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The Influence of Industrial Automation on Educational Enrollment: A State-Level and Country-Level Analysis

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THE INFLUENCE OF INDUSTRIAL AUTOMATION ON EDUCATIONAL ENROLLMENT: A STATE-LEVEL AND COUNTRY-LEVEL ANALYSIS

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ABSTRACT

The thesis investigates the effects of industrial automation on post-secondary education enrollment. To assess the effects, we build linear regression models to estimate the impact of the surge in the stock of industrial robots on post-secondary enrollment across 50 U.S. states and 41 countries. Drawing upon these estimates and the literature documenting the structural shift in the labor market, we find that recent developments in the fields of automation and robotics have contributed to a shift in demand for post-secondary education, with panel data models that control for both country and time fixed unobservables indicating a significant decline in enrollment for 4-year degree programs internationally.

Keywords: Automation, Technological Unemployment, Human Capital, Job Polarization, Educational Attainment, Enrollment Rate

I dedicate this thesis to my mother and father for supporting me with love and affections and their dedicated role for success in my life.

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I. INTRODUCTION

The rapid development and innovation of automation in the last century have taken labor markets by surprise. These developments have raised concerns that automation will lead to mass technological unemployment. McKinsey and Company (2019) confirms that nearly 40 percent of current U.S. jobs are in occupational categories that could shrink through 2030. Furthermore, the OECD reports that 14 percent of jobs are automatable and another 32 percent will experience a shift in the way they are performed (OECD, 2018). Occupations that commonly require routine and some physical tasks will shrink as demand grows for work involving socio-emotional, creative, technological, and higher cognitive skills.

An important long-run figure in U.S. labor markets indicates a decline in middle-skill occupations, and growth in both high- and low-skill occupations, fueling “job polarization” (Goos et al., 1993; Autor and Dorn, 2013). A number of studies associate this polarization with what is known as the skill-biased technological change—the shift in production technology that favors skilled over unskilled labor. For example, researchers have found that the share of jobs in the U.S. economy using higher-level digital skills rose from 4.8 percent in 2002 to 23 percent in 2016 (McKinsey and Company, 2019).

The objective of this thesis is to empirically investigate whether job polarization from industrial automation will increase the demand for post-secondary education. One particular flashpoint of industrial automation is the use of industrial robots—machines designed to be automatically controlled and reprogrammable machines designed to replace labor in routine tasks. The main contribution of this study is to show that integrating robots across industries is associated with a rise in demand for new skills attainable by post-secondary education. Various studies report that education does not automatically confer job skills but can be relied on as a proxy for skills, and it stands out as a key indicator of displacement risk from automation.

The study extends from two earlier studies. First, it builds on the findings of Autor and Dorn (2013) concerning the skill-biased technological change in labor markets and how it induces employment polarization. We expand upon their findings that local labor markets that are intensive in routine employment also experience greater polarization of educational attainment. Second, we explain the connection between employment and human capital, as emphasized in Peters et al. (2019). We expand on their study by estimating the effects of the adoption of robots on educational attainment by following their perspective that education and human capital can offset the disruptive negative consequences of automation in labor markets.

In building the empirical models for this study, we use two different methodologies to address two related questions. First, what is the impact of the adoption of robots on post-secondary education enrollment across the U.S.? To address this question, we estimate linear regression models with a cross section of data from 2015 spanning all 50 states. Second, what is the impact of the adoption of robots on post-secondary education enrollment across countries? To address this question, we estimate linear regression models with panel data from 41 countries between 2010 and 2017. The remainder of the study will proceed as follows. The next section discusses the literature and history of the topic being investigated. The third section discusses the data used in the analysis and the U.S. and international model specifications. The fourth section discusses the estimation results. The final section concludes the study by discussing its limitations and provides directions for future research.

II. LITERATURE REVIEW

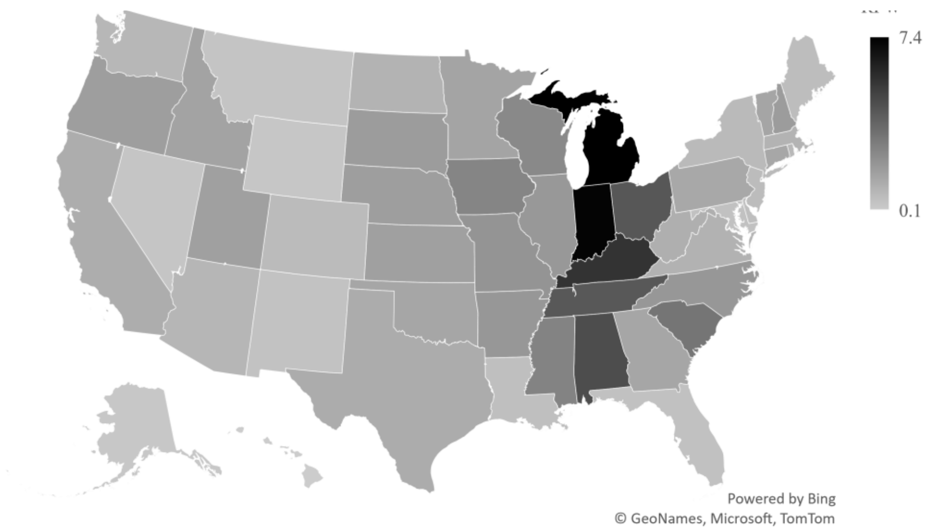
Since the Industrial Revolution, a series of technological advancements have offered tools and innovations that transformed economies. While technology has been a primary catalyst of economic progress, it has left a wake of socio-economic anxiety (Mokyr et al., 2015). The race between technology and employment has been of interest to economists for centuries. Offering warning signs throughout history, technological unemployment has been an on-going concern for many societies. This concern has firmly stood with perceptions that the development of machines is against the interests of the working class. A notable example of this is the story of a clergyman and inventor from England. In 1589, the inventor of the stocking knitting machine, William Lee, traveled to London to seek patent protection for his invention. Concerned about depriving her subjects of employment, Queen Elizabeth I refused to grant him the patent (World Bank, 2019). Five centuries later, the socioeconomic ramifications of technological progress remain unsettled.

