Immigrant Workers in a Changing Labor Environment:
A study on how technology is reshaping immigrant earnings

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Abstract

This research determines how automation affects immigrant wages in the US and how closely this impact follows the skills-biased technical change (SBTC) hypothesis. The present study addresses this question using American Community Survey (ACS) data from 2012 to 2016 and a job automation probability index to explain technological change. This research leverages OLS regressions to evaluate real wage drivers, grouping data by year, immigration status, and education level. According to the SBTC hypothesis, high skill immigrant wages should be less negatively affected by technological change than low skill immigrant wages. Univariate analysis suggests that the SBTC hypothesis is even stronger for US immigrants than native-borns, as high skill immigrants have a lower average probability than low skill immigrants of having their jobs automated, and the difference in effect on high versus low skilled workers is larger for immigrant than native-borns. However, multivariate analysis asserts that technological change affects low skill immigrants' wages less than high skilled individuals' wages, which counters the SBTC hypothesis.

JEL Codes J15, J24, J31, J61, E24

Keywords: SBTC hypothesis, immigrant wages, technology, skill level

Contents

Introduction

Centuries of history reveal that fears about worker displacement are not a new phenomenon. Much research has been done in recent decades on the impact of technology on the labor force, with particular consideration for how impacts of technology differ based on workers' skill levels. This research led to the SBTC hypothesis, a theory which suggests that skilled workers are more likely to serve as complements to technological innovation, while low-skilled workers become substitutes as technology advances.

Based on the importance of immigrants in the US workforce who are skilled, often trained in STEM fields, and contribute to innovation as well as immigrant who fill low skill jobs, it is essential to consider not only how technological change and the SBTC hypothesis impact the labor force overall but how they influence immigrant workers specifically. This exploration is especially important given the increasingly high proportion of immigrants in the US (Migration Policy Institute). Though some economists are beginning to discuss the impacts of technology on immigrants (Jaimovich and Siu, 2017; Basso, Perri, and Rahman, 2017), there is work to be done in this area. In particular, there is a need for a direct evaluation of the SBTC hypothesis for the immigrant work force specifically, as the vast body of critiques of the SBTC hypothesis focuses primarily on the US work force more generally. Additionally, in considering skill level pertaining to the SBTC hypothesis, it is important to hone a more comprehensive method of evaluating workers' skill level, particularly given the discrepancies in research on "job polarization" and changing wage gaps, which often leverages more simplistic breakdown of workers into groups based on income levels or basic skill breakdown of low, medium, and high skill workers (Schmitt, Shierholz, & Mishel, 2013; Goos & Mannings, 2007). As such, beyond considering education level (Manning, 2004) and how "routine" a worker's everyday job tasks are (Autor, Levy, & Murnane, 2003), this research evaluates skill level using a variety of metrics, including education level, English speaking abilities, area of educational study, mobility, and disability. Next, the present study leverages the American Community Survey (ACS), as opposed to the Current Population Survey (CPS) that is frequently used in SBTC research, as the ACS data is conducive to answering questions about immigrants and will provide a different body of data to draw conclusions from. Finally, my research evaluates the impact of technology on immigrant *wages* specifically. While some research has evaluated wages, other studies have considered task changes within an occupation (Spitz, 2004; Autor, Levy, & Murnane, 2003), frequency of individuals entering routine versus nonroutine jobs (Cortes, Jaimovich, & Siu, 2016), or worker displacement more generally (Baum-Snow, Freedman, & Pavan, 2018), while paying less attention to the interesting question of how changes in wage earnings specifically are driven by technological advance.

This paper explores the impacts of automation on the US immigrant labor force in the face of recent advances in technologies, leveraging a variety of metrics to determine skill level. More specifically, this research will consider how immigrant wages are effected by automation. Based on these findings, we will be able to consider the extent to which the SBTC hypothesis is a comprehensive way of characterizing current impacts of technological change on the immigrant labor force in the US. More concisely, the present study seeks to answer the question: *How are technological advances currently impacting immigrant wages in the US, and how closely do these trends follow the SBTC hypothesis?*

To address this question, this paper begins by addressing existing research on the SBTC hypothesis and immigrant workers, highlighting the areas of this vast body of literature that need further exploration. Next, the there is an overview of the theoretical model supporting the SBTC hypothesis, following by an introduction to the ACS data set and a discussion of important variables and summary statistics. Finally, the paper includes a methodology section to detail the present research, as well as a discussion of the results and concluding thoughts.

Literature Review

Technological Change: Old Issue, New Relevance

For hundreds of years, there has been concern about the effects of technology improvement on the labor market. From Queen Elizabeth I's rejection of a patent for a stocking frame knitting machine in 1589 to the Luddites of the 19th century, who destroyed weaving machinery, to Keynes in the 1930's, many have feared the impacts of automation. While always an important topic of discussion, this topic is causing particular concern currently in the field of economics and popular culture given recent advances in technology. With the advent of the computer and more recent innovations in artificial intelligence (AI) and machine learning (ML), many are uncertain about what the upcoming decades and centuries will hold, particularly with companies such as Amazon, Anheuser-Busch, and Toyota already adapting their business models to leverage new AI and ML technologies (King, Hammond, & Harrington, 2017). Some fear that computers and robots will become so advanced that they will be able to adopt emotions and be able to imitate human nature in a science fiction-like manner. Others are concerned that increasing reliance on technology is changing the way humans interact and even think.

Today, The Wall Street Journal reports on impacts of technological advancements on jobs, explaining that, "On average, 15% of occupations could be significantly impacted by automation [by 2030]," with advanced economies in particular danger (2018). With the advent of computers, the job landscape changed not only in sectors like manufacturing, where much of job displacement occurred in the mid-20th century, but also in areas such as finance and retail as computers began to replace cognitively routine tasks (Lordan & Neumark, 2017). Rather than causing substantial declines in the number of jobs available, automation shifts the occupational mix in the labor force towards growth in non-routine tasks (Aaronson & Phelan, 2017; Autor, Dorn, & Hanson, 2015; Autor, Levy, & Murnane, 2003)[1].

[1] Frey and Osborne (2017) postulate that the lack of technology-induced mass unemployment is due to production becoming more efficient with the use of technology, which leads to price declines, ultimately driving up demand.

Based on the recent concerns about how new technologies are shifting the current labor environment, additional research on how workers are affected by shifts in high and low skilled labor demand is essential. Research on the changing wage environment as a result of technological improvements, and on implications for specific groups of workers such as immigrants, is particularly important given the increasing wage inequality (Furman, 2017).

SBTC Hypothesis Background, Wage Extensions, and Research Gaps

Skills biased technical change (SBTC) hypothesis suggests that changes in technology lead to a shift in labor demand towards high skilled labor and away from low skilled labor. Groundbreaking work on the topic began with Tinbergen's research (1974), which initiated discussions surrounding the idea that technical advancements might be leading to increased demand for skilled workers. Early research[2] determined that computers and skilled labor are complementary production inputs, giving skilled workers an advantage in the job market over low-skilled workers as technology becomes increasingly prevalent and is seen as a productivity enhancement for high skilled workers (Autor, Levy, & Murnane, 2003; Bresnahan, Brynjolfsson, & Hitt, 2002; Acemoglu, 1999; Autor, Katz, & Krueger, 1998). Early extensions on the theory focused on the degree to which routine labor is hurt by automation, while non-routine labor is complemented by new technologies[3] (Autor, Levy, & Murnane, 2003). See Appendix 1 for an overview of early SBTC research and its extensions.

Expanding wage gaps complement the SBTC hypothesis. Along with SBTC, there is substitution towards skilled labor, leading to growth in the wage gap. As illustrated by Figure 1 below, there is an association between high automation probability and low income. Because low income is associated with low skill level, this graphic and corresponding research by Frey and Osborne (2017) generally supports the SBTC hypothesis and its extension to wage gaps.

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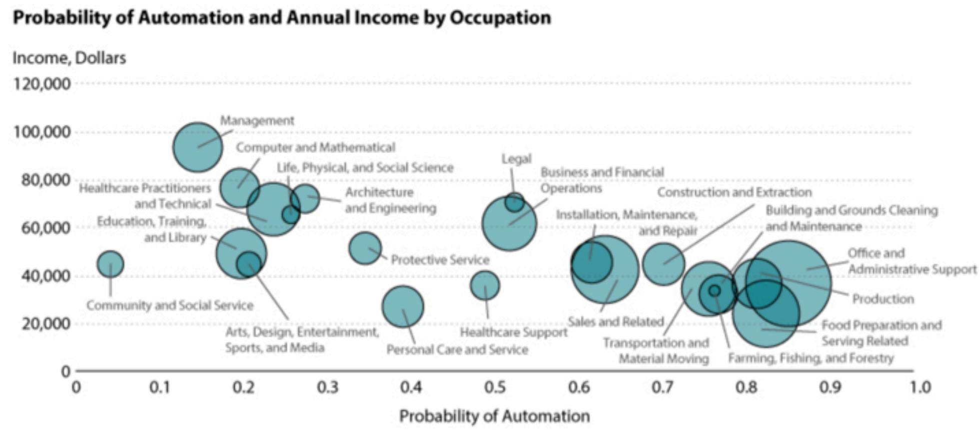
[2] See Appendix 1 for flowchart detailing early research and extensions.

[3] Routine jobs are characterized by routine and predictable tasks that typically involve a minimal amount of reasoning, personal communication, and expert mastery (e.g. manual labor; secretarial work). They tend to include low and medium skill levels, while non-routine labor involves more complex tasks or personal communication and is often performed by high skill workers.



Source: Federal Reserve Bank of St. Louis based on Frey and Osborne (2017) data

Figure 1: Probability of Automation and Annual Income by Occupation

Some economists are not convinced that the SBTC hypothesis is valid, or at least comprehensive. See Appendix 2 for a chart with an overview of critiques and updates to the SBTC hypothesis in recent decades (Jaimovich & Siu, 2017; Beaudry, Green, & Sand, 2016; Autor, 2015, 2013; Schmitt, Shierholz, & Mishel, 2013; Goos & Manning, 2007, 2003; Autor, Levy, & Murnane, 2003; Card & Lemieux, 2003; Mishel & Bernstein, 1998, 1994). Mixed and even contradictory results on the SBTC hypothesis and extensions, such as theories on speed of education acquisition and job polarization[4], reveal a need for additional research on this topic.

Additionally, recent research counters the SBTC hypothesis by revealing that demand for skilled workers is not growing at the rate that it had been and that this demand could even be declining, despite increasing supply of skilled labor (King, Hammond, & Harrington, 2017; Beaudry, Green & Sand 2016; Autor, 2015)[5]. Contrary to the original SBTC hypothesis, current research focuses on automation of skilled, routine labor, such as "mathematical calculations

[4] Extensions of the SBTC hypothesis assert that the increasingly high wages for high skill workers compared to those for low skill workers may be due to slowness of the workforce to adapt to increased demand for high skill labor (Autor, 2013; Card and Lemieux, 2001). Job polarization emphasizes that in addition to growth of demand for high skill workers, there is also increased demand for low skill workers and diminished demand for medium skill workers (Autor, 2015; Goos and Manning, 2003, 2007).

[5] Beyond recognizing this changing trend, the reason for this "boom and bust" pattern is likely linked to the idea that there is an initial boom when new technology is introduced as companies demand skilled labor to create and implement new processes that leverage the new technology. However, once the technology is created and implemented, the demand for skilled labor will slow.

involved in simple bookkeeping [or] the retrieving, sorting, and storing of structural information typical of clerical work" (Autor, 2015, p. 11). This misalignment in the supply and demand for skilled labor seems to have negative implications for both wages among skilled laborers and for unemployment among lower-skilled workers who are now being displaced by over-qualified employees. Hundreds of billions of dollars could be lost in wages in the next decade as "technology is now encroaching on people with more sophisticated skill sets[,] from financial and accounting analysts, to those who practice law or even medicine may find technology competition in the relatively near future" (King, Hammond, & Harrington, 2017, p.61). This idea is particularly concerning given the increasing proportion of individuals pursuing advanced degrees in hopes of being qualified for more lucrative, high skill jobs.

The present study seeks to address holes in existing SBTC literature in three ways. First, the present study focuses on immigrant workers, which have not been explored deeply with regards to the SBTC hypothesis, and how SBTC impacts immigrants as compared to native-born workers. Second, past SBTC literature largely focuses on low skill, routine work, while the present study will span both low and high skill workers, as the high skill work force is an important part of the immigrant work force and drives innovation in the US. Consideration of high skill workers is also particularly important given recent findings that demand for skilled workers is not growing at the rate that it had been and that this demand could even be declining (Beaudry, Green, & Sand, 2016; Autor, 2015). Third, this study will expand the definition of skill level to consider a variety of different metrics beyond just education level or degree to which a job contains routine tasks. With these extensions on existing SBTC research, the present study will fill a significant gap in a vast pool of existing literature on SBTC theory.

