NATIVE-IMMIGRANT WAGE GAPS AND THE GROWING IMPORTANCE OF SOCIAL SKILLS

Abstract

I explore whether the growing importance of social skills played a role in the native-immigrant wage gap increase in the U.S. since the 1980s. Using historical routine employment share to measure cities' likely technology adoption, I show that local labor markets that specialized in routine tasks experienced differential increases in native-immigrant wage gaps, and the result is strongly related to immigrants' English language abilities and other measures of social assimilation. This is consistent with the hypothesis that native workers have an advantage in U.S.-specific social skills, and the returns to these skills have increased due to technology replacing routine labor.

I. INTRODUCTION

While the native-born have earned higher wages than the foreign-born on average in the recent decades (Chiswick, 1978; Alba and Nee, 2003), these wage gaps have been increasing significantly since the 1980s (Figure 1). While a simple explanation is that the more recent cohorts of immigrants have worse human capital characteristics than earlier cohorts, an alternative is that market circumstances have changed in a way that disproportionately rewards skills in which natives have a comparative advantage. This would increase wage gaps between natives and immigrants even if the recent cohorts of immigrants had the same human capital characteristics as the earlier cohorts. This paper formally tests the hypothesis that the growing returns to U.S.-specific social skills are an important factor in driving the increase in native-immigrant wage gaps.

There is evidence that the more recent cohorts of immigrants have worse language skills and lower education levels relative to earlier cohorts. In a series of papers (Borjas, 1985; 1990; 1991; 1995; 2015), Borjas suggests that these changing characteristics might explain the slower rates of assimilation of the more recent cohorts. In this paper, I start by showing that the part of the wage gap that cannot be fully explained by differences in observable characteristics between natives and immigrants also increased since the 1980s. I then use cross-city variation in historical routine task shares to explore whether native-immigrant wage gaps increased more in cities that were more likely to have undergone a more extensive process of technology replacing routine labor, i.e., the routinization process.

A growing body of work documents that the labor market increasingly rewards social skills and a vast literature suggests that this phenomenon is likely to be a product of routinization caused

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by skill biased technological change.[1] The canonical model of skill biased technological change developed by Acemoğlu and Autor (2011) categorizes labor input by tasks and argues that the diffusion of technology greatly reduces the cost of accomplishing routine, codifiable job tasks. The skills and tasks that cannot be substituted away by automation, such as those relying on social-interaction and abilities to read and react to others based on tacit knowledge, are instead complemented by it. As a result, the U.S. labor market has seen growing demand for social skills relative to routine physical skills (Acemoğlu and Autor, 2011; Autor and Dorn, 2013; Autor et al., 2015; Deming, 2017). Similar empirical evidence can also be found in the UK (Card and Lemieux, 2001), Germany (Fitzenberger and Kohn, 2006), and other OCED countries (Atkinson, 2008).

A separate literature investigating immigrants' labor market success finds that changes in the wage structure in the U.S. have caused the increase in wage gaps between natives and immigrants since the 1970s, but the reasons behind such wage structure changes are not explicitly investigated (Butcher and DiNardo, 2002). It is possible that these changes are partly due to the growing importance of host-country-specific social skills. The simple economic theory states that successful transactions occur when buyers and sellers can mutually agree on a price for a good or service that leaves both parties better off, and the process of arriving at such agreement depends critically on the ability of parties to communicate with one another efficiently (Lazear, 1999). While a common language is an obvious prerequisite for effective communication, other types of cultural differences might forestall mutually beneficial transactions (Vigdor, 2015). For example, a Chinese seller accustomed to a culture where price haggling is the norm might set the price of goods higher than the "true" price. In response, buyers in the U.S. might walk away from a viable

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[1] See the following seminal works for a comprehensive survey of the increasing returns to education and social skills: Katz and Murphy, 1992; Bound and Johnson, 1992; Autor et al., 1998; Autor et al., 2003; Acemoğlu and Autor, 2011; and Deming, forthcoming.

transaction after seeing the high list price. Empirically, immigrants who have higher English proficiency are found to be better substitutes for native workers in the U.S. (Lewis, 2013) and earn higher wages than immigrants with worse English language skills (Bleakley and Chin, 2004). Using marriage to a native as a measure of social assimilation of immigrants, Furtado and Song (2015) show that the returns to social assimilation have increased over the past three decades even when holding constant English language fluency. Consistent with the idea that immigrants have a comparative advantage in manual-physical labor-intensive occupations and natives have a comparative advantage in social-cognitive occupations, several researchers have shown that natives increasingly pursue jobs more intensive in communication and language tasks in response to immigrant inflows (Peri and Sparber, 2009; Foged and Peri, 2013). Furthermore, low skill immigrants' concentration in low skill service jobs has been cited as one of the reasons for the general wage polarization in the U.S. (Mandelman and Zlate, 2016).