Since the early 1900s, concerns of technological progress intensified due to the poor performance of the labor markets across advanced economies. With increasing concerns of rapid unemployment growth between the 1950s and 1960s, U.S. President Lyndon B. Johnson commissioned a panel of experts labeled the Blue-Ribbon National Commission on Technology, Automation, and Economic Progress. The Commission's primary mission was to study the impact of technological progress on productivity and employment. The conclusion of the Commission was the following:

"Technological change…has been a major factor in the displacement and temporary unemployment of particular workers. Thus, technological change (along with other forms of economic change) is an important determinant of the precise places, industries, and people affected by unemployment. But the general level of demand for goods and services is by far the most crucial factor determining how many are affected, how long they stay unemployed, and how hard it is for new entrants to the labor market to find a job. The basic fact is that technology eliminates jobs, not work." (Bowen, 1966, p. 9).

Analogously, robots are a technology that has left people anxious. Studies have shown that robots improve productivity by improving efficiency and consistency in product quality. An International Federation of Robotics (IFR) study concluded that robot adoption increased annual GDP growth by about 0.37 percentage points and labor productivity by about 0.36 percentage points between 1993 and 2007 across 17 countries studied (IFR, 2017). These increases represent about 10 percent of total GDP growth in the countries studied compared to the 0.35 percentage point estimated total contribution of steam technology to British annual labor productivity growth between 1850 and 1910 (Graetz and Michaels, 2018). However, a Pew Research Center survey conducted in 2017 concluded that 85 percent of Americans are in favor of policies that restrict the adoption of robots. According to IFR, the average number of robots per 10,000 manufacturing workers around the globe rose from 66 in 2015 to 85 in 2017 (Atkinson, 2019). Figure 1 illustrates where robot adoption has increased with respect to the regional labor force. As shown on the map, the greatest concentration lies in the East North-Central and the East South-Central regions of the U.S., which have historically been highly industrialized regions. These industries include automakers and product manufacturers.

Figure 1: Robots per Thousand Workers Across the United States, 2015



Source: Brookings analysis of Moody's Analytics data. *Where the Robots Are. 2017*

The hypothesis of this study develops from the theory of human capital concisely summarized in the quote below by Adam Smith.

"The acquisition of such talents, by the maintenance of the acquirer during his education, study, or apprenticeship, always costs a real expense, which is a capital fixed and realized, as it were, in his person." (Smith and Stewart, 1963, p.122)

Human capital refers to the stock of knowledge and skills a worker possesses to stimulate productivity. Since its establishment by Smith, human capital theory was a vague concept underlining the value of skills and knowledge to the *acquirer*. Not until after WWII were there signs of increasing interest in the idea. This partly explained theory was formalized by Knight (1941), Friedman (1943), and Fisher (1971). But, "It was not until the work of Becker, Schultz and their colleagues that the analytical possibilities of [Human Capital] began to be realized" (Ferber, 1973, p.1322).

Throughout history, there have been debates on whether human capital theory is vital for insights on further economic advancements. The theory is that "The acquisition of knowledge and intellectual stock through the means of education…" provides room for expansion of productivity and output (Akinyemi and Zainal Abiddin, 2013, p.150). Established by Adam Smith in 1776 (Smith and Stewart, 1963), human capital theory cemented the role of educational attainment and skill demand for the promotion of economic goals. Centuries after the work of Smith, Becker (1962) developed a theoretical model that offered a new approach to human capital theory. Becker asserted that education could play a significant role in narrowing the gap in income, adopting an investment rational towards education and training.

Becker's theory was set to rival the neoclassical and Malthusian approaches to economic growth and capital investment. Becker argued that neither Malthus' nor the neoclassicists' approaches paid much attention to the role of human capital in stimulating economic growth, whereas human capital theory suggested that societies can acquire economic benefits by investing in humans. Becker's model offered compelling evidence of the role of education and training in advancing worker welfare. His model established that education can be used as a tool for workers to access higher-paying occupations. Assessing wage differentials, Becker's approach toward human capital concludes that rising demand for skilled labor, induced by technological progress, has widened wage inequality between groups with different levels of educational attainment. This pattern reinforced Keynes technological progress hypothesis.