Immigrants and Skill Level in the US Work Force

An important subtopic of SBTC research is how individual types of workers will be affected by technological changes. Conversation about immigrants in the American labor force is a prevalent topic for economists today (Hanson, Kerr, & Turner, 2018; Kerr, Kerr, & Lincoln, 2015; Peri, 2012; Peri & Sparber, 2011; Chiswick & Taegnoi, 2007). These conversations are especially important given the growing percentage of immigrants in the US as a percentage of the total US population since 1970 (Migration Policy Institute). While there has been some research done on the impact of recent technological advances on the immigrant workforce, it is unclear how the SBTC hypothesis will operate in the US immigrant labor force given recent changes in technology and how these impacts on immigrants will compare to impacts on US-natives. This lack of research on the intersection of the immigrant labor force and the SBTC hypothesis is one of the major gaps in literature that the present research seeks to address.

Given recent trends in global talent flows, it is important to consider not only low skill immigrants, who historically have been at greater risk of automation according to the SBTC hypothesis, but also high skill immigrants. Beyond representing an increasingly large percentage of immigrants[6], skilled immigrants are important to consider given the essential role they play in US innovation and STEM work (Jaimovich & Siu, 2017; Nathan, 2014). These skilled immigrants are currently frequently from Asia, representing a shift from previous skilled immigration flows from Europe (Hanson & Liu, 2018). This influx of skilled, innovative workers has been accompanied by immigrant wage inequality as the past few decades have seen technological advances that advance non-routine labor (Jamoivich & Siu, 2017, p.25).

Inflows of skilled workers are particularly important given findings on the shortcomings of US STEM education, which is problematic because the majority of innovation is in STEM fields (Jaimovich & Siu, 2017; Peri, Shih, & Sparber, 2015). Atkinson and Mayo (2010) fear that the US's share of global innovation is declining, which may be linked to inadequate US education system in STEM fields, which is a gap that skilled immigrants may fill. STEM

[6] There is currently more growth in skilled migration and unskilled migration, as "the number of migrants with a tertiary degree rose by nearly 130 percent from 1990 to 2010, while low-skilled (primary educated) migrants increased by only 40 percent during that time" (Kerr, et al., 2016, p.83-84). Nathan (2014) notes that 29% of migrants in OECD countries are skilled, an increase of 5 percentage points since 2000. Jean, Causa, Jimenez, & Wanner (2011) predicts that this trend of high levels of migration will continue in upcoming decades in the midst of "widening demographic imbalances between developing and OECD countries, coupled with diminishing transport and information costs, in the context of persistent income disparities across regions" (p.2).

immigrant workers may even raise help diminish overall US wage inequality, though more high paid immigrants may lead to further wage disparity within the immigrant population specifically (Jaimovich & Siu, 2017).

Aside from STEM education, other literature reveals that English speaking abilities is another skill factor for immigrant workers, and language abilities lead native-borns and immigrants have comparative advantages in communications and manufacturing work, respectively (Peri & Sparber, 2009). English speaking may even be an impediment for skilled immigrants in certain jobs, as highly skilled are more likely to take jobs where English communications is a limited part of the job (such as computer and engineering occupations) if their first language is linguistically distant from English (Chiswick & Taegnoi, 2007).

Though there is less research on the impacts of recent technological advances on the immigrant workforce specifically compared to the US workforce more broadly, there is some recent literature in this area. However, existing literature in this areas has important gaps that will be addressed in the present research.

Several recent articles address the immigrant workforce, but they do not evaluate immigrant workers comprehensively, instead looking at low-skill workers specifically and often considering the impacts of immigrant influxes rather than immigrants themselves. Lewis (2011), for example, challenges the SBTC hypothesis and the validity of technology-skill complementarity, but rather than focusing on the impacts of automation on immigrants, he uses influxes of immigrants as a proxy for increased low-skill workers. This approach fails to fully consider the impact of technology on low-skill immigrants and omits consideration high skilled workers. Similarly, Peri (2012) focuses on low-skill immigrants, and the impact of these immigrants on US labor markets. Peri's conclusions, however, link to the results of an influx of low-skill immigrants on native workers and US labor markets as opposed to the immigrants themselves. A relevant and useful finding, however, is that when evaluating immigrant workers, "unskilled-biased technological adoption survives all controls" (Peri, 2012, p. 357, 248), implying that the SBTC hypothesis does not hold for immigrant workers. The research, however, lacks careful attention to skilled immigrants and also does not use up-to-date data, as the data used stops in 2006, leaving room to expand the evaluation of the SBTC hypothesis for immigrants in the present study. Basso, Perri and Rahman (2017) similarly evaluate the relationship between automation and low-skill immigrants, considering polarization, where both low and high skill jobs have increased demand for workers, as an alternative to the SBTC hypothesis. They find that along with the enhancements in technology, there have been influxes of immigrants to the US, including both high and low skilled immigrants, with low-skilled immigrants tending to specialize in manual-service occupations. They illustrate that with automation, there is an increase in manual labor jobs for low-skilled immigrants, which immigrants benefit from. At the same time, native workers shift towards less routine jobs.

Similar to literature connecting the SBTC hypothesis and low-skilled immigrants, there are obvious gaps in literature on the SBTC hypothesis and skilled immigrants. Jaimovich and Siu (2017) look at the impacts of skilled immigration on the US labor market, pointing out that high skilled workers tend to work in non-routine jobs while low skilled workers tend to select routine jobs, and that technological innovation leads to what they term non-routine-biased technical change (NBTC), which is an extension of the SBTC hypothesis. They explore the "tendency of the foreign-born to work in innovation, on the pace of technical change," which is accompanied by wage inequality as the past few decades have seen technological advances that advance non-routine labor (p.25). This paper, however, focuses more on the impact of immigration on the labor market and less on the direct relationship between automation and immigrant workers.

While several of these authors tackle the question of how automation is impacting the US immigrant workforce, there is much to be learned in this area. By using the Frey and Osborn automation probabilities index, as described below, the present study can add more nuance to the consideration of technological change by occupation. Another area of needed expansion on is the definition of skill level. As existing research reveals (Peri, 2012), there are important considerations of skill level that frequently aren't accounted for, such as immigrants' educational background (STEM or otherwise), language background (English speaking or otherwise), disabilities, job mobility, and others that haven't been incorporated into some existing models. There is also room to expand research on the topic by comparing how automation effects immigrants of different skill levels, thus testing the SBTC hypothesis, and then comparing how these automation impacts differ for immigrants versus native-born Americans. Therefore, this research has the potential to not only add more nuance to existing findings but also to expand understanding of the intersection of automation, education level, and immigration in a period of steep technological change.

Theoretical Framework

Starting in the late 20th century, economists adopted the SBTC hypothesis as the primary model to explain how technology advancements increase demand for skilled labor while decreasing labor opportunities for non-skilled groups. While there have been many extensions and critiques to the model in recent decades (see Appendix 2), the present study is rooted in the theoretical foundations and assumptions of the model, outlined in a cornerstone paper by Autor, Levy, and Murnane (2003). Both supply and demand of the SBTC hypothesis are important to consider for the present study, as the intersection of supply and demand for labor determine wages. First considering demand, the authors leverage a Cobb-Double production function with constant returns to scale:

(1) $Q = (L_R + C)^{1-ß} L_N^{ß}, 0 < ß < 1$

where Q is output, L_R and L_N represent routine labor and non-routine labor, and C is technology (or computer capital). There are three key assumptions that accompany this model:

1) Routine tasks are more substitutable with technology than nonroutine tasks
2) Routine and nonroutine tasks are not perfect substitutes; in fact, elasticity of substitution between these tasks is 1

3) Increased quantity of routine production inputs increases the marginal productivity of nonroutine inputs

Summing L_R and C in the Cobb-Douglas production function, the authors assume that technology and routine tasks are perfect substitutes, meaning that as price for technology falls, demand for routine labor falls. Using the Cobb-Douglas production function, the theory also implies that routine and nonroutine labor are relative complements and thus that technology and nonroutine labor are also relative complements, meaning that as price of technology falls, demand for nonroutine labor increases. Another important assumption that the authors call less explicit attention to is that the production function is not entirely comprehensive. The authors apply the model to four type of tasks: routine cognitive, routine manual, nonroutine analytic, and nonroutine interactive tasks. They do not intend the model to be applied to nonroutine manual tasks, as there is less clarity whether these tasks are substitutes or complements for technology.

This production function and accompanying assumptions are important for the present study because the model outlines how to approach substitutability between labor and technology for two different types of labor: routine and nonroutine. An extension that must be made to consider this theory in the context of the present study is how routine and nonroutine task inputs relate to skill level of workers. The jobs that have historically been automated are most frequently those with routine task inputs, as would be assumed based on Autor, Levy, and Murnane's (2003) theory. However, as revealed by Autor, Levy, and Murnane's empirical work, these jobs that are automated are frequently done by low-skilled workers, which the authors define as workers without a college education. Using this information, the Autor, Levy, and Murnane model could be extrapolated to use high and low skilled workers, rather than routine and nonroutine workers, as the production function inputs. Later models, such as Acemoglu and Autor's (2012)[7], do incorporate skill level directly into the production function.

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[7] Acemoglu and Autor's (2012) production function is $y(i) = A_L\alpha_L(i)l(i) + A_M\alpha_M(i)m(i) + A_H\alpha_H(i)h(i) + A_K\alpha_K(i)k(i)$, where A is factor-augmenting technology and α represents the productivity schedules for each type of labor, including low (L), medium (M), and high (H) skill, and for capital (K). Under the assumption that $A_H > A_L$, the

Autor, Levy, and Murnane's (2003) production function and its assumptions about substitutability and complementarity are relevant for the present study because these production function assumptions outline how we expect technology to affect immigrant wages. If these assumptions under the SBTC hypothesis hold, as both high and low skill immigrants become inputs in the production function, we expect high skill immigrants to be complements to new technology. Accordingly, economic theory states that as demand for these skilled immigrants rises, holding supply of skilled immigrant workers relatively constant, wages for these workers would also rise. On the other hand, low skill immigrants are expected to be substitutes for technology, meaning that as new technologies are invented, demand for low skilled immigrants will decline. Assuming that supply of low skill immigrants remains relatively constant, low skill immigrant wages would decline as demand for technology rises and demand for low skill workers falls[8]. Building on Autor, Levy, and Murnane's (2003) model, the SBTC hypothesis for immigrants specifically, based on skill level, could be described:

(2) $Q = (L_{LSI} + C)^{1-ß} L_{HSI}{}^{ß}$, $0<ß<1$

where L_{LSI} is labor of low skill immigrants, L_{HSI} is labor of high skill immigrants, and C is technological advances, acknowledging that wages will fluctuate based on the demand for high and low skill labor, which changes as the production function inputs shift.

In considering the supply side of the labor market, Autor, Levy, and Murnane (2003) assume "a large number of income-maximizing workers, each of whom inelastically supplies one unit of labor … [with a] heterogeneous productivity endowment in both routine and nonroutine tasks" (p.1287). They assume that each worker selects their own amount of routine and nonroutine task input to supply. Accordingly, as wages for routine workers declines with price

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model can be used to assert that technology is more complementary to high than low skilled workers, supporting the SBTC hypothesis.

[8] For example, highly educated immigrants with STEM background help drive technology innovation, making them complements to the technology and driving up wages, while low skill immigrants working in manufacturing decreases the cost of manufacturing an item, pushing down wages for low skill immigrants as they are forced to compete with new technologies as the inputs to produce goods.

drops for technology (due to the substitutability of technology and low skill labor), workers will substitute towards nonroutine jobs in favor of nonroutine wages. Wages for nonroutine task inputs will be rising as declines in price of technology cause quantity of C to rise, complementing nonroutine task inputs and thus pushing up nonroutine wages. The changes in wages and the subsequent labor supply shifts are important for the present study because, as technology advances and subsequently becomes cheaper, wages for routine and, by extension, low skill jobs are expected to decline. Conversely, as technology advances, complementary nonroutine and, by extension, high skill jobs are expected to experience increased wages. These theoretical predictions are thus important for the present study because they predict how labor supply, and subsequently wages, will respond to a changing technological environment, predicting that workers will attempt to substitute towards nonroutine or, by extension, higher skill jobs in attempt to avoid wage declines. This theory is in line with empirical evidence that in recent years, skill levels such as education have been increasing as technology has advanced, leading to strategic complementarity in skilled wage gains (Census Bureau, 2016).

Despite benefits of using Autor, Levy, and Murnane's (2003) SBTC model to consider the supply and demand shifts that result from technological change, there are limitations to this model and applying the model directly to the present study. First, Autor, Levy, and Murnane's model and subsequent theoretical extensions do little to address skill metrics, which is a gap that the present study seeks to fill. More specifically, on the demand side, this framework considers how technology prices change demand for labor inputs. However, the present study will not consider technology prices specifically. Instead, the present study uses the probability of automation to explain changes in demand for labor, accounting not only for cost savings but also increased efficiency that firms may benefit from by leveraging the new technology. Additionally, as the authors note, their production function does not account for nonroutine manual workers, whereas the present study aims to account for all types of workers. Finally, the authors do not specify how the theoretical model will apply to immigrant workers specifically, which is a hole in existing understanding of SBTC theory that the present study will address. On the supply side, the model is limited because the assumption that workers will switch task inputs, likely necessitating an occupational switch, is less feasible given that there are often barriers to entry, such as education, for many nonroutine jobs. Therefore, the present study seeks to understand how wages actually change with technological advances considering that, while individuals are often income maximizing as the model assumes, their ability to pursue high paying jobs is dictated largely by their skillset. The present study thus seeks to both leverage and build on the existing SBTC theoretical model.

