significant, Greenland and Lopresti (2016) found that there is a positive relationship between high school graduation rates and an increase in Chinese import competition. The reason is that the opportunity cost of leaving school increases.

2.9 Conclusion

This paper finds that trade composition affects educational attainment. Consistent with Hypothesis 1, we find a positive and significant impact on educational attainment which results from an increase in the educational intensity of exports. In other words, an increase in educationally-intensive exports is linked to an increase in educational attainment. In contrast to Hypothesis 2, we find a positive but insignificant effect of educationally-intensive

imports on educational attainment.

Our second set of hypotheses, Hypothesis 3 and 4, provide insight into this apparently perplexing result. The results show that educationally-intensive intermediate imported inputs have a positive and significant relationship on educational attainment. The implication is that high-skilled workers are complementary to intermediate imported inputs, since these educationally-intensive imported inputs are used in the production process where high-skilled workers are required. In contrast, final educationally-intensive imported goods have a negative but insignificant relationship with educational attainment. This could occur when importing a high amount of educationally-intensive final consumption goods will result in a decrease in the average years of schooling in the future. This reduces local industries' need for high-skill workers, creating a high opportunity cost for individuals to invest in education. Since our results are not statistically significant, this hypothesis remains unproven.

According to Blanchard and Olney (2017) and Duncan (1965), shifting production patterns and skill intensity of a country's exports is responsible for the reallocation of labour across sectors and thus can affect the opportunity cost of continued education. Greenland and Lopresti (2016) find that poor labour market conditions increase the opportunity cost of education and increase the graduation rate. In our study, only the export market seems to affect education across the board but import competition only seems to influence older workers. This is difficult to interpret because older workers are more likely to encounter disability and retirement but they also seem to increase their educational attainment. Perhaps younger workers access the TAA temporarily and only consider a return to schooling after the benefits run out. In that case, our figures may not include workers whose benefits have not run out who may return to school in the future. It would be useful to redo this study at a later date to see if the figures change for younger workers.

We have completed a country case study focusing on the regional effects of trade according to its educational intensity, the nature of goods in the production process and their combined contribution towards educational attainment. We have found that the demand-side of international trade is highly significant for educational attainment on the export-side but not on the import-side. As David et al. (2013) conclude, workers exposed to Chinese import competition access relatively permanent retirement and disability benefits at a greater

rate than the TAA - a temporary benefit for workers displaced by import competition. Only those accessing the TAA would consider further education and thus fewer people would do so. This study concludes that countries might encourage the exports of educationally-intensive goods and discourage the imports of educationally-intensive final goods. On the other hand, countries might discourage the exports of non-educationally-intensive goods and encourage the imports of educationally-intensive intermediate goods which are complementary to the productivity of highly-skilled workers.

Furthermore, our case study has implications for trade policy. Bajona and Kehoe (2010) relate that economic differences across countries may be exacerbated by trade through its impact on educational attainment. Therefore, it is worth considering establishing trade policies that increase human capital formation, which is key for a nation to achieve long-term economic growth (Blanchard and Olney, 2017; Li, 2018). In order to ensure long-term economic benefits, countries might prioritize trade policies that encourage young people to continue their education while simultaneously supporting an export-oriented educationally-intensive industrialization strategy. Research needs to be done into what types of jobs young people are prepared to do if their wages were sufficiently attractive to them. Governments may need to decrease the opportunity cost of further education and increase the opportunity cost of working in low-skilled non-educationally-intensive jobs. The important point is that the state has a major role to play in ensuring that the opportunity cost of further education decreases and the opportunity cost of school-leaving increases.

Chapter 3

The Impact of Industrial Robots on Educational Attainment: Evidence from the U.S.

3.1 Introduction

The debate over whether robot adoption has a measurable impact on the labour market has been going on for decades and seems no closer to consensus (Acemoglu and Restrepo, 2017; Autor et al., 2003; Curtis, 1983; Graetz and Michaels, 2018).[8] In this paper, we plan to expand the discussion about robots and the U.S. labour market by investigating the relationship between robot use and educational attainment. We explore the effect of robot adoption exposure in the labor market to identify the effect of technological-induced changes on educational attainment in the U.S. from 1993 to 2007. Like Acemoğlu and Restrepo (2017), we only use data until 2007 because of the possible confounding effects of the Great Recession. We use commuting zone data to determine the effect of robot adoption (robots per thousand workers) on educational attainment.

In light of this current debate on the effect of industrial robot adoption on the labour market and migration, an analysis of the effect of industrial robots on educational attainment is a new area of research that complements existing literature. According to Faber et al. (2019), industrial robot adoption affects the demand for skilled and unskilled labour in the manufacturing and non-manufacturing sectors of the economy. How industrial robot adoption affects educational attainment is not well understood even though there is some

[8] Acemoglu and Restrepo (2020) show that areas in the U.S. labor market that face most of robot exposure after 1990 do not 'exhibit any differential trends before then' and the impact from robots differs from other capital and technological effects. Curtis (1983) quotes Wassily Leontief predicting the dominance of machines in workplaces; as a result, a massive reduction in labor demanded by firms. Graetz and Michaels (2018) find with industrial robot exposure, a rise in productivity but reduction in employment for low-skilled labourers. Autor et al. (2003) find that technological change has had an 'accelerating impact on the task structure of employment since the 1970s'.

literature about how firms facing technological advancement demand a more educated labor force. In contrast to the literature on educational attainment, there is literature on how robots are shaping the environment of educational institutions – how students receive education. For instance, there is a lot of literature on the use of robots to support teaching and learning, the redesigning of curriculums incorporating AI intelligence and whether teachers should be replaced by robots in the future (Greenhow and Gleason, 2017; Morikawa, 2017; Park and Kwon, 2016). Yet, the actual economic mechanism by which industrial robots affect educational attainment remains unclear. Our research seems to indicate that the middle-aged and those with only a high school education or one or two years of college respond by increasing their education.

We examine for educational attainment by the overall sample (ages 15 to 65), age group, educational share, and gender. Our results indicate that exposure to robots has a positive impact on the educational attainment of middle-age groups across U.S. commuting zones which indicates the opportunity cost of schooling is less for middle-aged groups. We can interpret from this result that robots can be more easily substituted for middle-aged groups than the other two age groups (i.e., young and old age groups). As well, there is a significant and positive relationship between robot adoption and the educational level of those with high school education but not a college degree. We did not find any significant relationship for the overall sample (ages 15 to 65) and gender with robot adoption. We obtain our baseline results using an instrumental-variables (IV) approach adopting Acemoğlu and Restrepo (2017) methodology. Our results are robust to a range of controls allowing for differential trends across commuting zones in robot adoption. Following Acemoğlu and Restrepo (2017), our study controls for demographic differences across commuting zones, the impact of trade with China, IT capital and offshoring.