In 1930, Keynes famously coined the term technological unemployment. The economy Keynes envisioned may complement the current status of the labor markets. Keynes predicted widespread technological unemployment "…due to our discovery of means of economizing the use of labor outrunning the pace at which we can find new uses for labor…" (Keynes, 1930, p.3). Currently, technological unemployment is estimated to be as high as 47 percent of the occupational categories defined in Frey and Osborne (2013).

A study by Peters et al. (2019) aimed to merge the theory of human capital and technological unemployment. Their work identifies a trend of employers steadily replacing workers with machines and information software, leading to technological unemployment. Despite this, state and federal government can increase worker's skill-sets through investments in education. Thus, by growing the skill level of the labor force, policymakers can help make workers become complements with automation rather than getting substituted by automation. The study argues that by enhancing the skillsets of workers, they become more valuable in the labor markets.

Recently, there has been growing debate between economists about effects of technological development on the economy. Recent U.S. occupational employment data indicate a decline in employment in routine occupations. In contrast, occupations requiring higher cognitive skill have experienced growth in employment (Autor and Dorn, 2013; McKinsey and Company, 2019). It is fair to say that automation has substituted routine tasks performed by low-skilled workers while complementing the abstract and creative tasks performed by highly educated workers.

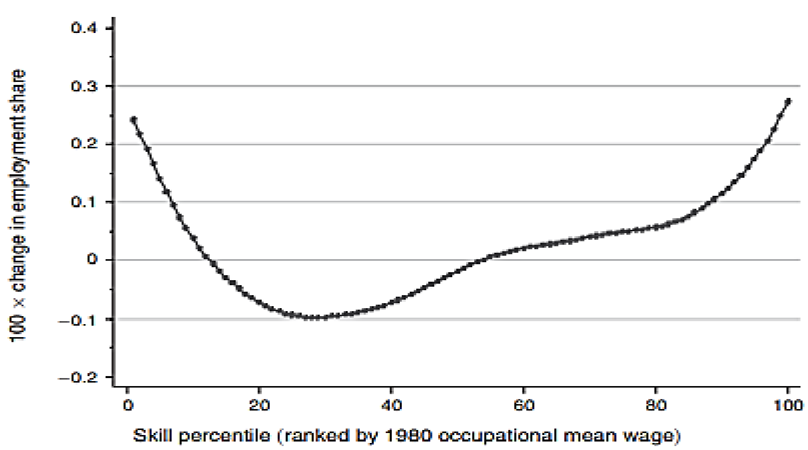
Goldin and Katz (2008) provide further insights into the impact of technological development on the labor markets. Using econometric methods, they identify the relative shifts in the supply of and demand for educated and uneducated workers. Their model, based on Becker (1962), provides markers of the educational and occupational wage differential. The findings of Goldin and Katz provide evidence for wage differences between occupations. One main finding of the study is the polarization in wage growth from 1988 to 2008. Workers in the upper and lower deciles of the skill-level distribution experienced growth in wages, unlike the median worker.

Analogous to wage polarization, some occupations have also experienced employment polarization. The polarization of occupations concentrated employment growth in high-skill, high-wage jobs, and low-skill, low-wage jobs. Supported by recent studies documenting the structural shift in labor markets, it has become apparent that skill-biased technological change (SBTC) is the primary driver. SBTC "…is a shift in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, therefore, its relative demand…" (Violante, 2008, p.10). SBTC provides an explanation for the growth in wage inequality since the early 1950s.

One of the most influential papers on the topic of employment polarization and skill-biased technological change is Autor and Dorn (2013). Their study hypothesizes that employment polarization in the U.S. labor market is driven by the interaction of consumer preferences and non-neutral technological progress. Expanding from Acemoglu and Autor (2011), they build a spatial equilibrium model to test the differential degrees of specialization in routine-based industries across local labor markets. Their conclusions are consistent with Goldin and Katz (2008). Parallel with the principle of skill-biased technological change, employment for occupations in the upper two quartiles and the lowest quartile of the skill-level distribution expanded sharply. Furthermore, median skill level occupations fell as a share of employment, leading to employment polarization in the tails of the distribution. The surprising finding is the expansion in the lower tail—low skill occupations. The authors credit the spike to rising employment of workers in service occupations, such as food service workers, security guards, janitors, and childcare workers.

It is fair to say that automation does not reduce the number of jobs, rather it modifies the jobs and the skills required to undertake the tasks the jobs entail. Since the early 1900s, there has been a surge in technological change and automation adoption. Studies have documented that with these rapid shifts, polarization of employment by skill level has been ongoing for several decades. To provide an overview of the polarization across occupations, Figure 2 illustrates the U-shaped distribution of employment change by skill level. It indicates that employment for occupations in the upper two skill quartiles and the lowest skill quartile expanded sharply while employment shrank in the median skill level.

Figure 2: Changes in Employment by Skill Percentile, 1980 to 2005



Source: Autor and Dorn (2013, Panel A.)