Data Overview

Among the large, public data sets that are typically used for research on the SBTC hypothesis or US immigrants, the American Community Survey (ACS) Public Use Microdata Sample (PUMS) stands out as the data set that best fits the needs of the present research. Based on availability of data and certain merging limitations, the present study will use ACS PUMS 2012-2016 data. Additionally, ACS data is merged with automation probabilities from research done by Frey and Osborne (2017) and GDP data from the Bureau of Labor Statistics (BLS).

Introduction to ACS PUMS Data

The American Community Survey (ACS) is a survey started in 2000 by the Census Bureau to have a continuous form of data collection to pull from rather than the decennial census long-form sample. According to the Census Bureau, this data set "offers broad, comprehensive information on social, economic, and housing data and is designed to provide this information at many levels of geography, particularly for local communities." The 2012-2016 data set spans the US and contains about 5% of the US population, with 1% of the population per year[9].

[9] While the ACS PUMS data attempts to capture 1% of the US population annually that generally represents the US population set as a whole, the Census Bureau (2017) recognizes that there is inherent potential for error in the data and accompanying analysis. In particular, the Census Bureau points out potential for sampling error because ACS data is collected using probability sampling, which inherently presents the possibility of misrepresenting the US population or pieces of the population. Furthermore, the ACS PUMS data is a subset of the larger ACS dataset,

The particular part of the ACS data used in the present study is PUMS, which is a publicly accessible set of individual ACS responses, creating a subset of the original dataset. Each record in the file represents either an individual respondent or an individual housing unit, which correspond to groups of respondents that live in shared quarters. The housing records, which are taken on a household rather than individual level, include 208 variables and cover topics such as house location and characteristics of the physical household they live in, English speaking abilities of the group living there, intergenerational characteristics within the household, and more. Personal records, which ask individual questions of each household member, such as education level and income, contains 283 variables, including information such as gender, age, wage earnings, occupation based on SOC codes, race, and more.

ACS was launched in 2000 with an official rollout in 2005 after a trial period. At the end of this period, the Census Bureau found ACS to be successful, both in terms of cost and quality, though tweaks continued to be made. The Census Bureau notes that "the evaluation concluded that the ACS was well-managed, was achieving the desired response rates, and had functional quality control procedures" (p.5). With the full implementation launch in 2005, there was an annual household unity sample of about 3 million and 36,000 in Puerto Rico, with another 20,000 group quarters added in 2006. During these early years, only housing units were counted in the survey, but starting in 2006, group quarters were added to the sample in order to capture smaller areas than covered in other surveys. The current monthly sample size is 250,000. The ACS survey is collected via the internet, mail, telephone, and in-person visits. The Census Bureau attempts to gather information first via the internet option, followed by the mail, then

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which may increase standard errors of PUMS above the size of standard errors in the larger ACS data set. However, the present study uses weighting provided by the Census Bureau to limit such error as much as possible.

Beyond sampling error, the Census Bureau (2017) also points out that there is the potential for nonsampling, including error in data entry or editing, or potentially systematic nonsampling error, which could lead to bias results. The Census Bureau "conduct[s] extensive research and evaluation [of] programs on sampling techniques, questionnaire design, and data collection and processing procedures" to try to limit such errors (p.11).

using computer-assisted telephone interviewing (CATI) and finally computer-assisted personal interviewing (CAPI).[10]

Benefits and Limitations of the Data

As described, there are a variety of benefits of the ACS data set. First, there are numerous questions asked in the survey, which provides a wide range of variables to use in the analysis. In particular, the questionnaire asks questions about location of birth, citizenship, location of birth, time of last move, English speaking abilities, and others that could be helpful when considering the US immigrant population specifically. Based on this availability of information useful for research on immigrant populations, existing literature that considers immigrants in the US labor force leverage ACS data (Baum-Snow, Freedman, & Pavan, 2018; Basso, Perri, & Rahman, 2017; Jaimovich & Siu, 2017; Peri, Shih, & Sparber, 2015; Chiswick & Taegnoi, 2007)[11]. See Appendix 5 for an overview of literature that leverages ACS data.

Second, the ACS data has a variable for occupation using SOC coding, which is the same occupational index as is used by Frey and Osborne. Thus, using the ACS data enables a merge with Frey and Osborne data, providing a robust method of calculating automation probability for individuals in the ACS data set, which would not be possible with similarly large data sets, such as CPS. A third benefit is the large size of the ACS PUMS data set, which captures approximately 5% of the US population over the 5 years that the present study evaluates.

[10] Each monthly sample is collected independently, though there are 3 sampling processes occurring at any given time, as individuals from each sample are contacted repeatedly over a three-month period until data is hopefully obtained from the individuals. Based on the 2012 sample, CATI makes up about 7% of interviews, 48% mail, 42% CAPI, and 3% noninterviews.

[11] For example, Jaimovich and Siu (2017) leverage ACS for their research on immigrants in the labor force as they explore the “tendency of the foreign-born to work in innovation, on the page of technical change,” which is accompanied by wage inequality as the past few decades have seen technological advances that grow demand for non-routine labor (25). Basso, Perri and Rahman (2017) also use ACS data to research how immigration leads to higher skill distribution for natives and a slight boost to employment for natives with some skill level. They also evaluate the idea that natives' wages decrease with immigration are mitigated or even reversed due to capital growth. Peri and Sparber (2011) use ACS in their research to evaluate highly educated immigrants’ impact on the labor market, looking particularly at occupational choices for native-born Americans and the substitutability between native and immigrant highly skilled workers.

Despite these benefits, there are limitations to the data set that should be noted. The greatest limitation is that this data set surveys individuals a single point in time, excluding the possibility of using them in a panel that looks at change over time[12]. Second, as discussed, there are challenges with merging the data over a longer time period due to differences in variables across time periods. As such, it is challenging to extend the use of the data set for the purposes of this research beyond the 2012 to 2016 data set, though considering a larger number of years could be helpful. There are also a number of missing variables that are necessary for the present research, such as how automatable the individual's job is and what growth looks like within their industry and geographic region. Therefore, the ACS data must be merged with several other data sets to conduct the present research. Finally, there is the possibility of underdamping for illegal immigrants, because these individuals may be less likely to respond to ACS questionnaires. If this is the case, there's the possibility for immigrant data that is skewed more towards skilled immigrants entering the US with an H-1B visa rather than illegally.

Other Considered Data Sets

For a review of data sources used by existing research addressed in the literature review, see Appendix 3. The three primary data sources used for research relating to automation and the SBTC hypothesis are CPS, ACS, and Census data. Though the ACS only started in 2000 while CPS started in 1940, CPS surveys about 60,000 people per month while ACS surveys 250,000 monthly, making ACS "the largest household survey in the United States" (Census Bureau). The CPS also doesn't include non-institutional group quarters, while the ACS encompasses all group quarters starting in 2006. ACS response is also mandatory, so response rates tend to be very high (only 3% nonresponse), which is another benefit.

Because the present study focuses on the impacts of automation on immigrants by education level, the ACS seems to be the best fit with my research topic, considering that

[12] While others has leveraged the ACS to run panel reseach, these studies segment the population, for example, by commuting zones rather than considering individuals over a period of time.

existing research relating to immigration and labor largely uses ACS, though CPS is used more widely for general SBTC research. The ACS's size and inclusion of group living quarters, as well as comprehensive survey methods, makes it an appealing data source, particularly because the present study does not require decades worth of data, as the present study focuses on the current labor environment. The ACS includes most variables needed for the present study, though there are some variables that need to be merged into the data set, as previously described.[13] Importantly, the CPS data also doesn't have a variable to connect occupation to Frey and Osborne's automation probabilities, which are connected in the ACS data set through the 2010 SOCs. Therefore, finding automation probabilities for CPS data would be challenging.[14]

Another data source that is frequently used to evaluate the SBTC hypothesis is US decennial census data. The decennial census has the benefits of high response rates and many years of data, as the decennial census started in 1790. Despite these benefits, because my research focuses on recent years, a decennial census makes less sense than the constantly updated ACS data set.

Incorporation of Measurement of Technological Change

An essential variable in considering how workers are affected by technology advances is how likely each occupation is to be automated. Different existing empirical research has evaluated automation using different methods[15]. Building on the work of authors such Blinder

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[13] One variable CPS offers that ACS doesn't is a binary for whether respondents live in a metropolitan area, which is a variable valued by Lewis (2011) in research on immigrants in the labor force. However, because this variable is not essential for the present study, ACS remains the most useful data set for the study.

[14] Autor, Levy, and Munane (2003) leverage a question in the CPS data that asks individuals whether they use a computer directly at work. This approach is more simplistic that the Frey and Osborne probabilities leveraged in the present study, as the computer usage binary considers use of a single type of technology for a particular worker rather than evaluating automation of job categories more holistically.

[15] Card and DiNardo (2002), for example, evaluate technological change in the decades leading up to the turn of the century by simply evaluating change in employment over time during this period, during which they know there were substantial innovations in technology along with the advent of the computer. Haskel and Slaughter (2002) measure automation as "the share of computer investment in total investment averaged for the two years 1982 and 1987" (1771), and Brasch (2012) similarly looks at capital investment. Autor, Levy, and Murnane (2003) evaluate automation using the CPS question of whether or not the individual uses a computer directly in their jobs. Rather than using technical change as an actual variable, Autor and Acemoglu (2012) look at change over time of incomes at a state level depending on education level, and relatively skill level.

(2009) and Jensen and Kletzer (2005, 2010), Frey and Osborne (2017) define tasks as non-substitutable with computers when the tasks have a focus on perception and manipulation, creative intelligence, and social intelligence. In doing so, they expand on the more simplistic task framework of Autor, Levy, and Murnane (2003), which assumes that technological advances substitute for routine labor and complement nonroutine labor. To further strengthen the technique, the authors hand-labeled 10% of occupations (702 2010 SOC jobs) to ensure accuracy in the methodology. This model provides a more comprehensive view of automation than in past models defining automation because, rather than assuming that all routine jobs are complements to new technology and nonroutine jobs are substitutes, Frey and Osborne model draw several different elements of job task composition into the model.

Automation probabilities can be merged with ACS data based on 2010 SOC codes that are part of both ACS data and Frey and Osborne's automation probability index. Frey and Osborne published their findings in 2017, but a working copy of their document and probabilities table was available in 2013, making their calculations for automation probabilities perfectly timed for the ACS data in present study. The present study leverages these automation probabilities as a way to capture technological change.

Data Management

There were numerous merging and recording processes needed to prepare the ACS data for analysis. The ACS 2012-2016 data is split into 8 files, including 4 housing and 4 personal records files, which were all merged to obtain one row for each individual in the survey. In this process, all 15,681,927 personal records were matched with their corresponding housing record for 2012-2016, though 601,028 housing records did not have individual records.

Two variables from two separate data sets were merged into ACS. Automation probabilities from Frey and Osborne's (2017) computerization probabilities index were merged into ACS using 2010 SOC codes. GDP growth rates by industry and state were also merged into the data after copious recoding to match 2012 NAICS codes in ACS to the broader 2012 NAICS groups included in the Bureau of Labor Statistics (BLS) GDP data. Subsequently, GDP variables were merged into ACS using 2012 NAICS and 2010 Census definitions of states. Following this merge process, I created GDP growth variables for each year between 2012 and 2016[16]. There were many missing 2017 growth rates, making it impossible to calculate GDP growth in 2016. In these cases, 2015 GDP growth is used as a substitute for 2016 data. In addition to the merging, a variety of variables are recoded, including education, immigration, race, married, sex, intergenerational household, English, STEM education, mobility, disability, and industry (NAICS). A particularly time-intensive recoding process was categorizing the industry codes in the NAICS variable into 19 broader job categories to allow for easier data analysis. A new variable was created for wages to account for inflation by multiplying the wage variable by an annual inflation adjustment factor included in ACS data.

To ensure accuracy, the present study also uses weighting for the ACS data. ACS provides personal weights and 80 replicate weight variables, which are used to ensure accurate weighting of individuals in the sample, as well as correct errors. These 81 variables were used to run all regressions and summary statistics.

Discussion of Variables, Summary Statistics, and Trends

The present discussion is based on summary statistics and trends in the 2012-2016 ACS data. See tables in Appendix 3 for summary statistics broken down by immigration status and education level.

Real Wages

Immigrants have a larger income gap between those who have a bachelor's verses those who do not than native-born Americans. Overall, real mean wages in the sample have been trending upwards from 2012 to 2016, with total change of 10.9% and CAGR of 2.1%, indicating a bit

[16] There were several industries within states that had very low GDPs and for some of the years, they had no GDP listed at all. In these cases, null values were entered.

higher growth than the national trend, which only suggests small upward movement in recent years (Pew, 2018). Native-born and immigrant populations both experience real wage growth, though native-borns have slightly higher wages ($p<.01$), and in both groups, those with a bachelor's have consistently higher wages than those without ($p<.01$).