The remainder of the paper is divided into the following sections: literature review, background on industrial robots, the data, the construction of robot exposure variables, the empirical strategy, the results, the instrument variables approach, various extensions; and conclusions.

3.1.1 Literature Review

Starting from the Industrial Revolution, technological developments and innovations have continued to redefine how industries carry out job tasks such as with faster production rates and greater efficiency. With the rise of information technology, we are able to do far more complex tasks but with the same resources. According to Acemoğlu and Restrepo (2017), there has been historic interest among economists about the effect of automation technologies on the labour market. They quote Wassily Leontief (quoted in Curtis (1983)) "Labour will become less and less important . . . More and more workers will be replaced by machines. I do not see that new industries can employ everybody who wants a job". In other words, Leontief predicted that machines would replace workers and create unemployment. While Acemoglu and Restrepo argue that Leontief's predictions have not been realized (i.e. the use of automation technologies has not led to mass unemployment), they recognize there is increasing evidence that the automation of low- and medium-skill occupations has contributed to wage inequality and employment polarisation. Our findings show that for people with only a high school education or only one or two years of college, robot adoption is positively and significantly associated with an increase in schooling, that is, these people respond to robot adoption by returning to school. Furthermore, our results show that middle-aged people affected by robot adoption seem to increase their schooling in response. This is a much more positive result than Leontief predicted since those workers most affected by robot adoption do not remain unemployed but seek further education and thus presumably find another job.

Some studies link the adoption of industrial robots to huge decreases in overall employment (Acemoglu and Restrepo, 2017; Dinlersoz et al., 2018; Graetz and Michaels, 2018; Mann and Püttmann, 2018). Our results would seem to indicate that there is a link between robot adoption and unemployment, at least for those with only high school education, because their response to robot adoption seems to be to advance their education. Acemoğlu and Restrepo (2017) predict that one robot could replace six workers in the U.S. Graetz and Michaels (2018) examine 17 countries and find that robot adoption reduces work hours for low-skilled workers. However, Autor and Salomons (2018) believe that, even though large

numbers of jobs are lost, eventually new jobs are created which more than make up for the initial job loss. According to Koch et al. (2019), firm-level data indicates that robot-adopting firms increase employment through greater productivity. The new employment may be jobs that complement robot adoption and may indicate a change in the composition of jobs at those firms. In the same vein, Acemoglu et al. (2020) use firm-level data from France's manufacturing sector between 2010 and 2015. They find that robot adoption reduces employment for the sector as a whole but increases competitiveness of firms that embrace this technology. Hence, there is a clear difference between firms that embrace robotics technology and those that do not. In fact, when the authors combine the internal effects (effects on the company that introduces robots) and spillover effects (the effect of introducing robots on the sector as a whole), the overall impact on employment is negative: a 20% increase in robot adoption is accompanied by a 3.2% decrease in industry employment. In Germany, the situation is different because Germany has adopted robots earlier than elsewhere. Dauth et al. (2021) conclude that German companies, because of strict labour laws, have absorbed the workforce displaced by robots either within the manufacturing industries themselves or in the service industry. As well, younger workers have changed their educational decisions: fewer are attending vocational schools and more are attending college and university.

This research paper uses Acemoglu and Restrepo's analysis of technological impact on employment. Acemoğlu and Restrepo (2017) state there are two main ways technological innovations can affect employment. The first is through the negative displacement effect – by reducing the use of labour in routine tasks, robots directly displace workers from tasks they were previously performing. The second way is through a positive productivity effect – by an increase in the demand for occupations that require the use of robots. In another paper, Acemoğlu and Restrepo (2017) actually quantify the impact of automation technologies, and especially of robots, on unemployment and wages. Similarly, a study conducted by Chiacchio et al. (2018) on six EU countries finds that one additional industrial robot per thousand workers reduces employment rates in the EU by 0.16-0.20 percentage points.

However, the effects of robot adoption are not nearly as simple as robots replacing workers. Faber et al. (2019) suggest another way that industrial robots can affect employment and this is through migration. In their paper, they investigate the impact of industrial robots

and Chinese import competition on the U.S. labour market and migration patterns. They analyze trade and the shock of robot adoption across U.S. Commuting Zones (CZs) between 1990 and 2015. They first find that, in line with existing studies, these shocks have a negative effect on manufacturing employment. They also find that the introduction of industrial robots is accompanied by a net decrease in the population size of the commuting zone. This is due to a reduction in in-migration rather than an increase in out-migration.

Unlike the effects of robot adoption on migration, however, Faber et al. (2019) find that Chinese import competition does not have a significant impact on either in-migration or out-migration and thus, population size. Furthermore, they find an increase in the use of industrial robots has a spillover effect on other industries such as the business and professional services industry and the retail industry. The shocks of robot migration contrasts with those of Chinese import competition whose negative effects stay in the manufacturing sector and do not affect employment outside of manufacturing.

In further research on the effects of robot adoption, Dixon (2020) uses comprehensive data on Canadian businesses from 2000 to 2015. Robot adoption increases total employment, but different types of workers are impacted quite differently, and robot adoption has varying effects. Managerial employment seems to be reduced though non-managerial employment increases. Robots are adopted not to reduce labour costs but to increase productivity and product quality. Dixon (2020) states that "robots reduce variance in production processes, diminishing the need for managers to monitor workers to ensure production quality". Jobs for low-skilled and high-skilled workers increase but those for middle-skilled workers decrease which reduces the need for managerial workers. There are residual tasks, those that robots cannot do, that human labour must fulfil and do efficiently and cost-effectively (Autor et al., 2003; Brynjolfsson and McAfee, 2011). However, a firm might use more high-skilled workers to design and market new products and optimize production processes (Felten et al., 2019).

As far back as 1965, Duncan (1965) noted that changes in labor market conditions affect the opportunity cost of continued education. Much later, Greenland et al. (2019) found that changes in import competition have an impact on human capital formation. Our hypothesis is that there could be a similar effect of industrial robots adoption on educational attainment. If there is a change in robots' adoption, individuals will reassess their educational decision

in light of a resulting decrease or increase in employment opportunities in the labor market: the opportunity cost of further education might increase or decrease as a result of robot adoption.

3.1.2 Background on Industrial Robots

According to the International Federation of Robotics (IFR), the four characteristics of an industrial robot are: 1) the ability to be automatically controlled; 2) the ability to be reprogrammable; 3) a multipurpose manipulator in three or more axes; and 4) the use of these robots in industrial automation applications (IFR, 2018). Industrial robots are fully independent - they do not need an operator and can be reprogrammed for another purpose entirely. They are often used to perform manual tasks, for example, painting, assembly, handling materials, and packaging. Machines that require a human operator to set or reset them like a textile loom are not considered industrial robots.