Autor and Dorn (2013) concluded that labor markets that are intensive in routine employment experience greater polarization of educational attainment. It is proportionate between the fraction of workers who are college graduates and high school dropouts, which increased relative to the fractions of workers with some college or with high school education.

With recent technological developments, the world of robotics advanced its potential to integrate with more and more industries. As costs decline and efficiency increases, robots stand to automate thousands of jobs. To counteract the loss of certain occupations, the workforce can be expected to turn to education to gather the skills necessary to adapt to the modern economy. Predictably, such an approach will justify an uptick in enrollment around the globe. Deducing from current trends, the following sections of study will seek to address whether a relation exists between adoption of industrial robotics and post-secondary enrollment.

III. DATA AND METHODOLOGY

The proceeding analysis evaluates two groups of models formulated to measure the relationship between the adoption of industrial robots and the post-secondary enrollment. The first model analyzes the U.S. using the number of robots per thousand workers in each state in 2015.[1] The second uses a balanced panel of 41 countries from 2010 to 2017 collected from IFR.

Public data sources that are utilized include the U.S. Census Bureau American Community Survey (ACS) and the World Bank Organization Database. Private data sources include the International Federation of Robotics (IFR) and the Brookings Institute. Table 1 summarizes the variables used in the analysis, including their sources.

U.S. Data and Model Specifications

The dependent variables used in the U.S. models measure the number of people enrolled in a post-secondary 4-year degree institution. The first is *ENR*, which is defined as the percentage of 18- to 24-year-olds (the traditional college-age population) enrolled in 4-year degree-granting post-secondary institutions. The data, sampled in 2016, was collected from the National Center for Education Statistics.

The second dependent variable is enrollment participation rate (*EPR*), defined by Levine et al. (1988) as the total degree credit enrollment percentage of the sum of high school graduates

[1] Data come from the Brookings Institute. A panel of U.S. data would ideally be used for estimation, however, the cost to acquire multiple years of U.S. data from International Federation of Robotics (IFR) was prohibitive, so a single year is evaluated here.

for the current and three preceding years. *EPR* is calculated using data from the National Center for Education Statistics between 2013 and 2016. Equation (1) illustrates how *EPR* is calculated.

$$EPR = \frac{HSGrad_{2013} + HSGrad_{2014} + HSGrad_{2015} + HSGrad_{2016}}{Number\ of\ Students\ Enrolled} \times 100 \qquad (1)$$

EPR provides an alternative to *ENR* as a measure of post-secondary enrollment. Instead of measuring enrollment from the general population age group, *EPR* measures enrollment from the direct source of college students, which are high school graduates. The 4-year pool of high school graduates acts as a primary source for college students, where $HSGrad_t$ references the number of high school graduates in year t. Any *EPR* value exceeding 100 percent means that there are non-traditional sources for students such as international students and older students.

The main source of data used to measure the number of industrial robots per thousand workers is IFR. The data measures the stock of operational industrial robots delivered to a state or a country in a particular year. As defined by International Organization of Standardization, an industrial robot is an "automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (IFR, 2020).

The independent variable of primary interest is robots per 1,000 workers (*RPW*). It is calculated using the stock values of industrial robots divided by the number of people in the local labor force. This provides a measure adjusted to the size of the labor force in each state and each country. The U.S. model only uses data reported in 2015. It is expected that *RPW* is positively related to both dependent variables.

The cost of attending or the tuition of a post-secondary institution can have a great impact on an individual's school choice. As the cost of attending increases, fewer people can be expected to enroll. In this study, the tuition variable is exclusive for the U.S. model. To estimate the relationship between tuition and enrollment, the study constructs a consolidated price variable (*PRICE*). *PRICE* is the average tuition charged by public and private institution weighted on the number of public and private institutions in each state. Equation (2) shows how *PRICE* is constructed. In constructing *PRICE*, public tuition and private tuition were weighted by the number of public and private institutions, respectively, versus being weighted by enrollment. This is to avoid having enrollment (*ENR*) on both side of the regression model.

PRICE =Public Tuition x % of Public Institutions + Private Tuition x % of Private Institutions (2)

Per capita personal income (*PI*) is from the Bureau of Economic Analysis. It reflects the standard of living and the quality of life of a population and quantifies a person's ability to pay for their education. It is expected that *PI* is positively related to *ENR* and *EPR*.

The number of high school graduates (*HS*) is also expected to affect enrollment. *HS* is sampled from 2015 data. It is important to note that *HS* is only used in the model with *ENR* as the dependent variable. This is to avoid endogeneity between *HS* and *EPR*. *HS* is expected to have a positive relationship with the dependent variable *ENR*.

Another variable exclusive to the U.S. model is the percent of jobs at risk across states (*JAR*). *JAR* is a proxy for how local labor markets are affected by automation, as it is defined as percent of occupations that are at risk of automation. Predictably, as the risk of automation rises across occupations, the number of people expected to seek post-secondary education will rise, indicating of a positive relationship between *JAR* and *ENR* and *EPR*.