Automation[17]

Automation is used in the present study as a proxy for technological change and is measured using a job automation index created by Frey and Osborne (2017). Among immigrants and native-borns, the discrepancy in mean automation probabilities between those with and without a bachelor's reflects the SBTC hypothesis, as those with higher education levels have jobs that are less likely to be automated ($p<.01$). Additionally, immigrants have a slightly higher mean probability of having their jobs automated than native-borns ($p<.01$). Interestingly, there is a smaller difference in job automation probability means by education level for those born in the US compared to immigrants. In line with these findings, of those without a bachelor's degree, immigrants have a larger mean automation probability than native-borns ($p<.01$); conversely, of those with a bachelor's, immigrants have a lower mean automation probability ($p<.01$). These findings likely link to the bimodal distribution of education levels among immigrants as compared to native-borns. Mean automation probability in the sample declined slightly from 2012 to 2016, with a total decrease of 2.8% and a CAGR of -0.6%, likely reflecting elimination of jobs that had high automation probabilities, leaving remaining jobs with a lower mean automation probability. Immigrant mean probabilities are slightly more volatile, though both immigrant and native-born mean automation probabilities trend slowly downwards.

Measures of Skill Level

There is some lack of consistency in the literature about what defines workers' skill level. In SBTC hypothesis research, skill level is often identified by the skills required for their job and

[17] While only about one third of responses in the data set that have an automation probability based on the individual's occupation, the majority of responses that don't have a probability assigned lack an automation probability because the occupational code was blank in the ACS.

the degree to which their job tasks are routine. Jobs that are characterized as low and medium skill frequently include routine and predictable tasks, while high skill jobs frequently include nonroutine tasks[18]. Historically, routine tasks have been more substitutable with technology than nonroutine tasks. There are also various ways that skill level is defined in the literature, including education (Manning, 2004), English speaking abilities (Peri, 2012), and STEM educational background (Nathan, 2014). These disparate methods of finding skill level are not individually comprehensive. The present study has a more nuanced approach to addressing skill level, accounting for education level, STEM education, English speaking abilities, job mobility, and disability. Though routine and nonroutine job composition are components of the automation probabilities, they will not be used to determine how skilled workers themselves are.

Education: The present study breaks down education level by those who do and do not have a bachelor's degree, as done in existing literature (Baum-Snow, Freedman, & Pavan, 2018). From 2012 to 2016, the proportion of individuals in the sample with a bachelor's grew 12.4%, with a 2.4% CAGR, reflecting larger proportions of individuals with a bachelor's both among native-borns and immigrants. This upward trajectory is reflective of the national trend towards an increasingly high proportion of adults 25 and older having a college degree (Census Bureau). Immigrants in this sample have a higher proportion with a bachelor's, and national trends similarly reveal that immigrants have a higher proportion of individuals with advanced degrees, though they have a slightly lower proportion with bachelor's alone and a significantly higher proportion with less than a high school education[19].

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[18] Routine jobs involve a minimal amount of reasoning, personal communication, and expert mastery, typically including jobs such as manual labor in manufacturing or a secretarial position. Frey and Osborne (2017) describe non-routine, on the other hand, labor as including perception and manipulation, creative intelligence, and social intelligence. This is the labor that Autor (2015) calls "abstract," which includes "professional, technical, and managerial occupations … [that] employ workers with high levels of education and analytical capability, and they place a premium on inductive reasoning, communications ability, and expert mastery" (12). These positions include doctors, lawyers, business executives, and professors.

[19] These increases in education level are important for the idea of strategic complementarity, which highlights how, as demand for high skilled jobs increases, workers simultaneously increase their education level to become more appealing members of the labor force.

English Speaking Abilities[20,21]**:** There is a higher proportion of individuals in non-English speaking households among immigrants without a bachelor's compared to immigrants with a bachelor's. Nationally, individuals with limited English proficiency (LEP) individuals tend to go into certain areas of work[22] (Batalova & Zong, 2016). Automation could impact non-English speakers differently because enhanced technology could make it easier to do jobs that couldn't previously be done without speaking English. Alternatively, if non-English speakers are largely in low-skill jobs, automation might displace them from routine, low-skill work.

STEM[23]**:** The stem variable determines whether the individual has education in a STEM field. A higher proportion of immigrants are STEM educated than native-borns ($p<.01$), which is in line with existing literature (Hanson & Liu, 2018). From 2012 to 2016, STEM education proportions in the sample were relatively consistent, with 2% growth overall and a 0.4% CAGR. The increased proportion of individuals in the same with STEM education may be confounded by the increase in the proportion of individuals with a bachelor's degree overall.

Mobility: Not surprising, immigrants are more likely to be mobile than native-born Americans ($p<.01$), though the difference in proportions is small. While native-born Americans' mobility is consistent by education level, immigrants with a bachelor's degree have a higher proportion of individuals that are mobile compared to immigrants without a bachelor's degree. The proportion of mobile individuals in the sample remained largely consistent from 2012 to 2016[24].

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[20] From 2012 to 2016, the proportion of individuals in the household who don't speak English decline by 10.4%, with a CAGR of -2.2%. This trend seems to be contrary to the relative national stability of limited English proficiency (LEP) speakers (Batalova and Zong 2016). It is important to note, however, that the variable used from the ACS data is a bit different than whether an individual has limited English proficiency, as the variable in the sample is based on household English speaking abilities.

[21] English speaking is defined as a household where at least 1 person over the age of 14 speaks English as their only language or speaks English "very well."

[22] LEP women are more likely to go into service occupations, while LEP men are more likely to go into service occupations; production, transportation, and material-moving occupations; and natural resources, construction, and maintenance occupations. LEP individuals are also less likely to work in management, business, science, and arts occupations.

[23] Note that an individual must have a bachelor's degree to be considered STEM educated

[24] 1.5% growth over these years

Disability: There is a higher proportion of native-born Americans than immigrant with disabilities[25], which is likely linked to difficulties with emigration for disabled individuals. Among both immigrants and native-borns, there is a higher proportion of individuals with disabilities among those without a bachelor's than those with a bachelor's. The proportion of individuals in the sample with reported disabilities has been relatively consistent[26].

Demographics

Immigration: From 2012 to 2016, the proportion of immigrants in the sample increased by 3.3%, with a 0.7% CAGR, in line with national immigration growth (Migration Policy Institute). Of those that are native-born, 98% were born on the US, 1% was born in Puerto Rico, Guam, the US Virgin Islands, or the Northern Marianas, and 1% was born abroad of American parents. 52% of immigrants in the sample are US citizens by naturalization and 48% are not US citizens. Of the immigrants in the sample, 47.3% are from Latin America, 32.1% from Asia, 13.4% from Europe, 4.1% from Africa, 2.5% from Canada and Bermuda, and 0.6% from Oceania and at Sea.

Age: Age for those with at least a bachelor's degree is higher than without a degree, which is in line with the idea that acquiring a degree requires time. On average, immigrants are older than native-borns ($p<.01$), though when looking only at those with a bachelor's degree, immigrants are younger, on average, than native-borns, mirroring Kerr, Kerr, and Lincoln's (2015) findings that skilled immigrant workers tend to be young. Mean age increases marginally from 2012 to 2016, with growth of 2.1% with a 0.4% CAGR, reflecting the national trend that the percentage of the population age 65 and over increased over this period (Ortman, Velkoff, & Hogan, 2014).

Race: Race mixes vary by education level, with a higher proportion of white individuals among those with bachelor's than without a bachelor's ($p<.01$).Race is evaluated using a binary for white versus nonwhite in the present study. Interestingly, in this sample, there are more nonwhite individuals among immigrants with a bachelor's than immigrants without, while with native-

[25] Disability in the ACS includes individuals who are deaf, blind, and limiting physical, mental, or emotional conditions

[26] 2.7% increase from 2012 to 2016 and a 0.5% CAGR, though the increase is only about 0.5 percentage points.

born workers, there are more nonwhite individuals among the college educated. A confounding factor is that Hispanic people are included in the white population. The proportion of nonwhite individuals in the sample changed very marginally from 2012 to 2016[27], reflecting a national trend towards a smaller proportion of white individuals in the US (Cohn & Caumont, 2016).

Married: Marriage rates vary by immigration status and education level, with immigrants and those with a bachelor's degree having a higher average marriage rage ($p<.01$). The proportion of those married remained relatively consistent from 2012 to 2016[28], reflecting the relative stability of marriage rates nationally in recent years, despite the drastic drop in marriage rates in the past 50 years overall (Cilluffo & Cohn, 2018).

Gender: The proportion of women is higher among immigrants than native-borns ($p<.01$). For native-borns, there is a higher proportion of women among those with a bachelor's degree than those without, while for immigrants, there is a lower proportion of women among those with a bachelor's degree than those without ($p<.01$). Proportion of women in the sample remained relatively consistent from 2012 to 2016, the proportion of women only decreasing 0.4%.

Region: There is a higher proportion of individuals in this sample from the South than any other region, followed by the West. The West and Northeast have a higher ratio of individuals with bachelor's degrees to total individuals from the region and immigrants to total individuals from the region compared to the Midwest and South. This trend reflects a migration towards the south, particularly among minorities (Leibbrand, Massey, Alexander, & Tolnay, 2019).

Intergenerational Households: The proportion of individuals in intergenerational households is higher among those without a bachelor's degree than among those with a bachelor's ($p<.01$) and among immigrants than among native-borns ($p<.01$). Proportion of individuals living in intergenerational households remained relatively consistent in the sample from 2012-2016, growing only 0.9% over the 5-year period, with a 0.2% CAGR. Nationally, the percentage of

[27] 1.4% growth overall and a CAGR of 0.3%
[28] 1.1% growth over the 5 years with a 0.2% CAGR

individuals living in intergenerational households is increasing, likely linked to the financial crisis (Cilluffo & Cohn, 2018).

Methodology

The present study leverages a regression to see what the impacts of automation are on wages. Because the ACS data is does not allow for a panel, the study leverages an OLS regression without controlling for fixed or random effects[29]. The dependent variable is log of real wages, with log used to control for a wide spread and outliers in wage data. Primarily independent variables include automation probability as an indicator of technological change and immigration status. The regression also includes a variety of variables to explain skill level, including education level, STEM education in college, mobility, disability, and English speaking abilities. The model also includes demographics such as age, race, marriage status, and sex.

In considering the SBTC hypothesis, past research in the area uses different dependent variables to evaluate changing employability of high skilled versus low skilled workers[30]. Rather than evaluating worker displacement or employment rates, as others have done in the past (Beaudy, Green, & Sand, 2016; Goos & Manning, 2007), this study considers wages. There is precedent for using wages as the dependent variable in evaluation of the SBTC hypothesis (Autor & Acemoglu, 2012; Card & DiNardo, 2002)[31], and the reason for using real wages in the present study rather than employment itself is first to evaluate how wages specifically compare

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[29] Given that the present study seeks to compare immigrants to native-borns and also consider a variety of metrics for skill level, running a panel is not possible. While the data could have been pooled by immigration status to evaluate impact of automation on wages over time, such pooling would drastically limit the number of data points for the 5 years of data in the data set. Accordingly, cross-sectional analysis is used in the present study.

[30] Card and DiNardo (2002) and Haskel and Slaughter (2002), for example, consider wages. Autor and Acemoglu (2012) similarly look at the college-high school wage gap. Autor, Levy, and Murnane (2003) look at change in task input within industries. Goos and Manning (2007) consider employment levels in particular occupations, and Beaudry, Green, and Sand (2016) similarly consider employment rates from 2000 to 2010.

[31] Card and DiNardo's (2002) research leverages wages, and wage inequality specifically between low and high skilled workers' hourly and annual salaries, to evaluate the validity of the SBTC hypothesis by looking at how the wage gap has shifted over time with implementation of new technology, such as the computer. Similarly, Autor and Acemoglu (2012) use change in college-high school log wage gap and changes in log per capital income as the dependent variables in two separate regressions.

for college educated and non-college educated workers by immigration status rather than just looking at displacement.

Given that this research does not use panel analysis, in order to capture change over time, the present study includes separate regressions for each year in the considered time period of 2012 to 2016. In addition to evaluating all data by year, the present study includes yearly analyses for 6 different sub-categories: native-borns, immigrants, native-borns without a bachelor's, native-borns with a bachelor's, immigrants without a bachelor's, and immigrants with a bachelor's. The reason for separating by immigration status and education level is to capture the individual effects of technological change on immigrant and native-born American groups, as well as to consider how immigrants of various skill levels are affected differently by technological change, using education as a proxy for skill for these regressions[32]. The OLS regression used is:

(3) $\ln(w_i) = C + \alpha t_i + \beta m_i + \rho_p \vec{s}_i + \Theta g_i + \delta_d \vec{d}_i + \eta \vec{I}_i + \varepsilon_i$

where $\ln(w_i)$ is the natural log real wage for individual i, C is a constant, t_i represents technological change's impact on individual i as captured by Frey and Osborne's (2017) automation probabilities, m_i indicates whether or not individual i is an immigrant, $\vec{s}_i$ is a vector explaining individual i's skill level, g_i is the GDP growth rate in individual i's industry and state, $\vec{d}_i$ is a vector with demographics for individual i, $\vec{I}_i$ is a vector of interaction terms for individual i, and ε_i is the error term for individual i. See tables in Appendix 4 for multicollinearity matrix and rational for each interaction term. See table in Appendix 6 for an outline of variables in the regression and a detailed explanation of variable coding, significance, and origin in the ACS

[32] Running separate regressions by gender would also have been useful for this analysis, as men and women behave differently in the labor market, and certain variables may have different variances for men versus women, which could lead to biased estimates if women and men are pooled. However, given that the present study needed to break down the analysis by immigration status and education level to fully address the research question, it would have been challenging to break down the regressions in yet another way. Therefore, gender is included as a demographic variable in the regressions.

questionnaire. See table in Appendix 7 for a list of interaction terms. Additionally, several of the variables (automation probabilities, GDP growth, intergeneration, and mobility) are imputed in order to account for missing data points. See Appendix 7 for imputed variables. Additionally, the regressions exclude agricultural workers, as these workers have fundamental differences from other types of labor considered and thus are omitted to maintain relative consistency between types of workers. Individuals who are not in the labor force are also omitted from regressions. The regressions are run using 80 replicate weights to ensure accuracy of results.