This paper contributes to these literatures by linking the changes in native-immigrant wage gaps with the routinization process of local labor markets. I argue that native-born workers in the U.S. are relatively better endowed with U.S.-specific social skills because of the language and culture advantages they have over immigrants. Therefore, routinization, which increases the relative price of such skills, is a likely additional factor explaining the growth of native-immigrant wage gaps.

Figures 1 and 2 show that the native-immigrant wage gap movement matches closely with the recent technological development in the United States. During the 1960s and the 1970s, both the average native-immigrant relative wages and output in IT industries were relatively stable. Starting in 1980, both increased significantly and continued to grow in the next two decades until leveling off in the early 2000s. These patterns may be suggestive of a potential link between

routinization induced by technological change and native-immigrant wage gaps, but to provide a clearer causal analysis, I examine whether U.S. cities that were likely to have been most strongly affected by the routinization process between 1980 and 2000 also had the largest increases in native-immigrant wage gaps.

Following the literature, I use the routine employment share of local labor markets before the technological boom to generate plausibly exogenous variation in degrees of routinization during the technology boom. To provide insight into the impact of routinization on native-immigrant wage gaps, I show that Metropolitan Statistical Areas (MSAs) that were historically routine intensive, and therefore more likely to have adopted technology to replace routine-intensive labor, experienced larger increases in native-immigrant wage gaps between 1980 and 2000, even after controlling for observable characteristics of immigrants and natives. This result is robust to including additional years' data and using an alternative measure of the routinization process. By separating the sample according to immigrants' English language skills and other measures of U.S.-specific social skills, I find evidence that consistently suggests that part of the increase in native-immigrant wage gaps was due to increases in the returns to U.S.-specific social skills brought about by technology replacing routine labor.

The remainder of this paper is structured as follows. Section II presents the background and theoretical framework that guides the empirical model. Section III introduces the empirical model, discusses the measurement of key variables, and describes data. Section IV presents and discusses the empirical results. Section V concludes the paper.

II. BACKGROUND AND THEORETICAL FRAMEWORK

The basic firm theory dictates that if two factors of production are imperfect substitutes, a decrease in the relative price of one input can create incentives for firms to substitute the less expensive input for the more expensive input. Since the beginning of the 1980s, the U.S. economy has experienced a secular price decline of new technology in the form of automation. This created incentives for employers to substitute technology for expensive labor in performing workplace tasks. Figure 2 presents IT industries' output share in GDP over time, with a timeline of key events associated with technological progress. The 1960s brought the advent of experimenting with robotics as a means of industrial development. In 1969, Stanford Arm, a 6-axis robot that could move and assemble parts in a continuous repeated pattern, was created. This method of robotic use to perform routine, repetitive tasks has continued to be applied in modern day use. The wide utilization of automation in industries, however, did not start until the 1980s. With the introduction of the first PC, IBM-PC, in 1981, technological development entered a period of great progress in the following two decades, marked by continued improvement of PC computing powers and more advanced graphical interface operating systems such as the Windows. Propelled by these improvements, industrial automation started to percolate into various aspects of production, machines became ever more sophisticated, and robotics became a key area to support industrial development and scientific research (Wallén, 2008). For example, the RFID tag was patented in 1983, which drastically changed tracking, identification and transportation; REX became the world's first autonomous excavation machine in 1985; Carnegie Mellon University unveiled Dante, a walking robot for surveying purposes, in 1993; and NASA's Pathfinder landed on Mars in 1997. A common thread of these innovations is that they can efficiently replace routine labors, and as a result, the share of IT industries' output in GDP soared beginning in 1980 and continued to

experience fast growth throughout the 1990s until diminishing marginal returns slowed down the development in the 2000s. This turning, interestingly, matches closely with the changes in average native-immigrant relative wages shown in Figure 1.