Representing the current employment status in the labor markets, the unemployment rate (*UNE*) is used to measure the percentage of labor force that is jobless in the region. The data is sourced from Bureau of Labor Statistics. The study specifically uses the U-3 unemployment rate, known as the official unemployment rate. It is expected that as the unemployment rate rises, enrollment will rise. Lastly, the *POP* is used to provide a measure for the population size in a geographical area. For estimation, *POP* is scaled by 10,000. It is expected that as population grows, enrollment will rise.

Table 2 reports summary statistics on the dependent and independent variables. Across the U.S., the dependent variable, *ENR*, has a mean of 41.106 percent. The highest enrollment percentage was in Rhode Island (54.90 percent) and the lowest was in Alaska (26.10 percent). Furthermore, the second dependent variable, *EPR*, has a mean of 1.61 (161 percent). The *EPR* values are divided by one hundred for better interpretation of the estimation results. The highest *EPR*, 231 percent, was found in Arizona, while the lowest, 91 percent, was found in Alaska.

The average *RPW* across the U.S. in 2015 was 1.812. The highest concentration of robots was in Michigan, mainly due to the large automotive industry at the state. The lowest concentration was in Alaska, indicating limited industrial activity. On average, the consolidated tuition is 25.500 ($25,500) in the U.S. The highest *PRICE* is found in California, while the lowest is found in Idaho. The variable *POP* has an average of 6,317,350 people. The largest population size was found in California with more than 38 million people. For *HS*, the average is 63,600 graduating students.

PI has an average of $47,620 with the highest income found in Connecticut. *JAR* averages 53.3 percent of occupations. Lastly, *UNE* in the U.S. averages 5.08 percent and it ranges between about 3 and 7 percent.

The U.S. model with ENR as the dependent variable is specified:

$$ENR_i = \beta_0 + \beta_1 RPW_i + \beta_2 PRICE_i + \beta_3 PI_i + \beta_4 JAR_i + \beta_5 UNE_i + \beta_6 POP_i + \beta_7 HS_i + \epsilon_i \qquad (3)$$

where ENR_i is the post-secondary enrollment for state *i*, and RPW_i is the number of robots per 1,000 workers in state *i*. In addition to modeling *ENR*, a model similar to (3) is estimated with *EPR* as the dependent variable. However, the number of high school graduates is dropped to avoid endogeneity since *EPR* is a function of *HS*.

International Data and Model Specifications

The international models are estimated with a balanced panel that features data spanning eight years across 41 countries. The models are constructed with one dependent variable and three independent variables. The data was mainly retrieved from the World Bank Organization Databank and International Federation of Robotics.

Similar to the U.S. models, the dependent variable used in the international models is *ENR*. Unlike the U.S., the *EPR* variable could not be constructed. This is due to the lack of data, in relations to high school graduates, in many of the countries involved in the study. The independent variable of interest in the model is robots per 10,000 workers (*RPW)*. Similar to the U.S. model, *RPW* is expected to have a direct relationship with *ENR*.

The income measure for the model is per capita national income (*NNI*) as the variable. As education is a normal good, *NNI* is expected to be positively related to *ENR*. The last independent variable used in the model is the unemployment rate (*UNE*). *UNE* proxies labor market conditions in a particular country in a particular year. It is expected that *UNE* is positively related to *ENR*.

As shown in Table 2, the average *ENR* was 60.643 percent, however, *ENR* ranges considerably across countries. By 2017, the country that experienced the highest enrollment percentage was Republic of Korea (94.349 percent), and the lowest was Uzbekistan (9.181 percent). Between 2010 and 2017, *RPW* averaged 0.746 per 10,000 workers. In 2017, the country with the highest robot concentration was the Republic of Korea with 9.716 *RPW*, and the lowest was Uzbekistan with 0 *RPW*. One important point to note is that between 2010 and 2017, average *RPW* increased from 0.551 to 1.015. The rapid growth in *RPW* can be explained by the declining price of industrial robots. Between 2010 and 2017, *NNI* averaged $20,633. In 2017, the highest income was in Switzerland with $64,629, and the lowest was in Uzbekistan with $1643. Lastly, *UNE* averaged 8.33 percent. In 2017, the highest unemployment rate was in Spain with 17 percent, and the lowest was in Qatar with 0.14 percent.

The international model is specified:

$$ENR_{i,t} = \beta_0 + \beta_1 RPW_{i,t} + \beta_2 NNI_{i,t} + \beta_3 UNE_{i,t} + \epsilon_{i,t} \qquad (4)$$

where $ENR_{i,t}$ is the post-secondary enrollment for country i in year t. The independent variables $RPW_{i,t}$, $NNI_{i,t}$, and $UNE_{i,t}$ are the number of robots per 10,000 workers in country i in year t, the per capita national income in country i in year t, and the unemployment rate in country i in year t, respectively.

To control for unobserved country and time effects, equation (4) is also estimated with region and country fixed effects, which control for unobserved characteristics fixed at the continent or country-level, respectively, (such as the demographic profile or degree of conservatism), and year fixed effects, which control for factors that are common across all countries in a given year.