After considering the effects of technological changes on immigrant wages, the present study considers how effects on immigrants vary from technology impacts on US natives' wages. This extension reveal how closely the native-born versus immigrant US labor force follows the SBTC hypothesis and how these groups respond to technological changes given recent data and technological progress, evaluating whether progress impacts wages for one group more drastically than another.

This regression is based on determinants of wage, which is driven by the equilibrium of the demand and supply for labor in the US. Variables are based on research on what drives wage and considering what creates the wage premium for skilled workers, including evaluation of various existing empirical models (Baum-Snow, Freedman, & Pavan, 2018; Haskel & Slaughter, 2002; Card & DiNardo, 2002). This empirical model ties back to the theoretical SBTC hypothesis because, if the SBTC hypothesis holds true for immigrants, we will expect the sign on the impact of automation to be negative for immigrants without a bachelor's degree and positive for immigrants with a bachelor's degree, or at least less negative than the impact on immigrants without a bachelor's. See Appendix 6 for a comprehensive table of expected signs of coefficients for each variable. In the regressions, imputations are used to fill in certain gaps in data, which may make results seem more significant than they actually are.

Results and Discussion

SBTC Hypothesis Applications

The SBTC hypothesis would suggest that automation most heavily impacts low skilled workers. Mean automation probabilities mirror this expectation: while immigrants without a bachelor's have a mean automation probability of 62.9%, immigrants with a bachelor's have a mean automation probability of 37.5%, and while native-born Americans without a bachelor's have a mean automation probability of 60.4%, native-born Americans with a bachelor's have a mean automation probability of 38.0%. This research extends existing literature on the SBTC hypothesis by revealing that currently, the trend that workers of lower skill levels more frequently have jobs that are prone to automation than higher skilled workers is true both for native-born and immigrant workers. A further contribution is that the gap between automation probabilities for immigrants of different skill levels is larger than the gap between automation probabilities for native-born workers. Therefore, the general framework of the SBTC hypothesis not only applies to the US immigrant population but is actually even more strongly applicable among immigrants.

Also a novel conclusion, however, is that the SBTC hypothesis is not reflected in the magnitude of automation on wage impact, particularly for immigrant workers without a bachelor's degree. Though immigrants without a bachelor's have the highest mean likelihood of having their job automated, automation has the lowest impact on their wages, a conclusion which is likely linked to the fact that this group of workers has lower wages to begin with, so the dollar amount that wages can shift is smaller than for those with higher wages.

Unpacking the Effects of Immigration Status on the Impact of Technological Change

As expected based on existing literature, there is a negative impact of automation on wages overall and for immigrants specifically ($p<.01$), as well as a negative impact of being an immigrant on wages ($p<.01$). The negative effect of automation on wages is to be expected based on existing literature (Acemoglu & Autor, 2011). Similarly, being an immigrant tends to result in lower wages, which is in line with existing research (Bonikowska, Hou, & Picot, 2011).

Automation also has a larger negative impact on wages for native-born Americans than for immigrants. This difference in magnitude appears to be driven, somewhat unexpectedly, by a relatively minimal negative impact of automation on wages of the immigrant population without a bachelor's. While automation causes only a slightly smaller decrease in wages of native-born workers without a bachelor's than native-born workers' wages with a bachelor's degree, automation causes a significantly smaller decline in wages of immigrant workers without a bachelor's than immigrant workers' wages with a bachelor's degree.

At least part of this discrepancy likely stems from the fact that immigrants have a wider real wage gap between those with and those without a bachelor's degree than native-borns do, as demonstrated by summary statistics (see Appendix 3). This difference by immigration status likely occurs because immigrant without a bachelor's degree tend to have lower education levels that native-born Americans without a bachelor's, while immigrants with a bachelor's degree tend to have higher education levels that native-born Americans with a bachelor's degree, creating a bimodal education distribution among immigrants (Census Bureau, 2015). Presumably, higher wage gaps lead to a larger difference in the ability of automation to drive large wage declines, measuring wages in terms of dollars rather than percentage change.

Low wages may also be more affected by automation than illustrated by the model because there may be overflow effects onto low skill workers from high skill automation. When high skill workers are displaced by automation, they may take jobs that they are overqualified for, taking the job away from someone with lower skill level. Therefore, both automation of low and high school workers have the potential to drive down wages among low skill immigrants even more than is demonstrated by these results.

Skill Level

Results indicate that the effects of skill level on wages are in line with existing research. Education level has a positive effect on wages, which is in line with existing research on the relationship between education level and wages (Ichim, Neculita, & Sarpe, 2018). The magnitude of the impact of education level on wages is larger for native-born Americans than for immigrants, a difference that is likely based on the difference in education distribution between immigrants and those natively born in the US (Census Bureau, 2016). Immigrants have both a higher proportion of individuals with advanced degrees and of very low education levels than native-born Americans. The education spread for immigrants is similarly bimodal in the ACS data. Therefore, immigrants' education level is more polarized, as there are more individuals with very low levels of education and with education beyond a bachelor's degree than with native-borns. This polarization is likely leading to a larger effect of education on wages.

English speaking abilities have a negative impact on wages, revealing that, as expected, those from non-English speaking households have lower wages (Lewis, 2011). STEM education, on the other hand, has a positive impact, indicating that those with a STEM bachelor's degree have higher wages than those without STEM education, which is as expected (Oreopoulos & Petronijevic, 2013). Disability, as expected, also has a negative coefficient, meaning that individuals with disabilities have lower wages (Gannon & Munley, 2009).

Though mobility has a positive coefficient when considering the pooled data regression, when regressions are broken down to consider smaller subsets of data based on immigrant status and education level, some of the effects on wages are negative. Mobility, as measured by whether or not the individual has moved in the past 12 months, had a positive effect on wages of native-born Americans without a bachelor's degree but a negative effect on wages of both native-born American with a bachelor's degree and immigrants. These results counterintuitively indicate that mobility, which is meant to be a proxy for skill, is correlated with lower wages.

These results may be confounded by the fact that there is no way to detect whether the individual moved because they wanted to, indicating that they had job mobility, or because they had to.

Considering these metrics of skill level separates the present study from other similar analyses of the SBTC hypothesis because other research has a less comprehensive evaluation of skill level, not considering all of these skill metrics together. Additionally, while some studies consider STEM as a skill indicator, they primarily focus on STEM workers rather than considering STEM-educated workers in comparison to low skill workers. Finally, very few existing studies account for disability as a skill metric, leaving a hole in existing research.

Demographics

Demographic characteristics also have a statistically significant effect on wages. Being nonwhite has a statistically significant, negative effect on wages, which is in line with existing research (Ananat, Shihe, & Ross, 2018). Age has a positive, statistically significant effect on wages, indicating that older individuals tend to have higher wages, likely because older individuals may be more likely to be more experienced. Similarly, Cardoso, Guimarães, and Verjão (2011) find that wages tend to peak around age 40 to 45, which supports regression results that wages climb at least until this peak age. Marriage has a positive effect on wages, which is expected based on existing research (Geist, 2017), those research on this topic has displayed mixed results. Gender has a negative effect, which is in line with existing literature indicating that women have lower wages than men (Blau & Winkler, 2018). Intergenerational household is also negative interestingly, indicating that individuals in intergenerational households have lower wages. The negative effect is stronger in magnitude for those with a bachelor's degree than those without a bachelor's, both for immigrants and native-born Americans, revealing that the wage impact of living in an intergenerational household is larger for those who have been to college.

GDP growth rate has an unexpectedly negative coefficient. Because real wage growth is associated with GDP growth (Estevao, 2005), the coefficient on GDP growth was expected to be positive. However, because this study is not a panel, we are unable to compare GDP growth to real wage *growth* but rather to real wages more generally. In evaluating which industries are experiencing the most growth, industries with the highest real wages (e.g. Extraction, Utilities, Finance, and Information) have relatively low GDP growth rates, indicating that high paying industries may tend to have lower GDP growth rates, creating a correlation between low GDP growth rates and high wages.

Industry Breakdown

As existing literature on immigration and automation points out, some of the differences in wages and automation between immigrants and native-born workers may stem from differences in industries that immigrants and native-born workers tend to work in (Peri, 2012; Lewis, 2011; Peri & Sparber, 2009). Accordingly, it is important to assess industry breakdown and how heavily automation impacts industries where immigrants are concentrated, particularly when considering that the magnitude of the negative effect of automation is smaller for immigrants than native-born Americans. See Appendix 9 for breakdown of automation probabilities by industry and concentration of immigrants and native-borns in each industry.

There are five industries that are particularly likely to automate jobs (mean automation probability > 0.5) in upcoming years where immigrants tend to concentrate in higher proportions than native-born Americans. These industries include construction; arts, entertainment, and creation; manufacturing; professional and business services; transportation and warehousing; and wholesale trade. By comparison, there are only two highly automation-prone (auto. probability > 0.5) industries where there is a higher concentration of native-borns than immigrants: financial activities and retail trade. 64.4% of immigrants are in industries with over 50% likelihood of automation compared to only 59.7% of native-born Americans in these industries. Accordingly, while automation has a larger negative effect on native-borns' wages than immigrants' wages, there are a higher proportion of immigrants in fields that are experiencing automation as compared to the proportion of native-borns in these fields. Breaking these groups down by education level reveals similar findings; though immigrant wages are less negatively affected by automation, immigrants both with and without a bachelor's degree are more highly concentrated in industries with high probabilities of automation compared to their native-born counterparts. The idea that immigrants without a bachelor's are heavily impacted by automation despite the low wage impacts of automation is reflected in the fact that immigrants without a bachelor's degree have the highest mean automation probability compared to immigrants with a bachelor's and all native-borns.

Interaction Terms

Interestingly, the interaction between education and automation is positive. Therefore, when an individual has a bachelor's degree, the negative effect of technology on wages is smaller than it would be for those without a bachelor's. As automation rises, the predicted wage benefits of a bachelor's degree are reinforced by technological advance, which seems to point towards the SBTC hypothesis idea that because technology and skilled labor are complements in production, skilled workers are less hurt than less skilled workers or may even benefit from technological change. This interaction term, however, is negative among immigrants, indicating that as the probability of automation increases for immigrants, the benefits of a bachelor's degree on wages declines and for those with a bachelor's degree, the effects of automation cause wages to decline more than they are predicted to decline without a bachelor's.

The interaction term between race and immigrant is positive while both race and immigrant have negative effects on wages, indicating that while being an immigrant and being a minority individually decrease wages, being both an immigrant and a minority makes the negative effect on wages smaller. The same relationship holds for the interaction term between immigrant status and being in an English-speaking household, though not always with statistical significance. Somewhat unexpectedly, the interaction term for married and age is negative, indicating these if a person is married, the wage growth as age increases actually are diminished. These results may be linked to familial responsibilities that frequently accompany marriage later in life, such as raising children that may leave less time and energy to earn high wages. Age and mobility have the same interaction implications, though this interaction is not statistically significant in most of the regressions.

Overall Fit and Limitations

Overall, the model is a reasonable fit considering that low R^2 values are common for cross-sectional studies. In this study, R^2 indicates that for the aggregate OLS by year, the model explains about 30% of the variance in wages. When breaking down the data into smaller groups by immigrant status and education level, the model continues to be a relatively good fit, explaining between 13% and 30% of the variance in wages, according to R^2, depending on the subset of data. The Wald Chi^2 test suggest the model is a good fit at the 1%[33].

One limitation is that because the present study evaluates individuals rather than an aggregation of individuals, and because the ACS samples different individuals every year, a panel was not possible. However, looking at individuals enables unique consideration of various skill metrics that has not been done in other studies. Additionally, though a panel would have enabled more comprehensive evaluation of change over time, the existing research enables us to parse out what is occurring on an annual basis and compare the effects of technological advancement on multiple groups. Additionally, I used a weighting procedure to try and ensure representative and accurate data. However, there is still potential for some bias in the data if there are fundamental sampling issues that the Census Bureau failed to address in creating its weights. Finally, because the present study considers 5 different still metrics, unlike studies have done in the past, it is impossible to have a single metric that comprehensively measures skill, making analysis of holistic skill challenging.

[33] Wald chi^2 rejects the null hypothesis that the model is not a good fit.