In our research, we use the IFR definition of a robot since we use their classification of what constitutes a robot-produced import. The IFR provides multiple examples of robots and their primary functions in its published material and on its website. This material includes activities such as assembly, welding, painting, packaging, picking and placing, and handling materials for metal casting. In principle, firms that are members of an IFR-affiliated industry association are likely to use a definition of robot that is consistent with the IFR. Using this definition, we see that these activities have become more economically influential over time. Industrial robots are primarily used in the manufacturing sector and are listed, in order from greatest to lowest use: the automotive industry, plastics and chemicals, food and beverages, and the metal industries. These industries have been growing.

Figure 3.1 shows the change in the stock of robots for the U.S. and European countries. It shows that the stock of robots has increased at a faster rate in more technologically developed countries, in particular, Germany, while stocks in less technology developed countries like the UK has increased more slowly. The U.S. robot stock increased from 0.4 robots per one thousand workers in 1993 to nearly 2 per one thousand in 2014. Indeed, the U.S. has caught up with more technological developed countries like Sweden and Denmark. Furthermore, these less technologically developed countries like Norway, Spain, and UK are falling behind

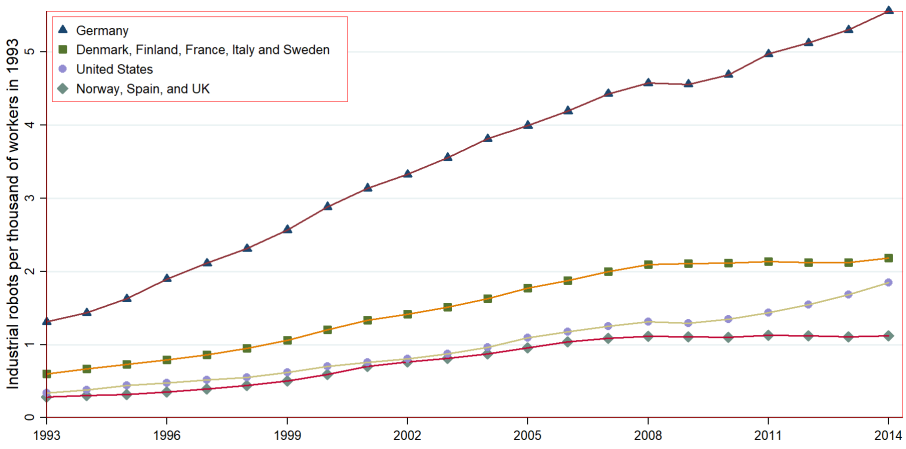

Figure 3.1: Stock of Robots for the U.S. and Groups of European Countries (1993 - 2014)

their more technology developed counterparts.

In 2017, there were 2,097,500 industrial robot units in use in the world and worth $48 billion (IFR, 2018). Since 2010, the continuing trend toward automation and advancing robot technology has spurred growth in the use of industrial robots. From 2010 to 2017, their use increased 19% per year (IFR, 2018). The number of new robots sold between 2005 – 2008 and 2011 – 2017 more than doubled from 115,000 to 236,000 units. From 2015 to 2017, new units increased to 310,000. The supply of industrial robots is not spread evenly across the world with 73% of the world's supply in only five countries: China, Japan, the Republic of Korea, the U.S. and Germany. Of that supply, China has 36% (IFR, 2018). Since 2010, the automotive industry has been using the most robots of any industry: in 2017, the use of robots increased 22% to a total of almost 125,700 units. This is 33% of the total supply of robots. The electronics and computer industry has also been increasing its use of robots and now has 32% of the total supply. In 2017, sales increased 33% to 121,300 units (IFR, 2018).

While the figures for the increased use in robots are revealing, so too are the figures of robot density. This statistic is useful because the overall number of robots used in a country does not reflect the size of the economy. The IFR defines robot density as "the number of multipurpose industrial robots in operation per 1,000 persons employed". In 2017, the manufacturing industry showed an overall robot density of 85 units per 10,000 workers but ranged from a high of 106 in Europe to 91 in North America to a low of 75 in Asia/Australia. The Republic of Korea had the highest density in the world at 710 while Singapore was close

behind with 658. Germany had a density of 322 and Japan 308. Global robotics stock has been increasing.

The start of the 1990s marked the beginning of increasing use of industrial robots in the U.S. and globally (Acemoglu and Restrepo, 2019). By 2015, 1.4 million robots were in use worldwide (BCG, 2015). Global robotics stock tripled between 1993 and 2015 because of the improvement in robot capabilities and cost reduction. During this period, the U.S. increased its stock of robots by approximately 1.5 robots per 1000 workers. Asia is driving growth in the market. Between 2012 and 2017, robot installations increased by an annual average rate of 25% while the number for Europe and the Americas was similar at 10% (IFR, 2018). China's position as the world's largest market for industrial robots is consolidating. In 2017, China accounted for 36% of industrial robot unit sales compared with 30% just before. Industrial robot unit sales in China increased by 59% in 2017 (IFR, 2018). The United States' contribution to global unit sales is decreasing. Industrial robot unit sales in the U.S. only increased by 6% in 2017 whereas globally the increase was 30% (IFR, 2018). The use of robots in the U.S. is still relatively insignificant, according to the BCG (2015). The U.S. uses robots in less than 8% of the transportation equipment sector where 53% of the tasks in that industry could use robots. As a comparison, Italy uses robots in only 0.5% of factories in the primary metal and chemical industries where 28% could use them (BCG, 2015). Thus, while robot sales are increasing, it appears there is still much scope for further growth. Long-term factors like the continued aging of the population are supporting growth.

Acemoglu and Restrepo (2018b) note that while the U.S. has made great progress in catching up with more technologically developed countries, excluding Germany, it remains behind them in respect to robot technology. The reason is that these more developed countries are aging rapidly and are, as a result, investing in robotic technology, which they can then export to the U.S. as the U.S. is experiencing a more gradual aging of its population.