IV. ESTIMATION RESULTS

This section presents and discusses the estimation results from the U.S. model (3) and the international model (4). Of particular interest in both cases is the effect *RPW* on post-secondary enrollment (*ENR* and *EPR*). Table 3 presents the results from the U.S. model, and the results from the international model are reported in Table 4. It should be noted that all estimations were performed using R 4.0.3. The code script is found in the Appendix.

U.S. Model Estimation Results

The U.S. models were estimated with and without regional dummies. The results indicate that several variables are significantly related to the enrollment measures, however, *RPW* and *PRICE* are not significantly related to either enrollment measure.

There are also two counter-intuitive results. First, the *JAR* estimates indicate a significant negative relationship. On average, a one percent increase in the number of jobs at risk of automation will decrease the number of people enrolled by -0.905 percent. This relationship contradicts expectations and is inconsistent with the hypothesis being put forth. Second, *UNE* shows a significant, yet negative relationship between unemployment and enrollment, contrary to economic theory. The effect of one percent increase in unemployment is estimated to be 1.29 percent on average. However, when regional dummies are included, the magnitude of the variable is significantly reduced to -0.070 and becomes insignificant.

The *POP* estimates indicate that the association between population size and enrollment is insignificant and is reduced to zero once the regional effects are added to the model. Columns 1 and 2 of Table 3 show that increasing the population by 10,000 impacts enrollment by -0.001 to 0.004 percent. The results also demonstrate that the high school graduates measure, HS, has an insignificant effect.

Controlling for population size (*POP*), the results indicate significant differences in *ENR* across regions, whereas no significant regional differences are found when enrollment is proxied by *EPR*. Overall, the model with regional effects is able to explain about 73 percent of the variation in *ENR* versus about 31 percent if the variation in *EPR.*

To provide an alternative examination of the relationship between enrollment and *RPW*, columns 3 and 4 report estimation results with *EPR* as the dependent variable. The estimates for *RPW* contradict the study's expectation as they show a statistically insignificant negative relationship with the dependent variable. Similar to the results in the *ENR* models, no significant relationship is found between *PRICE* and *EPR*. While price has been documented to affect enrollment in previous studies, no significant effects are found here.

The only significant variables were *PI*, *JAR* and *UNE*. Unlike the *ENR* models, the results show that *PI* is significantly related to *EPR*. However, the coefficient is negative, contradicting study's expectations. Similarly, *JAR* and *UNE* estimates are negative and highly significant. The *JAR* estimates range from -0.062 and -0.065 and the *UNE* estimates range from -0.076 and -0.095. Similar to the *ENR* models, the *POP* estimates show no significant relationship with *EPR*. The findings suggest that an increase in population size translates to small gains in enrollment (estimated to be less than 0.001).

In sum, the U.S. models did not offer any significant evidence regarding the relationship between post-secondary enrollment and industrial automation. The main shortcoming of the analysis is attributed to the lack of samples across time; a cross-section of a single year is the limiting factor. As we see below with the international models, expanding from a single cross-section to a multi-year panel can have sizeable effects on the size and significance of the effects of the control variables on post-secondary enrollment.

International Model Estimation Results

Table 4 reports estimates of the international model. Results are reported from the base model and with country- or regional level dummies and with year dummies. Considering *RPW*, the results show that its parameter (β_1) is significant at the 0.1 percent level. Introducing country fixed effects results in the sign of the *RPW* coefficient estimates changing from positive to negative. As shown in column (5), an addition of one robot per 10,000 workers is estimated to decrease enrollment by -4.562 percentage points on average, which contradicts the study's expectations. The strongest effects reside in column 2 and 3. Adding the regional fixed effects changes the magnitude of the effect of *RPW* significantly, with the coefficient estimates ranging between 7.487 and 7.617 on average.

As discussed previously, one expected determinant of enrollment is income. The base model in column 1 indicates a positive significant relationship between income and enrollment. An increase of $1000 in *NNI* is associated with a 0.327 percentage point increase in enrollment on average. However, as time, country and region effects are added to the models, the effect of income dampens and becomes insignificant. Lastly, *UNE* is estimated to have a significant positive effect.

Other than the insignificant negative estimate in column 3, the coefficient estimates range from 0.571 and 1.588, aligning with the expectations of the study.

The coefficients are significant with the majority of variables ($p<0.01$) and have the expected positive sign in the models that include the region and time controls, or which exclude these controls. In contrast, when the regions are disaggregated to the individual country-level, the direction of the effect of *RPW* on enrollment changes. A possible explanation is that there may be unobservable country-level factors that are correlated with *RPW*. For example, a country's investment in industrial manufacturing might have lowered the demand for skilled labor, especially if it were a developing country.

In summary, the simple panel data regression analysis shows that the growth in the stock of robots has a significant effect on post-secondary enrollment. However, estimates show evidence of decline in enrollment as the degree of automation increases and robots become more prevalent.

V. CONCLUSION

This study analyzed the relationship between automation and associated adoption of industrial robots and post-secondary education enrollment across 50 U.S. states and 41 countries. Using cross-sectional data for the U.S. and an 8-year panel data across countries, the study found that increased adoption of industrial robots is associated with a decline in post-secondary enrollment on the country-level. It is important to note that the estimated effects of robots per worker were found to be sensitive to whether the international model specifications included either regional or country-level fixed effects. Focusing upon the models with country-level effects, the study found that an increase of one robot per 10,000 workers contributes a substantial -4.562 percentage point decrease in enrollment on average. No significant relationship was found between the adoption of industrial robots and enrollment at the state level.