Since a machines' ability to accomplish a task is dependent upon the programmer's ability to write a set of procedures that take into account all possible contingencies, the tasks that current technology perform need to be fairly routine and "codifiable". Therefore, technology continues to substitute labor performing routine physical tasks, hence the term "the *routinization* hypothesis". On the other hand, tasks that rely on human interaction require a capacity referred to in Psychology as the "theory of mind"– the ability to read and react based on tacit knowledge and to "put oneself into another's shoes" (Deming, 2017). Technology thus far has not been able to automate this ability (Autor, 2015). Instead, it complements workers who specialize in social-intensive tasks because it frees these workers from doing the repetitive portion of their daily tasks. For instance, stores could utilize barcode scanners, RFID tags, and computers to automatically display information about products and record transactions in detail. As a result, there is no longer a need for workers at check-out counters doing repetitive tasks. Instead, stores can focus on catering to individual customers' specific needs by employing more customer service associates who can utilize technology to retrieve necessary information quickly and accurately. It is due to this uneven impact of technology on different types of labor inputs that the literature termed the current technological change as "skill biased". Specifically, the routinization process induced by skill biased technological change decreases the relative demand and relative price of routine manual skills, and increases relative demand and relative price of cognitive and social skills. Consequently, studies find that beginning in 1980 occupations that required higher routine task contents started to experience decreases in employment and wages, and occupations that required more cognitive

and social skills experienced significant growth (Plunkert, 1990; Deming, 2017). Workers who tended to have a comparative advantage in social skills, such as highly educated individuals (Acemoğlu and Autor, 2011) and women (Beaudry and Lewis, 2014), also experienced a significant increase in relative wages.

Apart from technology, some suggest that import competition and job offshoring could also exacerbate the decline in demand for routine skills in the manufacturing sector. Acemoğlu et al. (2016) find that import competition from China was a major force behind the reduction of manufacturing employment in the U.S. since the 2000s. Lu and Ng (2013) find that manufacturing industries that faced more intense import competition tended to employ more non-routine labors and demand less routine skills. Ebenstein et al. (2014) also find that workers in routine occupations in manufacturing, such as those in blue-collar production occupations, suffered the greatest wage loss from trade.

While distinguishing between the impacts of technological change and globalization on the labor market is important in today's socio-political environment, it is difficult to do so as they are interconnected. Besides the fact that the effects of import competition from countries such as China did not surge until the 2000s (Acemoğlu et al., 2016), Autor et al. (2015) also suggests that trade exposure causes a decline in relative demand for routine tasks, and sometimes even for the abstract task-oriented jobs, mainly in the manufacturing sector. Technological change, on the other hand, started in the 1980s and it seems to be more pervasive in that labors susceptible to automation experience decline in demand in both manufacturing and non-manufacturing sectors, and these displaced workers tend to switch to occupations in service sectors that rely on social interaction.

It is perhaps because of this reason that papers studying the increasing returns to social skills tend to be more focused on the routinization hypothesis rather than globalization.[2]

Nevertheless, for this paper, the cause of the increase in the importance of social skills does not matter. What matters is that there is a documented increase in relative demand and prices for social skills. This paper conjectures that immigrant workers are almost inherently inferior in terms of social skills specific to their host countries due to cultural and language barriers, so as the prices of these skills increase, immigrants should experience falling wages relative to natives, even after controlling for observable characteristics. Therefore, cities that are more likely to be affected by the relative increase in demand for social skills should experience a more pronounced widening of native-immigrant wage gaps.

III. MEASUREMENT, MODEL, AND DATA

A. Measuring Native-Immigrant Wage Gaps

The goal of this paper is to test whether routinization impacted native-immigrant wage gaps, so I begin by examining how native-immigrant wage gaps have changed over time. For the purposes of empirical implementation, I focus on the change in the wage gap between 1980 and 2000 because this time period, as shown in Figure 2, was the fastest growing period of technology and therefore it is considered to be the time that the routinization process was at its height (Autor et al., 2015; Beaudry and Lewis, 2014).