The trends of aging in Japan, South Korea, France and Germany, according to Acemoglu and Restrepo (2019), are spurring the development and use of robots because these countries do not now have the young and middle-aged workers necessary for routine, manual labour in production. The technological development of robotics is replacing these missing workers. These authors also demonstrate that the differences in the development and adoption of

robots between countries stem from a difference in the demographics of aging in these countries. Moreover, countries with a greater aging population are developing robotic technology that they can export to other countries that do not share the same demographics. But this is only part of the picture: industrial robot sales are increasing even in countries that are not aging. Nevertheless, Acemoglu and Restrepo (2019) suggest that there is a relationship between aging and the adoption of robots. Therefore, part of the reason for the relatively low adoption of industrial robots in the U.S. compared with Asia is related to demographic trends in the U.S. and the rest of the world. While the aging of the population is helping robot growth, another important factor is a lack of variation in robot prices. A lack of variation makes it easy for companies to buy robots.

Even across different sectors, robots of similar sizes provide similar capabilities and cost approximately the same amount. The average price of a new industrial robot ranges from $50,000 to $80,000 (RobotWorx, 2021), though, new robots that are engineered with additional application-specific peripherals are priced heavier, ranging from $100,000 to $150,000. The specific price tagged to a robot is specifically dependent on the application being executed.

As can be noted, industrial robots are having an increasingly significant impact across sectors in the economy. Therefore, it is worth investigating the type of impact industrial robots are placing on the labor force; notably, on the changes of educational attainment due to robot exposure. To measure the effect from robot adoption in the U.S., we use the robot exposure variable constructed using IFR industrial robot data by Acemoglu and Restrepo (2020).

3.2 Data

Our empirical analysis draws on the Census Integrated Public Use Micro Samples for 1970, 1980, 1990, 2000 and 2007 which each includes 5 percent of the U.S. population to construct measures of population, education, share of education level, and demographics for each commuting zone.[9] Our demographic cells are defined by gender and race. To

[9]Because the census data uses counties and not commuting zones, we follow the method of David Dorn which can be found at his website: http://www.ddorn.net/data.htm to match counties to c-zones.

evaluate the effect on educational attainment of a change in robot exposure on the 722 CZs as developed by Tolbert and Sizer (1996). These zones cover the continental U.S. except for Alaska and Hawaii. The authors use commuting data from the 1990 census at the county-level to create 722 clusters of counties. They are characterized by strong commuting ties within CZs, and weak commuting ties across CZs.

The advantages of using commuting zones as a definition of a regional economy are: first, they cover the entire U.S., thereby allowing researchers to analyze the entire country as opposed to just census metropolitan areas; second, the grouping of counties together based upon commuting flows (people who live in one county and work in another, in addition, those who live in that county but work in another county) implies a certain level of economic integration.

To control for potentially confounding changes in trade patterns, we utilize data on the exposure to Chinese imports from David et al. (2013). We also control for the effects of IT capital. Our robot exposure and IT capital variables come from the work of Acemoğlu and Restrepo (2017).

3.3 Robot Exposure Variables

In this section, we describe the construction of robot exposure variables. These variables come from Acemoglu and Restrepo (2017), who examine the effects of industrial robots on U.S. labor markets. The change in U.S. robot exposure is defined as follows:

$$US\ Exposure\ to\ Robots_{c,t:t+1} = \sum_i emp_{ci,1990} \left(\frac{(R^{US}_{i,t+1} - R^{US}_{i,t}) - g^{US}_{i,t:t+1} R^{US}_{i,t}}{Emp^{US}_{i,1990}} \right) \tag{3.1}$$

where $R^{US}_{i,t}$ and $Emp^{US}_{i,t}$ refer to the number of robots and employed people in U.S. industry i at time t, $emp_{ci,1990} = Emp_{ci,1990}/Emp_{c,1990}$ is the 1990 employment share of industry i in commuting zone c and $g^{US}_{i,t:t+1}$ is a U.S. industry i's output growth rate between t and $t+1$. $g^{US}_{i,t:t+1} R^{US}_{i,t}$ is the adjusted output expansion of industry i between t and $t+1$.

To measure the U.S. exposure to robots variable for a CZ, Acemoglu and Restrepo (2017) calculate a Bartik-style measure based on each industry's increase in robot density in the U.S. between t and $t+1$ which is adjusted for the overall expansion of each industry and baseline industry employment shares in a CZ.

The change in U.S. robot exposure from output growth in industry i is scaled by the U.S. labour force in the baseline year 1990. This gives us the change in robot adoption per 1000 workers in the U.S., which is weighted by commuting zone employment shares by industry, giving us the estimation of the contribution of each commuting zone by industry to national robot adoption. Industries c-zone specific values are summed up over all industries. The result is a c-zone level measure of changes in robot exposure that varies according to a c-zone's concentration in industries specializing with robot adoption.

The variable for U.S. exposure to robots in a commuting zone is computed from U.S. data. The U.S. exposure to robots could be correlated with the error terms, causing biased estimates in Equation 3.1. First, other changes that some commuting zones are undergoing may be causing the adoption of robots which could directly impact their labor demand. Second, any labour demand shock in a commuting zone could affect the decisions of businesses in that commuting zone, including robot adoption.

However, the focus is to use changes in robot penetration only caused by exogenous improvements in technology. To isolate the component of robot penetration caused by changes in technology, we instrument the U.S. exposure to robots by using a comparable measure calculated from the penetration of robots in European countries that are more advanced than the U.S. in robotics technology. For example, changes in population size or employment rates, rather than technological concerns, may trigger the adoption of robots. To overcome such endogeneity concerns, we employ the same instrument as Acemoglu and Restrepo (forthcoming), who substitute U.S. industries' robotization with that of five European countries and also the 1990 employment shares commuting zones from 1990 with those in 1970.

$$Exposure\ to\ Robots_{c,t:t+1} = \sum_i emp_{ci,1970} \left(\frac{(R^j_{i,t+1} - R^j_{i,t}) - g^j_{i,t:t+1} R^j_{i,t}}{Emp^j_{i,1990}} \right) \tag{3.2}$$

where j indicates the five European countries Denmark, Finland, France, Italy and Sweden.