Conclusion

This research reveals that technological change has negative effects on wages for the US immigrant workforce, similarly to how existing research has revealed the negative impacts of automation on the US workforce more generally (Acemoglu & Autor, 2011). The findings in this research provide novel contributions to the field of labor economics, as they suggest that real wage changes do not follow the SBTC hypothesis, both among immigrant and native-born workers. This insight fits into a vast body of SBTC hypothesis critiques (see Appendix 2). However, in univariate analysis, mean automation probabilities for low skill workers are lower than automation probabilities for high skilled workers, both among immigrants and native-borns, which adheres to the SBTC hypothesis. Additionally, the present study compares immigrants by skill level and contrasts immigrants with native-borns, while most existing literature analyzes one of these areas specifically. Consequently, this research reveals that low skilled, immigrant workers are at highest risk of automation and uniquely highlights that the bimodal distribution of immigrant skill level leads to a larger gap in automation probability between high and low skilled workers among immigrant workers than among native-born workers. These univariate findings assert that the SBTC hypothesis is even more strongly valid among immigrants compared to native-born workers when considering mean automation probabilities rather than impacts of automation on real wages.

Beyond significant findings that contribute in fresh ways to the vast body of research on this topic, the present study also takes a more nuanced, comprehensive approach to analyzing the SBTC hypothesis than much of the existing literature. First, the present study leverages the Frey and Osborne (2017) automation probabilities index to quantify technological advances. Frey and Osborne's approach to addressing job automation are more comprehensive than existing techniques, leading to a more nuanced approach to technological advance quantification in the present study. Additionally, while the majority of existing literature focuses on one or two skill metrics, the present study accounts for 5 different measures of skill, making this approach more comprehensive.

Future research is needed on how AI and machine learning will influence the labor market in upcoming years, as the labor market is currently in the early stages of experiencing the effects of these new technologies. While this study focuses on the wage implications of technological advances on the immigrant workforce, it would be useful to also consider other areas where technological change may affect immigrants and workers more generally. Finally, future research should conduct a cross-country comparison for how technological change affects immigrant workers, particularly in the face of changing immigration policies.

The implications of this research are vast. We have yet another critique of the SBTC hypothesis, which is that the theory does not predict real wage changes specifically, as those with higher wages to begin with will be disproportionately hurt by automation on a dollar-for-dollar basis compared to those with lower wages. More importantly, the research reveals that the immigrant wage gap for low versus high skilled workers is even more concerning than the wage gap for native-born Americans, highlighting that policy aimed at diminishing this gap should be focused particularly at immigrants. Skilled immigrants with STEM backgrounds, who primarily come from Asia currently, are well positioned for the changing technological environment, as they will lead the charge towards innovation. However, while skilled immigrants have low probabilities of automation compared to other subsets of the labor force, skilled immigrants are disproportionately represented in manufacturing and professional and business services as compared to their native-born counterparts, both of which are industries that face high probabilities of job automation in upcoming years. Additionally, skilled immigrant workers can expect wage changes as technologies continue to advance.

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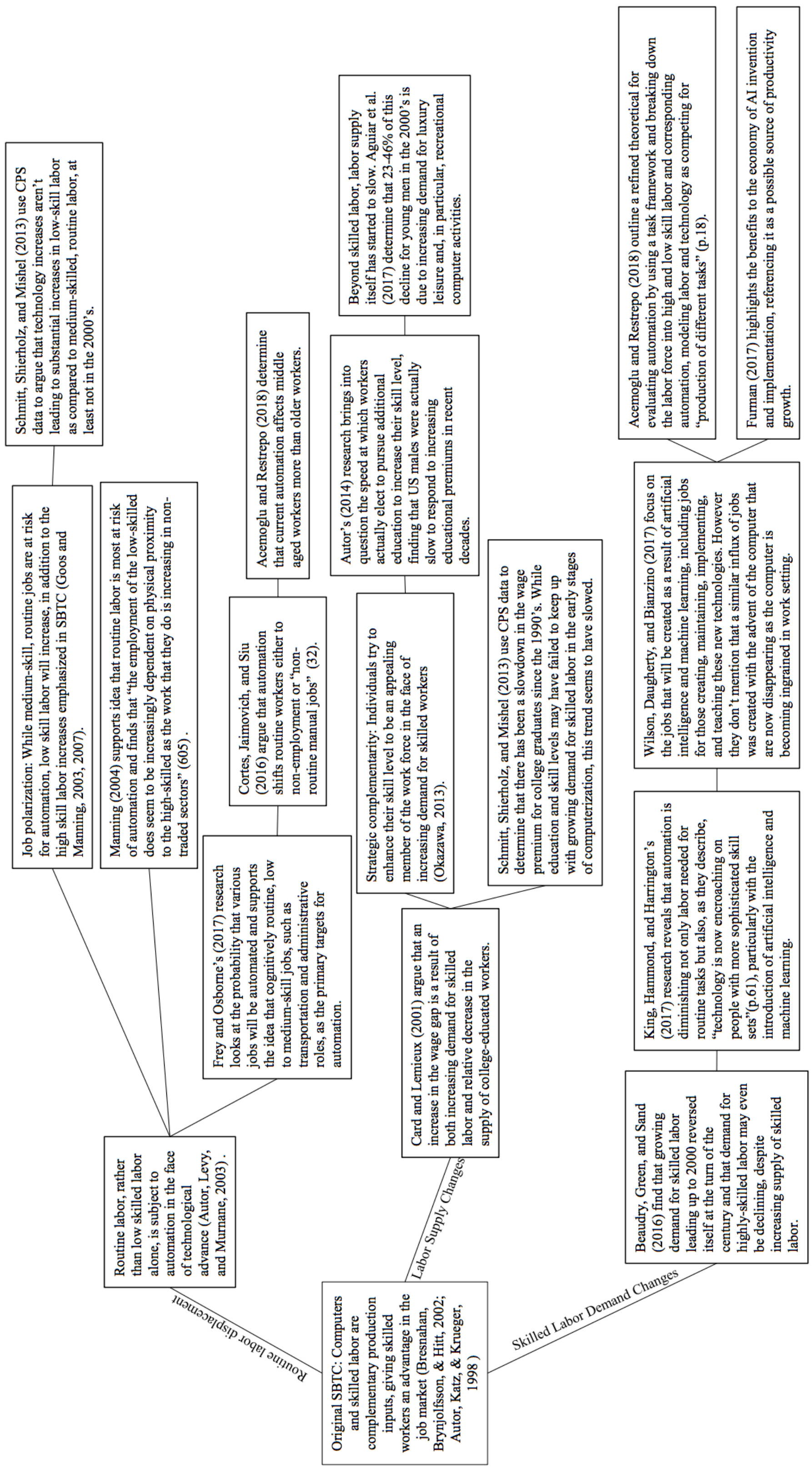
Appendix

Appendix 1: Flowchart of SBTC Literature



Appendix 2: Table Detailing Extensions and Critiques of the SBTC Hypothesis

Author	Year	Critique/Update to SBTC Hypothesis
Mishel and Bernstein	1994, 1998	Questioned the validity of the hypothesis that technology was driving wage and income inequality, as technological change had been relatively constant throughout the 20th century but didn't seem to be previously linked with changes in inequality. However, research done too early to account for impacts of computerization around the turn of the century/more recent technological advances.
Card and Lemieux	2001	SBTC is not solely to blame for the widening wage gap but rather that the labor force isn't becoming educated quickly enough to keep up for increasing demand for skilled labor. Increase in wage gap is a result of both increasing demand for skilled (college-educated) labor and relative decrease in the supply of college-educated workers
Autor, Levy, and Murnane	2003	Find that the lowest skilled jobs are not always the ones being replaced but rather routine jobs, and that declining prices of computer capital drives SBTC
Goos and Manning	2003, 2007	SBTC hypothesis is missing a key idea that the authors term "job polarization," which is the idea that while medium-skill jobs are at risk for automation, low skill labor will also increase, in addition to the high skill labor increases emphasized in SBTC
Schmitt, Shierholz, and Mishel	2013	Tempers job polarization findings of Goos and Manning (2003, 2007) with findings that the gap that separates the wages of low and medium skilled workers hasn't changed significantly in recent decades. These authors also point out that rising employment in low skill occupations are associated with falling wages. Also counters Card and Lemieux's (2001) findings on slowness of labor force's skill level adaptability by illustrating that education and skill levels now keep up with growing demand for skilled labor.
Autor	2014	Builds on Card and Lemieux's (2001) findings by bringing into question the speed at which workers actually elect to pursue additional education to increase their skill level, finding that US males were very slow to respond to increasing educational premiums in recent decades.
Autor	2015	Supports job polarization over SBTC hypothesis, finding that low-skill jobs that increase with technology improvements are largely "manual task jobs (haircuts, fresh meals, housecleaning)" (12)
Beaudry, Green, and Sand	2016	Counters SBTC by indicating that demand for skilled workers is not growing at the rate that it had been and that this demand could even be declining. Assert that growing demand leading up to 2000 reversed itself at the turn of the century and that demand for highly-skilled labor may even be declining, despite increasing supply of skilled labor
Jaimovich and Siu	2017	Do not acknowledge the SBTC hypothesis in their work, opting rather to use what they call non-routine-biased technical change (NBTC), which argues that it is non-routine rather than skill labor that is substituted towards when automation occurs. Research builds on Autor, Levy, and Murnane's (2003) definitions of routine and nonroutine workers.

Appendix 3: Tables of Summary Descriptive Statistics

These summary statistics are based on a sample from ACS data from 2012-2016, using ACS PUMS data housing and personal records. Bolded numbers represent differences significant at the 1% level.

Comparing Native-Borns and Immigrants in ACS PUMS, 2012-2016

Variable	Var label	Native Mean (Std. Err.)	Immigrant Mean (Std. Err.)	t-score (p-val)
Education (bachelor's or not)	No bach. = 0	**0.214**	**0.261**	97.7
	Bach. = 1	(.0004)	(.0007)	(.00)
Real wage (if wage income > 0)	-	**$45,610.27**	**$44,585.00**	-12.6
		($55,592.82)	($56,415)	(.00)
Automation probabilities	Probability	**0.550**	**0.562**	18.0
	from 0 - 1	(0.369)	(0.356)	(.00)
Age	-	**37.188**	**44.228**	-398.3
		(24.052)	(18.588)	(.00)
Race	White =0	**0.227**	**0.527**	475.5

	Minority = 1	(0.419)	(0.499)	(.00)
Married	Not mar. = 0 Married = 1	**0.361** (0.001)	**0.566** (0.001)	-287.1 (.00)
GDP growth rates	-	**0.035** (0.080)	**0.037** (0.079)	14.5 (.00)
Sex	Male = 0 Female = 1	**0.507** (0.499)	**0.513** (0.499)	20.1 (.00)
Intergenerational household	Not inter. = 0 Inter. = 1	**0.079** (0.270)	**0.126** (0.327)	79.3 (.00)
English speaking household	Not Eng. = 0 Eng. = 1	**0.018** (0.131)	**0.244** (0.429)	316.6 (.00)
STEM education (bachelor's)	No STEM=0 STEM = 1	**0.069** (0.253)	**0.127** (0.332)	158.3 (.00)
Mobility	No move = 0 Move = 1	**0.139** (0.346)	**0.154** (0.361)	26.7 (.00)
Disability	No dis. = 0 Dis. = 1	**0.135** (0.342)	**0.098** (0.297)	-129.2 (.00)

Native-Borns: Comparing with a Bachelor's Degree versus without a Bachelor's Degree

Variable	**Var Label**	**No Bachelor's Mean (Std. Erro.)**	**Bachelor's Mean (Std. Err.)**	**t-score (p-val)**
Real wage (if wage income > 0)	-	**$32,567.61** ($34,560.11)	**$73,159.58** ($77,313.70)	634.6 (.00)
Automation probabilities	Probability from 0 - 1	**0.610** (0.343)	**0.388** (0.384)	-443.0 (.00)
Age	-	**36.234** (23.501)	**48.012** (16.479)	603.3 (.00)
Race (white or minority)	White =0 Minority = 1	**0.247** (0.431)	**0.132** (0.339)	-274.5 (.00)
Married	Not mar. = 0 Married = 1	**0.312** (0.463)	**0.614** (0.487)	698.9 (.00)
GDP growth rates	-	**0.035** (0.084)	**0.037** (0.069)	27.4 (.00)
Sex	Male = 0 Female = 1	**0.503** (0.499)	**0.526** (0.499)	67.2 (.00)
Intergenerational household	Not inter. = 0 Inter. = 1	**0.088** (0.284)	**0.031** (0.173)	-267.8 (.00)
English speaking household	Not Eng. = 0 Eng. = 1	**0.019** (0.136)	**0.003** (0.051)	-186.9 (.00)
STEM education (bachelor's)	No STEM=0 STEM = 1	**0.000** (0.000)	**0.321** (0.467)	854.1 (.00)
Mobility	No move = 0 Move = 1	**0.135** (0.342)	**0.133** (0.340)	-4.2 (.00)
Disability	No dis. = 0 Dis. = 1	**0.155** (0.362)	**0.089** (0.284)	-241.8 (.00)

Immigrants: Comparing with a Bachelor's Degree versus without a Bachelor's Degree

Variable	**Var Label**	**No Bachelor's Mean (Std. Err.)**	**Bachelor's Mean (Std. Err.)**	**t-score (p-val)**
Real wage (if wage income > 0)	-	**$29,561.06** ($30,590.47)	**$77,148.20** ($80,641.18)	268.6 (.00)