I use the five percent Integrated Public Use Micro Samples (Ruggles et al., 2010) of the 1980 and 2000 Censuses to compute the wage gaps and other labor market variables. I restrict the

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[2] See Autor et al. (2003), Acemoğlu and Autor (2011), Autor and Dorn (2013), Beaudry and Lewis (2014), Deming (forthcoming).

sample to employed workers ages 18 to 64 who work full time full year.[3] An immigrant is defined as a person born outside of the 50 U.S. states, while a native is defined as a person born inside the 50 U.S. states. In this study, people born in outlaying areas such as Puerto Rico and the Virgin Islands are considered immigrants. Due to difficulties of interpreting female labor market outcomes, I restrict the sample to males.[4] In order to highlight the social skills differences between immigrants and natives, immigrants born in countries with English as the first language are excluded from the sample.[5,6] I use the natural log of hourly wage to calculate native-immigrant wage gaps. The hourly wage variable is constructed by dividing annual inflation-adjusted wages by total hours worked. The total working hours variable is calculated by multiplying hours worked in a typical week with the number of weeks worked in a year. I further restrict the sample to people with hourly wages between 2 and 200 dollars, measured in 1999 dollars. I use Census-provided person weights throughout.

Native-immigrant wage gaps are constructed separately for the 118 MSAs that are consistent across the sample years and for the four education groups - high school dropouts, high school graduates, those with some college education (but less than four years) and four-year college graduates.[7] Given the changes in immigrant composition in these two years, I use a regression adjustment process adopted in Beaudry and Lewis (2014) to ensure that the wage gap variable compares wages between otherwise similar native born and immigrants in terms of observable characteristics.

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[3] Full time full year is defined as working 35 hours or more in a typical week and working no less than 40 weeks in the previous year, as defined by the usual convention in the literature.
[4] In fact, similar results, not shown in this paper, are also found for the female sample. The magnitude of the estimated coefficients is smaller than those of the male sample but still statistically significant.
[5] The list of identified English speaking countries (countries that list English as either an official language or a language primarily used by citizens) is retrieved from the CIA Factbook (2014).
[6] Baseline empirical results do not change significantly when immigrants from English speaking countries are included in the sample.
[7] This paper further categorizes two broad education groups: individuals with at most a high school degree are considered to be low-skilled, while individuals with at least some college education are considered as high-skilled.

I first estimate the equation $\ln w_{iegt} = \alpha_0 + \alpha_1 H_{iegt} + u_{iegt}$, where $\ln w_{iegt}$ is the natural log of the hourly wage of person i who belongs to education group e and native-immigrant status g (where $g = n$ indicates natives and $g = m$ indicates immigrants) during year t. The vector H_{iegt} contains age, age squared, and a series of race indicators.[8] I estimate the equation for natives and immigrants, and for each education group separately. The wage gap is then evaluated at the city-education level immigrant mean $\overline{H_{emct}}$ where c denotes city, and the adjusted native-immigrant wage gap in education group e in city c during year t is given by $IGAP_{ect} = (\widehat{\alpha_0^n} - \widehat{\alpha_0^m}) + (\widehat{\alpha_1^n} - \widehat{\alpha_1^m})\overline{H_{emct}}$, and $\Delta IGAP_{ec} = IGAP_{ec,2000} - IGAP_{ec,1980}$. I use this measure because I am interested in the impact of routinization on the part of the wage gap that cannot be fully explained by differences in observable characteristics. This regression adjustment process ensures that the estimated native-immigrant wage gap trend is due to differences in intercepts as well as in returns to the observable characteristics between natives and immigrants.[9]

The average unadjusted and adjusted wage gaps for various demographic groups from 1980 to 2000 are compared in Table 1. The standard errors are obtained by regressing the respective wage gap on a constant. They are used to test whether the means of wage gap trends are significantly different from zero. Both unadjusted and adjusted changes in wage gaps are positive, meaning that the native-immigrant wage differentials have widened between 1980 and 2000. Since changes in racial composition, age, and education could explain part of the changes in wage gaps, the regression-adjusted wage gap trends are all smaller in magnitude. However, the growing wage

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[8] I identify four race groups in this paper: whites, blacks, Asians, and Hispanics.
[9] An alternative measure of adjusted wage gaps which utilizes differences in regression residuals between native group and immigrant group's wage equations yields interpretations similar to those presented this paper.

gaps do not disappear after controlling for observable characteristics, and this is the part of the wage gaps that I consider in this paper. [10]