Figure 3.2 (below) shows the comparison between U.S. and EU countries of exposure

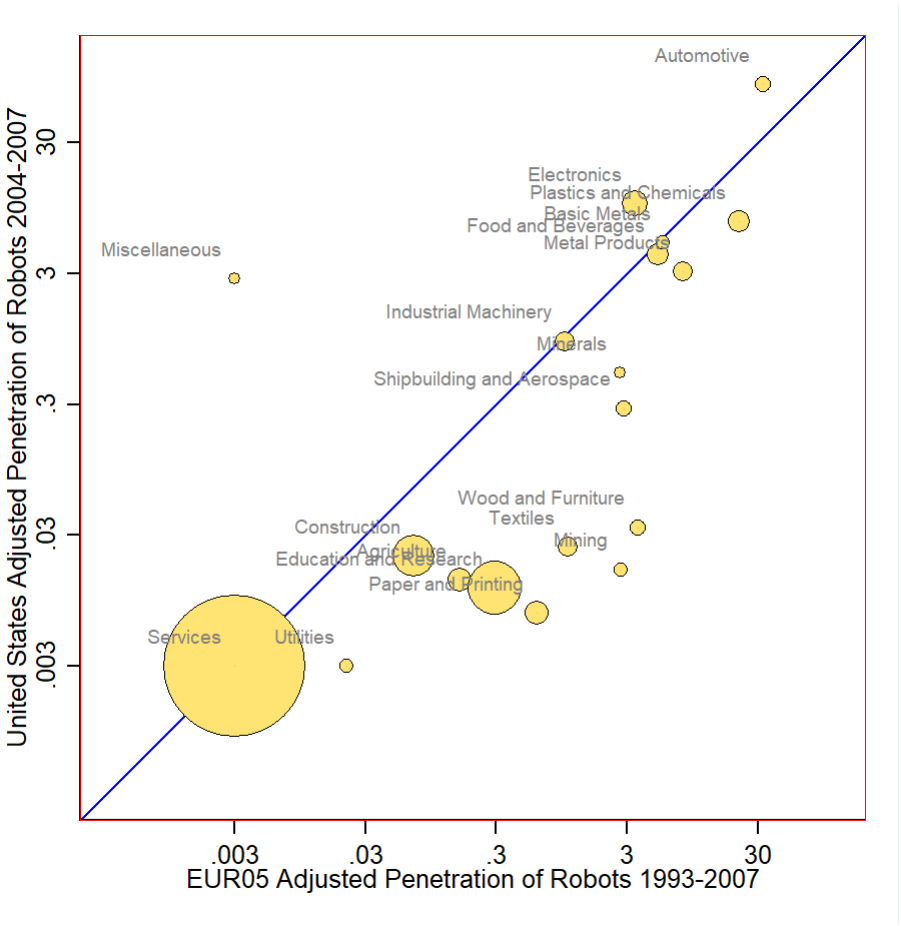

Figure 3.2: The Relationship between Robots Exposure in the United States and Europe

to robots (adjusted penetration of robots) in different industries (like services, automobiles, etc.). The x-axis depicts the number of robots per 1000 workers in EU countries (1993 - 2007). The y-axis is the number of robots per 1000 workers in the U.S. (2004 - 2007) extrapolated to 14 years. The size of the circle of different industries shows the number of employed people in a specific industry in the U.S. As the circle size of the services industry is larger than others, this indicates the number of employed people in the services industry is larger than that of other industries. The circle on the 45° line indicates a 1:1 correspondence, that is, there is the same adjusted penetration of robots (APR) in EU countries and in the U.S. For those industries lying below the line (like utilities), there are more robots in EU countries than in the U.S. On the other hand, if some industry is above the 45° line, there are more robots (APR) for that industry in the U.S. than in the EU. Mostly the industries are below the 45° line, meaning there is more APR in EU countries than in the U.S. As well, a few industries

are heterogeneous in the U.S. and the EU. For example, the miscellaneous category uses far more workers in the U.S. than in the EU but this category is not as significant because it includes any industries not covered by other categories and is difficult to assess. Overall, robots in the U.S. are correlated with robots in EU countries as both are increasing and therefore, the EU data is a good proxy for the U.S. data.

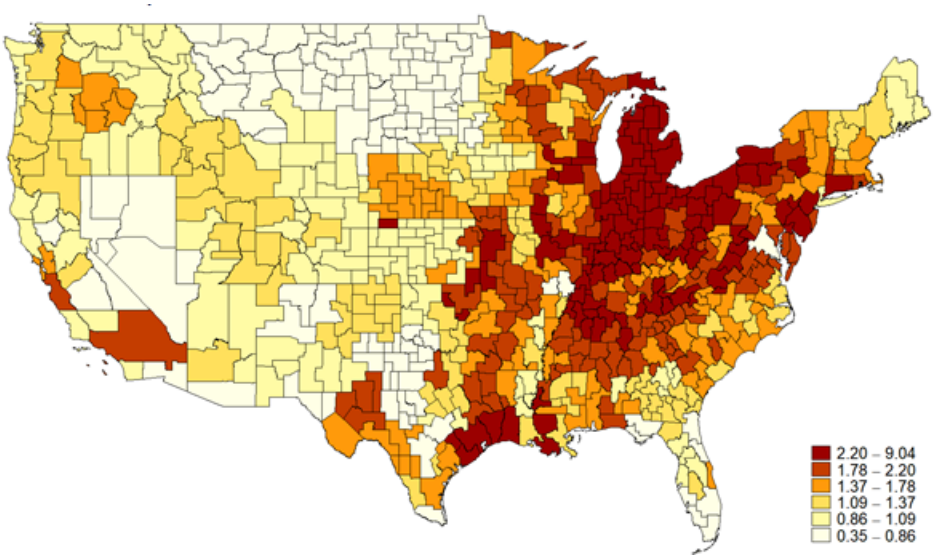

Figure 3.3: Exposure to Robots from 1993 to 2007

Figure 3.3 shows the geographic distribution of exposure to robots between 1993 and 2007. We see a large increase in robot exposure in the Midwest which is what we would expect since the U.S. automobile industry has a substantial presence there and this industry is responsible for a considerable contribution to robot use. In the rust belt, the Midwest, and parts of Texas, robot use has increased quickly, from 2.2 to 9.4 robots per thousand workers. What is interesting to note is that robot exposure has increased in the South: areas of Kentucky, Missouri, Tennessee, Virginia, West Virginia, Louisiana, and Texas show a significant exposure to robots of between 1.09 - 2.20 robots per thousand workers. In some other areas, the increase in robot exposure is quite small, only about 0.35 - 0.86 robots per thousand workers. It is clear that robot use is increasing across the U.S. and not just in particular regions of the country.

3.4 Empirical Specification

To identify the robot exposure effect on educational attainment across 722 U.S. commuting zones, we use the following specification:

$$\Delta edu_c = \alpha + \beta \Delta Robot\_exposure_c + \gamma_d + \epsilon_c \tag{3.3}$$

The regression coefficient, β, is identified from differences in the exposure to labor market shocks between CZs. Our main specifications focus on long differences, where the dependent variable is the change of average years of schooling of the population between the ages of 15 and 65, and the independent variable is the change in the number of robots per thousand (industry) workers between 1993 and 2007. γ is census division dummies and ϵ_c is error terms. In our cross-section model for robots, weighted working-age population in 1990 is used and the standard errors are robust against heteroscedasticity and spatial correlation at the state level. Like Acemoglu and Restrepo (2017), we do not use data after 2007 because of the possible confounding effects of the Great Recession. An OLS baseline specification for educational attainment is performed for the overall sample (ages 15 to 65) as well as subsamples based on, age group, educational share, and gender.