Automation probabilities	Probability from 0 - 1	**0.638** (0.316)	**0.382** (0.380)	-225.6 (.00)
Age	-	**43.776** (18.885)	**45.982** (14.953)	61.4 (.00)
Race (white or minority)	White =0 Minority = 1	**0.498** (0.499)	**0.608** (0.488)	87.7 (.00)
Married	Not mar. = 0 Married = 1	**0.524** (0.499)	**0.691** (0.462)	173.0 (.00)
GDP growth rates	-	**0.035** (0.084)	**0.040** (0.068)	28.6 (.00)
Sex	Male = 0 Female = 1	**0.514** (0.500)	**0.511** (0.500)	-3.34 (.00)
Intergenerational household	Not inter. = 0 Inter. = 1	**0.141** (0.348)	**0.082** (0.275)	-64.4 (.00)
English speaking household	Not Eng. = 0 Eng. = 1	**0.283** (0.450)	**0.133** (0.339)	-153.6 (.00)
STEM education (bachelor's)	No STEM=0 STEM = 1	**0.000** (0.000)	**0.487** (0.500)	555.1 (.00)
Mobility	No move = 0 Move = 1	**0.143** (0.350)	**0.183** (0.386)	43.8 (.00)
Disability	No dis. = 0 Dis. = 1	**0.112** (0.316)	**0.058** (0.234)	-94.9 (.00)

Appendix 4: Tables Detailing Multicollinearity

Correlation Matrix (correlation over 0.2 bolded and in a box)

	ln(wage)	Education	Auto. Prob	Nativity	Age	Race	Married	GDPgrow	Sex	Intergen	English	STEM	Mobility	Disability
ln(wage)	1.0000													
Education	0.3045	1.0000												
Auto. Prob	-0.2649	**-0.2950**	1.0000											
Nativity	0.0102	0.0307	-0.0085	1.0000										
Age	0.1162	0.0747	-0.0615	-0.0132	1.0000									
diverse	-0.0345	-0.0254	0.0250	**0.4475**	-0.0918	1.0000								
married	0.1924	0.1251	-0.1096	0.0622	**0.2678**	-0.0618	1.0000							
GDPgrow	-0.0036	0.0167	0.0357	0.0082	-0.0087	0.0126	-0.0110	1.0000						
Sex	-0.2142	-0.0173	0.1088	-0.0120	-0.0955	0.0437	-0.1118	0.0201	1.0000					
Intergen	-0.0356	-0.0860	0.0326	0.0913	-0.0130	0.1088	-0.0041	0.0041	0.0251	1.0000				
English	-0.0420	-0.0448	0.0270	**0.2918**	-0.0043	0.1637	0.0000	0.0004	-0.0091	0.0169	1.0000			
STEM	0.1161	**0.5456**	-0.1987	0.1286	-0.0100	0.0670	0.0457	-0.0180	-0.1173	-0.0005	0.0393	1.0000		
Mobility	-0.0669	0.0212	-0.0019	0.0360	**-0.2710**	0.0332	-0.1372	0.0046	0.0041	-0.0410	0.0381	0.0155	1.0000	
Disability	-0.0727	-0.0633	0.0209	-0.0324	0.1398	-0.0145	-0.0160	0.0013	-0.0168	0.0056	-0.0039	-0.0183	-0.0223	1.0000

Correlated Variables and Cross Terms for Regression

Variables	Corr. Coef.	Relationship Rational
Education STEM	0.5456	For an individual to be coded as having a stem education, the individual must by definition must also have a bachelor's degree. Interaction term not included in regression because would create collinearity with the education binary because to have a STEM education, the individual must also have a bachelor's.
Nativity Diversity	.4475	We would expect that immigrants are more frequently non-white than those natively born to the US, particularly given shifts in immigration trends since the 1960s away from European immigration and towards Asian immigration as a source of skilled workers in the US (Hanson and Liu, 2018)
Nativity English	0.2918	We would expect immigrants to more frequently be parts of non-English speaking families
Marriage Age	0.2678	We would expect individuals who are older to more frequently be married

Age Migration	-0.2710	May be driven by more flexibility among younger people who are not tied to certain locations due to familial obligations
Education Automation	-0.2950	Technological advances often automate routine tasks, which is frequently more heavily concentrated among low skill jobs that are less frequently held by individuals with bachelor's degrees (Autor, Levy, and Murnane, 2003)

Appendix 5: Table Showing Data Used in Existing Literature

Bold/italicized highlighted sources indicate research topic pertains to immigration.

Boxed sources indicate sources that use ACS data.

Author	Year	Data Source
Baum-Snow, Freedman, and Pavan	***2018***	***1980, 19990, and 2000 Censuses of Population; 2005, 2006, and 2007 ACS***
Lordan & Neumark	2017	1980 to 2015 CPS
Frey and Osborne	2017	2010 Bureau of Labor Statistics (BLS); O*NET Occupational Classifications
King, Hammond, and Harrington	2017	U.S. Bureau of Labor Statistics and the Office of Occupational Statistics and Employment Projections
Basso, Perri and Rahman	***2017***	***ACS 2009-2011, Census 1950, 1990, 2000***
Jaimovich and Siu	***2017***	***2010 ACS IPUMS, 1980 Census***
Cortes, Jaimovich, and Siu	2016	CPS for 1979-2014
Aaronson & Phelan	2016	O*Net database; 1999 to 2009 Uccupational Employment Statistics (OES); CPS data 2003-2009
Beaudry, Green, and Sand	2016	CPS 1980 to 2013, US Census and ACS 1980 to 2010
Peri, Shih, and Sparber	***2015***	***2005, 2010 ACS, O*NET, 1980, 1990, and 2000 IPUMS 5% census files; US State Department H-1B data***
Autor, Dorn, & Hanson	***2015, 2013***	***1990 Census, 1997 Dictionary of Occupational Titles***
Schmitt, Shierholz, and Mishel	2013	American Community Survey and CPS for 1973-2010
Peri	***2012***	***1960 to 2000 and 2006 Census data, IPUMS, and National Economic Accounts data from the US Bureau of Economic Analysis***
Acemoglu and Autor	2012	CPS data for earnings, 1963-2008 (applied to Katz-Murphy predicted wage gap model); State PCI is from Census Bureau Income Surveys; Census Bureau income survey from 1960-2000 and ACS data from 2006-2008
Lewis	***2011***	***Surveys of Manufacturing Technology (SMT) technology data, CPS, Censuses of Population, Census of Manufacturers***
Chiswick and Taegnoi	***2007***	***2000 Census data's 5% Public Use Microdata Sample (PUMS)***
Manning	2004	US CPS data from 1983-2002; UK LFS data from 1983-2002
Autor, Levy and Murnane	2003	Census Integrated Public Micro Sample of CPS Merged data
Goos and Manning	2003	New Earnings Survey (NES); Labor Force Survey (LFS); US Dictionary of Occupational Titles (DOT)
Bresnahan, Brynjolfsson, & Hit	2002	Survey data collected by authors in 1995-1996 on years 1987-1994 from 379 US companies. Data regarding IT capital levels, compustat measures, and organization and labor force characteristics
Card & Lemieux	2001	CPS
Katz and Murphy	1992	CPS for 1963-1987

Appendix 6: Table with Variables in Regression and Expected Relationship with Wages

Variable	Data Dict Name	Labeling Scheme After Recode	Question in ACS Survey	Expected Relationship with Wages
Ln(wage)	wagp (using adjinc)	Continuous based on annual wage	Q47) Wages, salary, commissions, bonuses, or tips from all jobs. Report amount before deductions for taxes, bonds, dues, or other items.	NA
Automat Prob	NA - merged	Continuous from 0 to 1	NA - from Frey and Osborne	(-) SBTC hypoth. and supporting works highlight that technological growth leads to decreased demand for automatable jobs and, accordingly, decreased wages. Low-skilled workers' real wages declined recently with the advent of new technologies (Acemoglu and Autor, 2011).
Nativity	nativity	0 = native-born in US 1 = foreign born	Q7) Where was this person born?	(-) Research based on data from 1980 revealed the immigrants had lower wages than those natively born to the US (Bonikowska, Hou, & Picot, 2011).
Education	schl	0 = if less than college degree 1 = if college degree or above	Q11) What is the highest degree or level of school this person has COMPLETED? Mark (X) ONE box. If currently enrolled, mark the previous grade or highest degree received.	(+) Higher education levels lead to higher wages and an accompanying wage gap between those with and without college education (Ichim, Neculita, & Sarpe, 2018).
English	lngi	over speaks English only or speaks English 'very well' 1 = No one in the household 14 and over speaks English only or speaks English 'very well'	Q14) How well does this person speak English? (ACS creates lngi variable based on aggregating family members)	(-) Lewis (2011) finds that differences in language abilities between immigrants and native-born workers important in explaining why Hispanic workers may have lower wages, despite comparable education and experience levels to their native-born counterparts.
STEM	fod1p	0 = non-stem primary major 1 = stem primary major	Q12) This question focuses on this person's BACHELOR'S DEGREE. Please pri below the specific major(s) of any BACHELOR'S DEGREES this person has received. (For example: chemical engineering, elementary teacher education, organizational psychology)	(+) STEM education is associated with higher wages (Oreopoulos and Petronijevic, 2013)
Mobility	mv	0 = have not moved in the past 12 months 1 = moved in the past 12 months	Q3) When did Person 1 move into this house, apartment, or mobile home?	(+) Percent of job-to-job transitions in US with a wage increase is 55.6%, compared to only 23.3% percent of job-to-job transitions with a wage decrease (Jolibet, Postel-Vinay, and Robin, 2006).
Disability	dis	0 = no disability 1 = disability	Q17) a. Is this person deaf or does he/she have serious difficulty hearing? b. Is this person blind or does he/she have serious difficulty seeing even when wearing glasses? Q18) a. Because of a physical, mental, or emotional conditionn, does this person have serious difficulty concentrating, remember, or making decisions? b. Does this person have serious difficulty walking or climbing stairs? c. Does this person have difficulty dressing or bathing? The disability variable I am using is an umbrella definition of disability to incoporate physical and cognitive disabilities.	(-) Workers with disabilities tend to have lower wages than workers without disabilities (Gannon and Munley, 2009).
GDPgrowth	NA - merged	Continuous year-over-year growth rate by industry and state	NA - from BLS data	(+) Real wage growth and GDP growth are positively correlated, so we expect individuals working in industries and areas with higher GDP growth rates to have higher wages (Estevao, 2005). However, as Huang, Liu, and Phaneuf (2004) point out, wages are not perfectly correctly with GDP due to stickiness in nominal wages.
Race	rac1p	0 = white 1 = non-white	Q6) What is Person 1's race?	(-) There is a wage premium on being white, meaning that higher wages are typically associated with being white as compared to other racial groups (Ananat, Shihe, & Ross, 2018).
Age	agep	Continuous	Q4) What is Person 1's age and what is Person 1's date of birth?	(+) Cardoso, Guimarães, and Verjão (2011) find that wages tend to peak around the ages of 40-44, while productivity gains peak around 50-54. However, Mahlberg, et al (2013) does not find higher wages at companies with a higher percentage of older workers.
Married	mar	0 = not married 1 = married	Q20) What is this person's marital status?	(+/-) According to Geist (s2017), "Research on men has identified a marriage earnings advantage and a specific earnings benefit of marriage entry (Bellas 1992; Cohen/Haberfeld 1991; Kaufman/Uhlenberg 2000; Nakosteen/Zimmer 1997), but recent work by Killewald and Lundberg (2017) has cast doubt on the causality of this association. Cheng (2015) notes that "research suggests that marriage is associte with a significant wage premium for men, but a much smaller wage premium, or even a wage penalty, for women."
Sex	sex	0 = male 1 = female	Q3) What is Person 1's sex? Mark (X) ONE box.	(-) Economic research, such as that of Blau and Winkler (2018) has well documented analysis that reveals males reeive higher wages than women, at least historically.
Intergen	multg	0 = if not intergenerational household 1 = if intergenerational household	Q2) How is this person related to Person 1? Mark (X) ONE box. (I think ACS ther aggregates family members to determine whether intergenerational)	(-) In the US historically, there has been a relationship between cohabitation and low levels of family wealth (Elman, 1998). When older individuals, particularly men, have the resources to live apart from their families, they frequently do so.