B. Measuring the Likelihood of the Routinization Process

Since the routinization hypothesis suggests that technological progress greatly reduces the cost of performing routine tasks and decreases demand for routine labor input (Autor and Dorn, 2013), markets that were historically specialized in routine task-intensive industries should adopt technology more aggressively, increase the demand for social skills more prominently, and reallocate labors from routine intensive occupations to non-routine service occupations more extensively. In practice, I merge two versions of the 1 percent metro samples of the 1970 Census, and I reference Autor and Dorn (2013) to calculate a routine employment share measure as $RShare_{ec,1970} = \left(\sum_i L^r_{eci,1970} \right) \cdot \left(\sum_i L_{eci,1970} \right)^{-1}$, where the numerator is the total number of hours worked by people in "routine occupations" who belong to education group e in MSA c in year 1970. [11] The denominator is the total employed hours in all occupations. Intuitively, $RShare_{ec,1970}$ measures the routine employment share of education group e in MSA c in year 1970, and it should correlate positively with technology adoption of that MSA-education cell after 1980. The scale of $RShare_{ec,1970}$ ranges from 0.08 to 0.71, with a median of 0.49.

This measure makes two small adjustments to the index adopted in Autor and Dorn (2013). First, I use the 1970 sample instead of the 1950 sample to construct the routine employment share

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[10] A figure of the growing regression adjusted native-immigrant relative wages from 1980 to 2010 is also presented in Appendix Figure A1.

[11] The routine occupations categorization follows Autor and Dorn (2013). Administrative support, retail sales, precision production, craft workers, machine operators, and assemblers are routine intensive occupations; managers, technicians, financiers, public safety are considered high skill non-routine cognitive occupations; while transportation, construction, mining professions, farmers, and service occupations are considered low skill non-routine manual occupations. This grouping method is developed through a procedure where the authors merge job task requirements from the fourth edition of the US Department of Labor's *Dictionary of Occupational Titles* (DOT) to the corresponding Census occupation classifications to measure each occupation's routine intensity, and then separate routine intensive occupations from non-routine intensive occupations accordingly.

variable. The technical reason is that the 1970 sample has a larger sample size. Moreover, I argue that a city's routine employment share immediately before the technology change should have the largest impact on its routinization tendency after the technology change.[12] Second, I calculate the routine employment share within education and MSA cells instead of just within the geographical unit. The education distribution of immigrants is largely bimodal in the sense that, relative to natives, high percentages of immigrants than natives have less than a high school degree and more than a college education (Baum and Flores, 2011). It is unlikely that the routine concentration of workers in the low skill group in 1970 would have any significant effect on the routinization process of the high skill groups between 1980 and 2000, and vice versa. Thus, using this measure, I effectively identify the impact of routinization within skill groups.

To test whether $RShare_{ec,1970}$ measures the routinization process likelihood well, I follow Autor and Dorn (2013) in considering the relationship between this baseline routine share and future changes in the shares of a city's employment that are in the low skill service sector and within routine task occupations. Results in Table 2 suggest that routine task shares in 1970, just like routine task shares in 1950, can successfully predict the job polarization of local labor markets where routine employment falls and low skill service sector employment rises.[13] Therefore, I consider the routine employment share of 1970 to be a good indicator of local labor markets' routinization process.

To provide a visual representation of different degrees of routine employment shares across geographical regions, I aggregate the routine employment shares into the MSA level and present

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[12] Replacing $RShare_{ec,1970}$ by $RShare_{ec,1950}$ in my model estimations do not change the results, but the estimated coefficient of the key independent variable becomes less statistically significant.

[13] I use $RShare_{c,1970}$ instead of $RShare_{ec,1970}$ because the change in low skill service sector and the change in routine employment share vary on the MSA level, not MSA-education level. A similar regression using $RShare_{ec,1970}$ yields similar results, but due to difficulties in empirical results interpretation, they are not presented or discussed in the paper.

the map of the United States according to each MSA's share of routine employment in 1970 in Figure 3. The most routine intensive cities were mostly in the "Rustbelt" states of Illinois, Indiana, Ohio, Pennsylvania, and Michigan, and the least routine intensive cities were the cities specializing services, such as Las Vegas.[14] In addition, I present the top and bottom five MSAs ranked by $RShare_{c,1970}$ in Table 3. Routine intensive MSAs are all industry-heavy cities and non-routine MSAs are all service oriented.