The adoption of industrial robots in the U.S. and globally has left a polarizing effect in labor markets. Shares of high-skill occupations and low-skill occupations have been on the rise while shares of routine occupations have been falling. As the quality improves and integration of industrial robots increases, and as their prices fall, it is reasonable to expect that workers displaced by automation will turn to post-secondary education to increase their skill-sets and marketability. However, no such evidence was found in this study.

The study focused only on 4-year post-secondary educations. However, with ongoing growth in educational programs, professional certifications, and massive online open courses (moocs), it is reasonable to expect that the impact of industrial robots on educational enrollment may be even larger than that found in this study. Future research is warranted to validate the conclusions drawn from this study. One proposed avenue for future research is to construct an educational attainment demand function that can be estimated with panel data spanning a rich set of developed and developing nations.

APPENDIX: CODE SCRIPT

U.S. Models

ENR Models

Model1 <- lm(ENR ~ rpw + Price1000 + PerCap_PI1000 + u31 + Dmsoutheast + Dmsouthwest + Dmnortheast + Dmmidwest + Dmwest, data = data)

summary(Model1)

Model2 <- lm(ENR ~ rpw + Price1000 + PerCap_PI1000 + Pop10000 + jar + u31 + HS_Grad1000 + Dmsoutheast + Dmsouthwest + Dmnortheast + Dmmidwest + Dmwest, data = data)

summary(Model2)

EPR Models

Model3 <- lm(EPR ~ rpw + Price1000 + PerCap_PI1000 + u31 + Dmsoutheast + Dmsouthwest + Dmnortheast + Dmmidwest + Dmwest, data = data)

summary(Model3)

Model4 <- lm(EPR ~ rpw + Price1000 + PerCap_PI1000 + Pop10000 + jar + u31 + Dmsoutheast + Dmsouthwest + Dmnortheast + Dmmidwest + Dmwest, data = data)

summary(Model4)

International Models

library(plm)

pdata <- pdata.frame(data, index = c(“ï..Country”, “Time”)) summary(data)

Model1 <- plm(ENR ~ RPW + UNE + NNI1000, data = pdata, model = “pooling”) summary(Model1)

Model2 <- plm(ENR ~ RPW + UNE + NNI1000 + AA + ME + EU + AF + NA. + SA, data = pdata, model = “pooling”)

summary(Model2)

Model3 <- plm(ENR ~ RPW + UNE + NNI1000 + AA + ME + EU + AF + NA. + SA + X2010 + X2011 +X2012 + X2013 + X2014 +X2015 + X2016 + X2017 , data = pdata, model = “pooling”)

summary(Model3)

Model4 <- plm(ENR ~ RPW + NNI1000 + UNE + X2010 + X2011 +X2012 + X2013 + X2014 +X2015 + X2016 + X2017 + Argentina + Belarus + Belgium + Bulgaria + Chile + China + Colombia + Croatia + Czech.Republic + Denmark + Egypt + Estonia + Finland + France + Hungary + India + Indonesia +

Ireland + Israel + Italy + Latvia + Lithuania + Malaysia + Moldova + Morocco + Norway + Poland + Portugal + Qatar + Rep..of.Korea + Romania + Saudi.Arabia + Serbia + Slovakia + Slovenia + Spain + Sweden + Switzerland + United.Kingdom + United.States + Uzbekistan, data = pdata, model = "pooling")

summary(Model4)

Model5 <- plm(ENR ~ RPW + NNI1000 + UNE + Argentina + Belarus + Belgium + Bulgaria + Chile + China + Colombia + Croatia + Czech.Republic + Denmark + Egypt + Estonia + Finland + France + Hungary + India + Indonesia + Ireland + Israel + Italy + Latvia + Lithuania + Malaysia + Moldova + Morocco + Norway + Poland + Portugal + Qatar + Rep..of.Korea + Romania + Saudi.Arabia + Serbia + Slovakia + Slovenia + Spain + Sweden + Switzerland + United.Kingdom + United.States + Uzbekistan, data = pdata, model = "pooling")

summary(Model5)

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Table 1: U.S. and International Variable Definitions and Data Sources

Variable	Abbreviation	Definition	Models
School Enrollment[a,f]	ENR	The number of people enrolled in post-secondary education as a percentage of the total population of their age group	Both
Enrollment Participation Rate[a]	EPR	The number of people enrolled in post-secondary education as a percentage of the sum of high school graduates for 2016 and three preceding year	U.S.
Robots Per Workers[b]	RPW	The number of robots per 1,000 workers (U.S.) and per 10,000 workers (international)	Both
Consolidated Tuition[a]	PRICE	A weighted average of public and private tuition by state	U.S.
High School Graduates	HS	Number of High School Graduates in 2015	U.S.
Personal Income[c]	PI	The personal income per capita	U.S.
Job at Risk[d]	JAR	The percent of occupations at risk of automation within a state	U.S.
Unemployment Rate[e,f]	UNE	The proportion of the civilian labor force that is unemployed but actively seeking employment	Both
National Income Per Capita[f]	NNI	Adjusted net national income per capita (current US$)	International
Population[g]	POP	The population size (scaled by 10,000 for estimation purposes)	U.S.