Appendix 7: Table Illustrating Imputed and Cross Terms

Imputed		Cross Terms	
Variable name	**Definition**	**Variable name**	**Definition**
Automat Prob	CompProb imputed	Edu*Auto	eduBin*autoImp
GDP	GDPgrowth imputed	Immigrant*Race	nativity1*diverse
Mobility	migration imputed	Immigrant*English	nativity1*engImp
Intergen	multg1 imputed	Married*Age	married*agep
English	lngi1 imputed	Age*Mobility	agep*mobImp

Appendix 8: Tables of Regression Results by Year

OLS Regressions by Year, 2012-2016:

Ln(wage)	(1) 2012	(2) 2013	(3) 2014	(4) 2015	(5) 2016
Edu	.5611***	.5759***	.5862***	.5927***	.5841***
	(.0048)	(.0051)	(.0042)	(.0040)	(.0043)
Automat Prob	-.5448***	-.5497***	-.5295***	.5309***	-.5390***
	(.0057)	(.0043)	(.0047)	(.0041)	(.0051)
Nativity	-.0710***	-.0686***	-.0748***	-.0612***	-.0603***
	(.0049)	(.0043)	(.0042)	(.0048)	(.0040)
Age	.0318***	.0313***	.0308***	.0298***	.0290***
	(.0002)	(.0001)	(.0001)	(.0001)	(.0001)
Race	-.0729***	-.0811***	-.0727***	-.0691***	-.0681***
	(.0032)	(.0032)	(.0034)	(.0033)	(.0034)
Married	1.4545***	1.4293***	1.4103***	1.3648***	1.3535***
	(.0091)	(.0077)	(.0083)	(.0066)	(.0074)
GDPgrowth	-.1672***	.1355***	-.2731***	-.7496***	-.1623***
	(.01457)	(.0149)	(.0122)	(.0177)	(.0130)
Sex	-.3634***	-.3637***	-.3633***	-.3614***	-.3714***
	(.0019)	(.0023)	(.0022)	(.0020)	(.0019)
Intergen	-.1385***	-.1216***	-.1326***	-.1083***	-.1087***
	(.0045)	(.0045)	(.0048)	(.0050)	(.0041)
English	-.2217***	-.2613***	-.2415***	-.2540***	-.2269***
	(.0179)	(.0178)	(.0172)	(.0178)	(.0164)
STEM	.1456***	.1379***	.1277***	.1311***	.1248***
	(.0037)	(.0038)	(.0039)	(.0033)	(.0037)
Mobility	.0076	.0333***	.0241	.0218*	.0476***
	(.0110)	(.0111)	(.0110)	(.0117)	(.0092)
Disability	-.4195***	-.4094	-.4171***	-.4185***	-.3957***
	(.0056)	(.0059)	(.0057)	(.0051)	(.0040)
Edu*AutoProb	.0619***	.0378***	.0243***	.0141*	.0205*
	(.0077)	(.0080)	(.0072)	(.0071)	(.0078)
Imm*Race	.0783***	.0804***	.0766***	.0598***	.0540***
	(.0061)	(.0059)	(.0073)	(.0071)	(.0056)
Imm*English	.0094	.0600***	.0316	.0303	.0062
	(.0188)	(.0185)	(.0189)	(.0189)	(.0183)
Married*Age	-.02678***	-.0260***	-.0255***	-.0246***	-.0242***
	(.0002)	(.0002)	(.0002)	(.0002)	(.0002)
Age*Mobility	.0001	-.0004	.0003	.0002	-.0001
	(.0003)	(.0003)	(.0003)	(.0003)	(.0002)
_cons	9.1312***	9.1323***	9.1651***	9.2412***	9.2902***
	(.0084)	(.0061)	(.0070)	(.0065)	(.0065)

Observations (N)	28,205,577	28,638,297	28,946,485	29,355,367	29,697,513
R^2	0.2946	0.2930	0.2952	0.2971	0.2931
Wald chi^2	346240.0	501114.8	411964.0	351892.1	443042.0
Prob>chi^2	.000	.000	.000	.000	.000

Significance levels: *** p<0.01, ** p<0.05 significance; * p<0.1

OLS Regression for 2012, broken down by immigration status and education level

	(1)	(2)	(3)	(4)	(5)	(6)
Ln(wage)	Native-born	Immigrant	Native-born no bach.	Native-born bach.	Immigrant no bach.	Immigrant bach.
Edu	.5374***	.6920***	-	-	-	-
	(.0056)	(.0125)				
Automat Prob	-.5661***	-.3787***	-.5453***	-.5044***	-.3808***	.5320***
	(.0060)	(.0128)	(.0060)	(.0073)	(.0143)	(.0171)
Age	.0327***	.0225***	.0366***	.0174***	.0240***	.0183***
	(.0002)	(.0004)	(.0002)	(.0003)	(.0005)	(.0008)
Race	-.0661***	-.0027	-.0736***	-.0440***	-.0190***	.0331***
	(.0032)	(.0054)	(.0038)	(.0052)	(.0065)	(.0103)
Married	1.5471***	.8548***	1.6849***	.9407***	.8122***	.8781***
	(.0100)	(.0237)	(.0119)	(.0141)	(.0243)	(.0466)
GDPgrowth	-.1764***	-.1088***	-.1411***	-.2925***	-.0727*	-.1946***
	(.0170)	(.0307)	(.0194)	(.0286)	(.0392)	(.0576)
Sex	-.3620***	-.3634***	-.3658***	-.3716***	-.3825***	-.3279***
	(.0022)	(.0048)	(.0029)	(.0035)	(.0058)	(.0096)
Intergen	-.1473***	-.0875***	-.1263***	-.2042***	-.0768***	-.1196***
	(.0055)	(.0087)	(.0060)	(.0118)	(.0107)	(.0182)
English	-.2175***	-.2153***	-.2355***	-.0843*	-.1785***	-.3696***
	(.0181)	(.0066)	(.0181)	(.0460)	(.0069)	(.0161)
STEM	.1290***	.2314***	-	.1234***	-	.2358***
	(.0040)	(.0097)		(.0039)		(.0101)
Mobility	.0249**	-.1728***	.1242***	-.3602***	-.0908*	-.3889***
	(.0120)	(.0284)	(.0145)	(.0207)	(.0348)	(.0536)
Disability	-.4328***	-.2996***	-.4453***	-.3937***	-.2773***	-.4033***
	(.0062)	(.0166)	(.0072)	(.0127)	(.0176)	(.0357)
Edu*AutoProb	.0968***	-.1591***	-	-	-	-
	(.0091)	(.0207)				
Married*Age	-.0282***	-.0164***	-.0307***	-.0158***	-.0159***	-.0159***
	(.0002)	(.0005)	(.0003)	(.0003)	(.0006)	(.0010)
Age*Mobility	.0003	.0022***	-.0020***	.0085***	.0007	.0064***
	(.0004)	(.0005)	(.0004)	(.0006)	(.0008)	(.0013)
Constant	9.0896***	9.4268***	8.9119***	10.34904***	9.376***	10.2591***
	(.0081)	(.0225)	(.0093)	(.0129)	(.0232)	(.0453)
Observations (N)	23,762,659	4,442,918	16,104,391	7,658,268	3,040,488	1,402,430
R^2	0.3029	0.2572	0.2537	0.1375	0.1311	0.1390
Wald chi^2	280280.9	70452.3	128480.3	49642.3	16565.8	7389.0
Prob>chi^2	.000	.000	.00	.000	.000	.000

Key: *bach*. indicates individual has bachelor's degree; *no bach*. indicates no bachelor's degree
Significance levels: *** p<0.01, ** p<0.05 significance; * p<0.1

OLS Regression for 2016, broken down by immigration status and education level
Note: 2013-2015 OLS regression outputs omitted; outputs are consistent across years

Ln(wage)	(1) Native-born	(2) Immigrant	(3) Native-born bach.	(4) Native-born no bach.	(5) Immigrant bach.	(6) Immigrant no bach.
Education	.5591***	.7102***	-	-	-	-
	(.0048)	(.0113)				
Automation Prob	-.5598***	-.3906***	-.5383***	-.5281***	-.3928***	-.5910***
	(.0056)	(.0116)	(.0055)	(.0070)	(.0114)	(.0167)
Age	.0298***	.0210***	.0338***	.0152***	.0227***	.0161***
	(.0001)	(.0004)	(.0002)	(.0003)	(.0005)	(.0007)
Race	-.0622***	-.0185***	-.0655***	-.0543***	-.0368***	.0179**
	(.0034)	(.0048)	(.0037)	(.0054)	(.0057)	(.0084)
Married	1.4299***	.8475***	1.5538***	.8980***	.82137***	.8184***
	(.0073)	(.0246)	(.0097)	(.0144)	(.0353)	(.0319)
GDP	-.1783***	-.0650**	-.2555***	.0419	-.2394***	.2859***
	(.0151)	(.0333)	(.0186)	(.0265)	(.0372)	(.0914)
Sex	-.3672***	-.3892***	-.3777***	-.3611***	-.4183***	-.3360***
	(.0022)	(.0054)	(.0023)	(.0037)	(.0063)	(.0094)
Intergen	-.1097***	-.0856***	-.0843***	-.1819***	-.0696***	-.1251***
	(.0048)	(.0090)	(.0055)	(.0097)	(.0098)	(.0182)
English	-.2236***	-.2208***	-.2190***	-.2038***	-.1770***	-.3883***
	(.0164)	(.0070)	(.0181)	(.0383)	(.0080)	(.0144)
STEM	.1066***	.2116***	-	.09961***	-	.2183***
	(.0042)	(.0087)		(.0043)		(.0089)
Mobility	.0777***	-.2322***	.17780***	-.2828***	-.1098***	-.4838***
	(.0105)	(.0304)	(.0124)	(.0184)	(.0369)	(.0570)
Disability	-.4093***	-.2742***	-.4253***	-.3612***	-.2611***	-.3198***
	(.0047)	(.0136)	(.0062)	(.0099)	(.0160)	(.0288)
Edu*AutoProb	.0607***	-.2061***	-	-	-	-
	(.0086)	(.0183)				
Married*Age	-.0253***	-.0156***	-.0276***	-.0141***	-.0157***	-.0136***
	(.0002)	(.0006)	(.0002)	(.0003)	(.0008)	(.0007)
Age*Mobility	-.0002	.0040***	-.0024***	.0072***	.0016*	.0091***
	(.0003)	(.0007)	(.0003)	(.0005)	(.0009)	(.0015)
Constant	9.2541***	9.5578***	9.0804***	10.4692***	9.5129***	10.4056***
	(.0065)	(.0185)	(.0074)	(.0139)	(.0222)	(.0330)
Observations (N)	24,836,519	4,860,994	16,361,783	8,474,736	3,225,359	1,635,635
R^2	.3016	0.2549	0.2508	0.1342	0.1381	0.1378
Wald chi^2	324455.4	89438.5	165304.4	53493.10	17227.31	9775.18
Prob>chi^2	.000	.000	.000	.000	.000	.000

Key: *bach*. indicates individual has bachelor's degree; *no bach*. indicates no bachelor's degree
Significance levels: *** p<0.01, ** p<0.05 significance; * p<0.1

Appendix 9: Tables illustrating automation probabilities and worker representation by industry

Bolded numbers highlight automation probabilities higher than 0.5

Industry mix by immigrant status and automation probability

Industry	% Working Native-borns in Industry	% Working Immigrants in Industry	Mean Automation Probability	SD of Mean
Public Administration	5.2%	2.6%	0.46	0.38
Agriculture, Forestry, Fishing, Hunting	1.6%	2.4%	0.20	0.30
Construction	5.9%	7.3%	**0.59**	0.33
Education Services	10.3%	7.2%	0.39	0.36

Arts, Entertainment, Recreation	9.3%	10.9%	**0.67**	0.34
Mining, Quarrying, Oil/Gas Explo.	0.6%	0.3%	0.48	0.38
Financial Activities	6.2%	5.5%	**0.59**	0.39
Information	2.1%	1.7%	0.48	0.37
Health Services	10.7%	10.7%	0.41	0.39
Manufacturing	9.9%	11.4%	**0.58**	0.38
Military	0.7%	0.2%	0.42	0.35
Professional and Business Services	10.5%	12.7%	**0.56**	0.38
Retail Trade	11.5%	9.5%	**0.65**	0.30
Social Assistance	2.4%	2.5%	0.35	0.34
Other Services (except Public Administration)	4.7%	6.3%	0.43	0.35
Transportation and Warehousing	3.9%	4.2%	**0.70**	0.27
Utilities	0.9%	0.4%	0.44	0.37
Wholesale Trade	2.5%	2.9%	**0.51**	0.37

Workers representation by industry, immigrant status, and education level

	Native-born		Immigrant	
Industry	% without Bachelor's in Industry	% with Bachelor's in Industry	% without Bachelor's in Industry	% with Bachelor's in Industry
Public Administration	4.6%	6.6%	1.9%	4.1%
Agriculture, Forestry, Fishing, Hunting	2.0%	0.9%	3.6%	0.3%
Construction	**7.7%**	**2.3%**	**10.1%**	**2.1%**
Education Services	5.6%	20.8%	4.0%	13.8%
Arts, Entertainment, Recreation	**11.7%**	**4.5%**	**14.2%**	**4.8%**
Mining, Quarrying, Oil/Gas Explo.	0.7%	0.4%	0.3%	0.4%
Financial Activities	**5.1%**	**8.6%**	**3.9%**	**8.8%**
Information	1.7%	3.0%	1.0%	3.1%
Health Services	10.0%	12.4%	8.6%	15.3%
Manufacturing	**11.2%**	**7.5%**	**12.3%**	**10.1%**
Military	0.8%	0.6%	0.3%	0.2%
Professional and Business Services	**8.4%**	**15.2%**	**9.9%**	**18.6%**
Retail Trade	**14.1%**	**6.3%**	**11.0%**	**6.9%**
Social Assistance	2.5%	2.5%	2.7%	2.2%
Other Services (except Public Administration)	5.2%	3.6%	7.9%	3.4%
Transportation and Warehousing	**4.9%**	**1.9%**	**5.1%**	**2.6%**
Utilities	1.0%	0.8%	0.3%	0.6%
Wholesale Trade	**2.6%**	**2.2%**	**3.1%**	**2.6%**