3.5 Results

3.5.1 Benchmark Results (OLS)

In this section, we present our results from the long difference which shows the effects of robot adoption, if any, on educational attainment in the U.S. from 1993 to 2007. We examine for educational attainment by the overall sample (ages 15 to 65), age group, educational share, and gender.

Table 3.1: **Impact of Robot Exposure on Average Years of Schooling**

VARIABLES	(1) Δ Years of Schooling
Δ US Robot Exposure	0.0345
	(0.0293)
Observations	684
R-squared	0.029

Note: The dependent variable is the change in average years of schooling and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.1 presents the results from the main specifications focused on long differences, where the dependent variable is the change of the average years of schooling of the entire sample (15 - 65+ years old), and the independent variable is the change in the number of robots per thousand (industry) workers between 1993 and 2007. Standard errors, reported in brackets, are clustered by state level. Column 1 presents a parsimonious specification which includes only census division dummies as covariates. There is a positive, yet not statistically significant, relationship between exposure to robots and the changes in average years of schooling in a commuting zone with a coefficient of 0.034 and standard errors 0.029. This result indicates that an increase of one robot per thousand workers corresponds to an increase in average years of schooling of 0.034 percentage points.

Table 3.2: **Impact of Robot Exposure on Share of Workers at Different Education Levels**

VARIABLES	(1) Level 1	(2) Level 2	(3) Level 3	(4) Level 4
Δ US Robot Exposure	-0.002	0.004***	0.001	0.000
	(0.002)	(0.001)	(0.003)	(0.002)
Observations	428	497	447	417
R-squared	0.095	0.057	0.075	0.024

Note: The dependent variable is the change in the different levels of education and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Next, we divide the population into four educational levels. We define Level 1 as those who have no schooling to Grade 11. We define Level 2 as those who have Grade 12 and less than one year of college; Level 3 as those who have from one to three years of college education; and finally, we define Level 4 as those who have four years and higher of college education. Result are presented in Table 3.2. In Column 1, we see the effect of robots exposure on Level 1's educational attainment is negative and insignificant. In Columns 3 and 4, we see the effect of robots on Levels 3 and 4 is positive but insignificant. Column 2 shows the results for Level 2 (those with one to three years of education after high school). There is a positive relationship between exposure to robots and educational level of Level 2 which is statistically significant at 1% level. This results indicates that an increase of one robot per thousand workers increases the educational level of the Level 2 by 0.004. The opportunity cost for Level 2 seems to be reduced so their educational level increases. This level is the most affected by robot exposure according to Acemoglu and Restrepo (2019) and more people may therefore go back to school. As well, this level would find it easier to return to school than Level 1 who would have to complete high school or pass the GED before entering college. Level 2 is ready to enter college without upgrading. The benefit of

returning to school would also be greater because the difference between no college degree and a college degree would be quite significant for Level 2 but the addition of a second college degree or graduate work for Levels 3 and 4 would be much less significant.

Table 3.3: **Impact of Robot Exposure on Average Years of Schooling by Gender**

	(1)	(2)
VARIABLES	Years of Schooling (Male)	Years of Schooling (Female)
Δ Robot Exposure	0.046	0.039
	(0.033)	(0.032)
Observations	557	530
R-squared	0.033	0.009

Note: The dependent variable is the change in average years of schooling by gender and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.4: **Impact of Robot Exposure on Average Years of Schooling by Age Group**

	(1)	(2)	(3)
VARIABLES	Young Schooling	Mid-Age Schooling	Old Schooling
Δ US Robot Exposure	0.015	0.047*	0.008
	(0.032)	(0.026)	(0.048)
Observations	449	463	516
R-squared	0.009	0.048	0.044

Note: The dependent variable is the change in average years of schooling by age groups and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.4 reruns the main specification for each of the three age groups. In all three

specifications, the dependent variable educational attainment is measured based on each of three age cohorts which are 15 - 29, 30 - 44 years old, and individuals 45 - 65 years old, respectively. Column 2 shows that robot exposure has a positive relationship with educational attainment and is also statistically significant at the 10% level. These results can be interpreted that the middle-age group is more sensitive to changes in educational decisions. They are more concerned about what is happening in the labour market than people belonging to other age groups.

Our results indicate that exposure to robots has a positive impact on middle-age groups across U.S. commuting zones which indicates the opportunity cost of schooling is less for middle-aged groups. We can interpret from this result that robots are more substitutable for middle-aged groups than other two groups. Acemoglu and Restrepo (2018a) found that robot adoption affects middle-aged workers more than other age groups. This is consistent with and explains our findings. Those in the highest age group are perhaps less likely to return to school because they may not have enough years of work left to make an investment. Younger workers would have enough years of employment left to benefit from further education, but as Acemoglu points out, they are not as affected by robot adoption and so lack the impetus to go back to school. It is only the middle-aged workers who have both the impetus and a large benefit by returning to school that show an increased educational attainment. Their opportunity cost is reduced so returning to school is a good option.

3.5.2 IV Results

To identify the effect of industrial robots' adoption (i.e. technological improvement) on labor market conditions and specifically the effects of robot adoption on educational attainment, we will employ the methodology developed by Acemoglu and Restrepo (2020) to address the endogeneity issue.

If we do not control for a change in demand which can then affect educational investment, this may lead to a biased estimate of the effect of robot adoption on employment, possibly biasing our estimates for educational attainment. The magnitude of the change in demand would affect employment and may bias our results as well. For example, an increase in pay demanded by the labor unions in the automobile industry might lead to more robot

adoption, affecting the labor demanded by industries. This effect on labor demand could bias our estimates about educational attainment. Secondly, if labor demand in a commuting zone is shocked, that shock will influence the decisions of any industries in that commuting zone, including any decisions about robot adoption. For example, an economic downturn in Detroit, Michigan, would also influence the automobile industry which is so dominant there.

If we use the U.S. robot exposure variable, two possible confounding effects result: trends that affect the industry as a whole could bias the impact on robot adoption at the commuting zone level and/or any economic changes at the commuting zone level might affect the adoption of robots as well. However, the focus is to use changes in robot penetration only caused by exogenous improvements in technology. To control for these confounding effects, we use a proxy, that is, constructed using the penetration of robots in the EU that are more advanced than the U.S. in robotics technology. Explanation on the constructed IV, exposure to robots, is in section 3.3, Robot Exposure Variables. We can recall from Figure 3.1 that the U.S. and the EU have similar patterns in robot penetration. This proxy method is similar to that used by Greenland and Lopresti (2016), David et al. (2013) and Bloom et al. (2016) to estimate the impact of Chinese imports. While this proxy does not control for all possible confounding effects, it controls for many of them and our resulting estimates will be relatively bias-free. While this strategy of a proxy does not eliminate all possible confounding effects, it does control for any U.S.-specific effects like worsening labor relations in some industries Acemoglu and Restrepo (2020). Though there are some possible confounding shocks that affect both the U.S. and the EU, like Chinese import competition, we control for these shocks and they do not affect our results as shown in the section 3.5.3, Threats to Validity.