Source:

[a]U.S. Department of Education, National Center for Education Statistics, Integrated Postsecondary Education Data System (IPEDS)

[b]International Federation of Robotics, 2020

[c]Bureau of Economic Analysis, Per Capita Personal Income by State, 2016

[d]Smart Asset, Most Vulnerable to Automation, 2018

[e]Bureau of Labor Statistics, U.S. Department of Labor, The Economics Daily, U-3 and U-6 unemployment by state, 2015

[f]World Bank Organization, 2020

[g]U.S. Census, American Community Survey, 2015

Table 2: Summary Statistics on the Dependent and Independent Variables

Variable	Mean	Std. dev.	Min.	25%	Median	75%	Max.
U. S. Data (N = 50)							
ENR	41.106	5.046	26.100	38.600	41.750	45.170	54.900
EPR	1.613	0.301	0.910	1.403	1.580	1.740	2.410
RPW	1.812	1.617	0.140	0.740	1.470	2.007	7.360
PRICE	25.500	5.852	13.65	21.860	26.120	29.690	35.890
POP	631.735	707.934	57.967	185.590	451.130	691.550	3,842.146
HS	63.600	75.973	5.550	18.420	40.480	67.950	422.830
PI	47.620	7.377	35.020	42.600	46.420	52.280	68.300
JAR	0.533	0.021	0.470	0.520	0.540	0.547	0.590
U3	5.080	1.103	3.000	4.000	5.000	6.000	7.000
International Data (N = 328)							
ENR	60.643	21.751	8.039	48.034	64.337	75.896	102.791
RPW	0.746	1.219	0.000	0.020	0.244	1.203	9.717
NNI	20,633	18,270	1,171	6,359	13,409	33,844	81,017
UNE	8.337	4.456	0.140	5.345	7.483	10.092	26.094

Notes: Population size (POP) is scaled by 10,000 for estimation purposes.

Table 3: U.S. Model Estimation Results

	Enrollment (ENR)		Enrollment Participation Rate (EPR)	
	(1)	(2)	(3)	(4)
RPW	0.346	-0.120	-0.041	-0.047
	(0.434)	(0.360)	(0.028)	(0.033)
PRICE	0.194	-0.037	-0.001	-0.006
	(0.146)	(0.112)	(0.009)	(0.010)
PI	0.061	-0.115	-0.019**	-0.023**
	(0.117)	(0.099)	(0.007)	(0.009)
JAR	-0.905**	-0.770***	-0.065 ***	-0.062**
	(0.361)	(0.270)	(0.024)	(0.025)
UNE	-1.295**	-0.705	-0.095**	-0.076*
	(0.572)	(0.452)	(0.037)	(0.042)
POP	0.004	-0.001	< 0.001	< 0.001
	(0.006)	(0.005)	(< 0.001)	< 0.001
HS	-0.043	0.028		
	(0.064)	(0.051)		
Southeast		2.668***		0.003
		(1.530)		(0.138)
Southwest		-1.480		0.027
		(1.912)		(0.178)
Northeast		9.413****		0.194
		(1.521)		(0.142)
Midwest		5.890****		0.133
		(1.520)		(0.144)
Constant	88.160****	88.349****	6.658****	6.678***
	(23.680)	(17.757)	(1.583)	(1.685)
R^2	0.429	0.732	0.268	0.307
Adjusted R^2	0.334	0.654	0.166	0.13

Note: Standard errors are reported in parentheses. ****, ***, **, and * denote significance at the 0.1 percent, 1 percent, 5 percent, and 10 percent level, respectively.

Table 4: International Model Estimation Results

	Enrollment (ENR)				
	(1)	(2)	(3)	(4)	(5)
RPW	6.497****	7.617****	7.487****	-1.844**	-4.562****
	(0.863)	(0.725)	(0.740)	(0.789)	(0.764)
NNI	0.327****	0.020	0.030	-0.073	0.159
	(0.058)	(0.057)	(0.058)	(0.127)	(0.132)
UNE	1.588****	0.571***	0.636***	-0.146	0.595****
	(0.230)	(0.219)	(0.228)	(0.166)	(0.174)
Constant	35.800****	65.050****	66.172****	9.434****	10.045****
	(2.670)	(3.511)	(3.979)	(1.969)	(1.832)
Time Effects	No	No	Yes	No	Yes
Country Effects	No	No	No	Yes	Yes
Regional Effects	No	Yes	Yes	No	No
R^2	0.310	0.582	0.584	0.955	0.965
Adjusted R^2	0.303	0.572	0.564	0.949	0.959

Note: Standard errors are reported in parentheses. ****, ***, **, and * denote significance at the 0.1 percent, 1 percent, 5 percent, and 10 percent level, respectively.