C. Model

Having obtained the measures of changes in native-immigrant wage gaps $\Delta IGAP_{ec}$ and routinization process likelihood ($RShare_{ec,1970}$), I use an empirical model similar to an analysis by Beaudry and Lewis (2014) on technology's impact on the gender wage gaps to test routinization's impact on changes in native-immigrant wage gaps:

(1) $$\Delta IGAP_{ec} = \beta_0 + \beta_1 RShare_{ec,1970} + \beta_2 X_c + \beta_3 Z_c + \delta_s + \varepsilon_{ec},$$

where the coefficient of interest, β_1, measures the impact of routinization on changes in adjusted native-immigrant wage gaps within MSA-education cells. I expect a positive and statistically significant estimated β_1 if native-immigrant wage gaps increased more in cities that were more likely to adopt technology to replace routine labor. Since I use the 1970 sample to calculate $RShare_{ec,1970}$, reverse causality is not a problem because the change in native-immigrant wage gaps from 1980 to 2000 cannot dictate the occupational structure in 1970. However, I acknowledge that markets of different routine intensity might have different social and cultural stance towards immigration, which could cause deterministic trends in wage gaps development. I will address this potential bias in Section 4.

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[14] Grey colored MSAs are the ones not included in this study – due to either lack of necessary data or inconsistencies across samples.

Following Beaudry and Lewis (2014), I include a vector of city level business cycle and composition controls in 1980: X_c. It contains city level unemployment rate, share of Hispanic workers, share of black workers, and share of immigrant workers as well as its square form. State fixed effects are labeled δ_s where s denotes states.

In some specifications, I also follow Beaudry and Lewis (2014) and include industry composition controls Z_c, which are shares of employment in durable and nondurable manufacturing industries, and shares of employment in high skill and low skill service sectors in 1980. Their interaction terms with a broad education group dummy (high school degree or less) are also included because industry mix could have different wage effects on individuals of different education levels (Beaudry and Lewis, 2014). These controls account for any changes in native-immigrant wage gaps that might be driven by changes in industrial composition, for example, as a result of changes in the characteristics of immigrant labor in a particular city. However, I do not include these controls in all specifications because industry expansion or contraction due to technological change could be a potential mechanism driving the increase in native-immigrant wage gaps. For example, as robots started replacing workers, cities that heavily invested in toy manufacturing industries in 1970 might move towards more service-oriented industries which would reward natives' skills relatively more. Ultimately, I include these controls in my preferred model specification as a strategy to be conservative not only because it follows the model specification in Beaudry and Lewis (2014) but also because it would control for any of the industry-wide effects that might not be associated with the routinization process. Therefore, the estimated results might be considered the lower bound of routinization's impact.[15]

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[15] The estimated impact of routinization on native-immigrant wage gaps is consistently larger in magnitude without industry composition controls in all estimations presented in this paper.

Table 4 presents summary statistics for the key demographic characteristics of immigrants and natives for the years 1980 and 2000. In the two decades after 1980, the natives' average real wage has been stagnant while immigrants' average real wage has decreased, causing the increase in observed wage gaps. Natives have become more educated as the share of natives with at least a college degree increased by 20.7 percent, while the share of natives without a high school diploma decreased sharply by 52.2 percent. At the same time, the immigrant population continued to grow, but their concentration in both high and low tails of education distribution remained steady. Over the two decades, there has been an increase in the shares of Hispanic and Asian immigrants but a decrease in the share of white immigrants.

IV. EMPIRICAL RESULTS

A. Baseline Regression Results

Table 5 shows OLS estimates of (1), that is, the effect of initial routine employment on the changes in adjusted native-immigrant wage differentials between 1980 and 2000, the standard errors are clustered at the MSA level and are heteroskedasticity-robust. Having $RShare_{ec,1970}$ as the sole independent variable, column 1's positive estimated coefficient on $RShare_{ec,1970}$ shows that the widening native-immigrant wage gaps are associated with cities' historical routine intensities. The estimated coefficient implies that each additional percentage point increase in routine employment share in 1970 is associated with a 0.115 percentage point increase in native-immigrant wage gaps between 1980 and 2000. Alternatively, the result suggests that each additional standard deviation increase in routine share is associated with approximately 2.1 percentage point greater increase in native-immigrant wage differential.

Since immigrants' labor market outcomes are particularly sensitive to business cycle fluctuations (Orrenius and Zavodny, 2010), the estimated coefficient in this specification might overestimate the effect of technology if the routine intensive cities also happened to not perform well economically after 1980. In order to address this concern, the second column adds the MSA level business cycle and composition controls. The estimated coefficient barely grows to 0.121, which is not significantly different from 0.115, meaning business cycle and labor supply factors did not affect native-immigrant wage gaps growth.