Table 3.5: **Impact of Robot Exposure on Level of Educational Share**

	(1)	(2)	(3)	(4)
VARIABLES	Level 1	Level 2	Level 3	Level 4
Δ IV Robot Exposure	-0.002	0.004***	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Observations	428	497	447	417
R-squared	0.095	0.054	0.076	0.025

Note: This table presents IV estimates of the effects of robot exposure on different levels of education. The dependent variable is the change in the different levels of education and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.5 shows the result using the exogenous instruments in the change of robot exposure. Columns 1 - 4 of Table 3.5 report the 2SLS estimates of the effect of robot exposure on the different levels of educational share. The results in Column 2 show that the change in robot exposure has a positive effect on the change in the educational share of Level 2 which is statistically significant at 1% level. Comparison of estimated 2SLS results to the OLS baseline specification findings in Table 3.2 reveal that the two sets of results are similar but that 2SLS result have a causal interpretation. An increase of one robot per thousand workers has the effect of increasing the educational level of Level 2 (those with one to three years of education after high school) by 0.004.

Table 3.6: **Impact of Robot Exposure on Average Years of Schooling by Age Groups**

Variables	(1) Young Schooling	(2) Mid-Age Schooling	(3) Old Schooling
Δ IV Robot Exposure	0.029	0.086**	0.013
	(0.040)	(0.036)	(0.050)
Observations	449	463	516
R-squared	0.009	0.049	0.044

Note: This table presents IV estimates of the effects of robot exposure on average years of schooling by age groups. The dependent variable is the change in average year of schooling and the independent variable is the change in the number of robots per thousand (industry) workers at the c-zone between 1993 and 2007. Standard errors are clustered at the state level.

Includes Census Division Dummies

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.6 gives an IV estimate of the change in robot exposure on the change of average year of schooling by different age groups. We find the robot exposure has a positive impact only on the change of average years of schooling in the middle-age group. Column 2 reports the IV estimate of 0.086 with a standard error of 0.036 which is significant at 5% level. Comparing with the OLS estimates in Table 3.4, we find a similar result but the IV estimate is more significant for the middle-age group.

3.5.3 Threats to Validity

In this section, we use reduced-form to control for the three main threats to the validity of our results: demographics, Chinese import competition and IT capital deepening. First of all, demographic differences like age, race and gender might confound our results but have been controlled for and are discussed in Table 3.7. We control for demographic effects because demographics clearly influences educational attainment. For example, the U.S. Census provides proof that all sorts of demographic factors influence educational attainment.[10] For instance, culture and family profoundly affect education. To cite but one specific example,

[10]see "Educational Attainment in the United States: 2020" at www.census.gov/data/tables/2020/demo/educational-attainment/cps-detailed-tables.html.

in many Asian countries, the societal pressure to achieve academically is immense and spurs educational attainment.

Secondly, the effects of Chinese import competition are discussed because studies such as Lee (2021) and Greenland and Lopresti (2016) conclude that one of the effects of import competition is on educational attainment. Thirdly, the trend of industrial robot adoption in the U.S. increased more than fourfold during our sample period - it was heterogeneous across industries. Labour market changes that will probably continue have, therefore, a clear impact on educational outcomes. As well, the period witnessed a general decline in the manufacturing sector driven in part by other technological changes in production processes (Acemoglu and Autor, 2011; Autor et al., 2015). The number of jobs for high school dropouts may be decreasing due to these other technological changes - not industrial robot adoption. We control for total capital or IT capital deepening in our regression to make sure that IT capitalization does not confound our results. In summary, we need to confirm whether the effects of demography, import competition or IT capital differ from those of robot adoption and make sure that we control for these effects so they do not change our main results.

Table 3.7: **Impact of Robot Exposure & Demographics on Different Levels of Education**

	(1)	(2)	(3)	(4)
VARIABLES	Level 1	Level 2	Level 3	Level 4
Δ Robot Exposure	-0.002	0.005***	0.001	0.000
	(0.002)	(0.002)	(0.003)	(0.002)
Female Share 1990	-0.695	-0.422	0.236	0.850**
	(0.467)	(0.344)	(0.245)	(0.363)
Hispanic Share 1990	-0.061***	0.049**	-0.038	-0.016
	(0.015)	(0.020)	(0.037)	(0.023)
White Share 1990	0.071	0.034	0.003	0.188***
	(0.111)	(0.099)	(0.118)	(0.055)
Black Share 1990	0.075	0.038	-0.053	0.259***
	(0.116)	(0.108)	(0.120)	(0.067)
Asian Share 1990	0.556**	-0.361**	-0.289	0.628***
	(0.237)	(0.178)	(0.189)	(0.088)
Observations	428	497	447	417
R-squared	0.118	0.065	0.092	0.066

Note: The dependent variable is the change in the different levels of education at the c-zone between 1993 and 2007. The controls are robot exposure, demographic characteristics of commuting zones in 1990 (Female share, White share, Black share, Hispanic share, and Asian share). Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.7 estimates the effects of robot exposure on educational attainment. It presents long-difference estimates for changes in the different levels of education for 1990 – 2007. It is weighted by the population in 1990. The covariates included in this model are demographic characteristics of commuting zones in 1990 which are defined as the Female share, White share, Black share, Hispanic share, and Asian share. Since our model involves changes, this specification allows for differential trends by these demographic characteristics. These demographic controls do not change our previous results in Table 3.2. It shows there is still a statistically significant relationship at the 1% level between robot exposure and the educational level of Level 2, indicating that an increase of one robot per thousand workers increases the educational level of Level 2 by 0.005.

Table 3.8: **Impact of Robot Exposure & Various Variables on Average Years of Schooling by Age Group**

	(1)	(2)	(3)
VARIABLES	Young Schooling	Mid-Age Schooling	Old Schooling
Δ Robot Exposure	0.040	0.083**	0.038
	(0.043)	(0.039)	(0.051)
Δ IT Capital	-0.003	-0.003	-0.019***
	(0.004)	(0.006)	(0.007)
Female Share 1990	0.084	14.029**	1.206
	(6.816)	(5.790)	(10.567)
Hispanic Share 1990	-0.301	0.571	1.870***
	(0.429)	(0.413)	(0.453)
White Share 1990	1.528	2.026	-2.514
	(1.259)	(1.927)	(1.893)
Black Share 1990	1.538	1.674	-1.895
	(1.344)	(1.946)	(1.908)
Asian Share 1990	2.553	8.471*	-4.273
	(1.982)	(4.394)	(3.722)
Chinese Import Competition	-0.042*	-0.010	0.030
	(0.023)	(0.020)	(0.041)
Employment Share Routine 1990	-1.574	-1.011	-3.069
	(2.068)	(3.266)	(2.794)
Observations	449	463	516
R-squared	0.022	0.063	0.069

Note: The dependent variable is the change in average years of schooling by age groups at the c-zone between 1993 and 2007. The controls are robot exposure, demographic characteristics of commuting zones in 1990 (the Female share, White share, Black share, Hispanic share, and Asian share), IT capital, Chinese import competition and the share of employment in routine jobs in 1990. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.8 estimates the effects of robot exposure on average years of schooling of different age groups. The covariates included in this model are robot exposure, IT capital and demographic characteristics of commuting zones in 1990 which are defined as the Female share, White share, Black share, Hispanic share, and Asian share. Chinese import competition and the share of employment routine jobs in 1990.

The result shows that improvements in robotics are not confounded by other industry-level trends. IT capital, Chinese import competition and routine jobs do not affect industries

that are adopting more robots. These controls do not change our previous results found in Table 3.4. It still shows that the average age of schooling for the middle-aged group has a positive and significant relationship with robot exposure.

Table 3.9: **Impact of Robot Exposure & Various Variables on Different Levels of Education**

	(1)	(2)	(3)	(4)
VARIABLES	Level 1	Level 2	Level 3	Level 4
Δ Robot Exposure	-0.003*	0.005***	0.002	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)
Δ IT Capital	0.001***	-0.000	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Female Share 1990	-0.917**	-0.233	0.358*	0.729**
	(0.422)	(0.335)	(0.212)	(0.344)
Hispanic Share 1990	-0.088***	0.059**	-0.019	-0.032
	(0.017)	(0.023)	(0.046)	(0.028)
White Share1990	0.058	0.032	0.003	0.180***
	(0.103)	(0.092)	(0.109)	(0.056)
Black Share 1990	0.041	0.051	-0.043	0.238***
	(0.104)	(0.104)	(0.112)	(0.070)
Asian Share 1990	0.256	-0.270	-0.071	0.456***
	(0.163)	(0.185)	(0.167)	(0.121)
Δ Chinese Import Competition	-0.000	0.002	0.000	0.000
	(0.002)	(0.002)	(0.001)	(0.002)
Employment Share Routine 1990	0.456***	-0.210	-0.254**	0.284*
	(0.153)	(0.164)	(0.124)	(0.160)
Observations	428	497	447	417
R-squared	0.148	0.073	0.114	0.075

Note: The dependent variable is the change in the different levels of education at the c-zone between 1993 and 2007. The controls are robot exposure, census division dummies, demographic characteristics of commuting zones in 1990 (Female share, White share, Black share, Hispanic share, and Asian share), Chinese import competition, the share of employment in routine jobs in 1990 and IT capital. Standard errors are clustered at the state level.

Includes Census Division Dummies.

*** p<0.01 indicates significance at 1%.

** p<0.05 indicates significance at 5%.

* p<0.1 indicates significance at 10%.

Table 3.9 documents long-difference estimates for changes in the different levels of education for 1990–2007. The covariates are census division dummies, demographics, Chinese

import competition, routine jobs and IT capital. The estimates for robot exposure on educational attainment remain qualitatively unaffected by the inclusion of these additional controls compared to our previous results in Table 3.2.

3.6 Discussion and Conclusion

Technological advancements are occurring across the globe and in every field of life, namely noted in the industrial sector. In the industrial sector, one of the most important uses of technology is automated working robots. Technological advancements like industrial robots continue to redefine how industrial operations and tasks are carried out across sectors. With the increasingly significant impact of industrial robots across economic sectors, this led us to take a closer look at the effects of robot exposure on educational attainment. Robot adoption has different positive and negative effects where they are being used. In the industry, robots also have different effects and one of them is on education attainment and the labor market. In this paper, we captured the effect of robot adoption exposure in the labor market to identify the effect of technological-induced changes on educational attainment in the U.S. from 1993 to 2007. We provided evidence that exposure to robots in the U.S. has led to an increase in the educational attainment level of middle-age (30 - 44 years old) groups across U.S. commuting zones, providing indication that the opportunity cost of schooling is less for middle-aged groups compared to younger and older aged groups. As robots are adopted by industries, some workers lose their jobs. These unemployed workers have different options and one option is to go for education. The middle age group does so. From this, we can draw the conclusion that robots replace a greater percentage of middle-aged groups than the other two age groups. A significant and positive relationship was also found between robot adoption and an increase in the educational level of those with a high school education but no college degree. No significant relationship was found between gender and robot adoption.

Our results contrast with those of Dauth et al. (2021) who were studying Germany. Because Germany has adopted significantly more robots than the rest of the world, it is not surprising that their situation is different. It will be interesting to see if the U.S. develops

similarly to Germany, that is, if younger workers will make the shift from vocational schools to university because of the reduction in manufacturing jobs. It will also be interesting to compare the reaction of the manufacturing sector to robot adoption. Will the workers replaced by robots stay employed within the manufacturing industry or be employed in the service industry like Germany? Or will some workers become unemployed or underemployed because of the weaker worker protection laws in the U.S.?

Further research is, of course, needed. We noted the positive and significant relationship between middle-age educational attainment and robot adoption, and a moderate education level (high school graduation but no college degree) and robot adoption but our research does not show if there is an interaction between age and education level where there is robot adoption. There may be an unnoticed cause of both, unrelated to robot adoption, which confounds our results. It would also be beneficial for policy makers to know why the other educational levels and age groups do not increase their educational attainment. Those that are increasing their educational attainment are probably responding to the negative effects of robot adoption in a useful way. Are the other age groups and educational levels relatively unaffected by robot adoption or are they unwilling or unable to deal with it in a useful way? As well, it comes as a surprise that gender does not seem to be connected to robot adoption since gender is a consistent variable in so many economic realities. If we examine gender and robot adoption in another way, are there significant relationships between the two that our research has not shown? We used U.S. data ending in 2007 to avoid the confounding effects of the Great Recession, but we should determine how robot adoption has been affected by it and how educational attainment has been changed by it.

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