In column 3, I add state fixed effects to the model. The benefit of including state fixed effects is that they control for any state-level characteristics that could potentially affect immigrants and natives differently. As shown in Figure 3, cities that are most routine-intensive are mostly concentrated in the rustbelt states. It is, therefore, possible that the estimated results are driven by the economic slow-down of these rustbelt states since the 1980s for reasons unrelated to routinization. The estimated coefficient increases marginally to 0.123 with the state fixed effects, suggesting that state-specific characteristics do not meaningfully influence native-immigrant relative wages.[16]

Finally, I include the industry mix controls in column 4. Since this specification holds constant the share of the labor force working in manufacturing, for example, it measures only the impact of routinization on wage differentials within sectors. This specification does not allow for the possibility that as robots replace workers, fewer manufacturing jobs become available in a city forcing workers into other jobs where their skills are less rewarded. Including these controls decreases the estimated coefficient to 0.056, and it is significantly different from the estimated coefficient in column 3 at 1 percent level. The estimated coefficient also suggests that each

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[16] Empirical results also hold when excluding observations from the rustbelt states of Pennsylvania, West Virginia, Ohio, Indiana, Michigan, Illinois, and Iowa.

additional standard deviation increase in routine share is associated with slightly more than a 1.0 percentage point greater decline in the native-immigrant wage differential. This significant drop is not surprising because the estimated coefficient should decrease if immigrants were disproportionally concentrated in manufacturing industries that were negatively impacted by routinization. Since I elect to follow the literature and include the industry mix controls in my preferred specification, I interpret the estimated coefficient 0.056 as the lower bound of routinization's effect, and I expect the true effect of routinization to be between 0.056 and 0.123. This also means that each additional deviation in routine share is associated with an increase in wage gaps between 1.0 to 2.2 percentage points.

The results in the last column in Table 5 imply that cities and education groups that were more likely to routinize the production process with technology experienced bigger increases in native-immigrant wage gaps. This offers the first piece of evidence suggesting that the increase in relative price of social skills induced by routinization may have been one of the reasons why we observe an increase in native-immigrant wage gaps since the 1980s.[17] In the following section, I continue to use the model specification with the full set of controls, including the industry mix variables, as the preferred model, and I interpret all estimated coefficients to be the lower bound of the impact of routinization.

B. Causal Relationship or Internal Migration?

All of the empirical analyses discussed thus far rely on the argument that routinization had significant impacts on local labor markets. Since the main regression is based on a reduced form

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[17] These results are robust to further adjustments in weights according to the share of workers in each education levels in the local labor market. An alternative difference-in-difference regression was carried out using MSAs with above average $RShare_{ec,1970}$ as the treatment group, similar interpretation was drawn.

model, it is possible that what I observe is merely the effect of changes in labor skill compositions that are correlated with both 1970 routine employment shares and changes in wage gaps. That is, if immigrants and native born exhibited distinct sorting behaviors according to skills in routine intensive cities, then the interpretation that increased prices in U.S.-specific social skills induced by routinization were a reason for the increase in native-immigrant wage gaps would become more problematic. In this section, I perform additional analyses to parse out whether the positive relationship between routine employment shares and changes in wage gaps is the result of compositional changes of labor input in different labor markets or indeed represents a causal relationship.

It is possible that a routine intensive city in 1970 could attract immigrants and natives of different types. It could be that more low skill immigrants, conditional on their formal schooling, moved to routine intensive cities for better job prospects. It is also possible that a city adopting technology more aggressively would be more attractive to high skill natives, again conditional on formal schooling. Either of these selective migration behaviors could cause a widening of wage gaps for reasons unrelated to the changing skill prices induced by routinization. To examine this possibility, Column 1 of Table 6 presents the result from a regression of changes in low skill (in terms of education level) immigrant share within MSAs between 1980 and 2000 on 1970 routine share. [18] The estimate of the coefficient is positive but statistically insignificant, which means that routine intensive cities did not experience any differentially large inflow of low skill immigrants since 1980. Column 2 shows the regression results when I use changes in high skill (also in terms of education level) native born share between 1980 and 2000 as the dependent variable. The insignificance of this estimated coefficient suggests that high skill natives were not moving

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[18] I use $RShare_{c,1970}$ instead of $RShare_{ec,1970}$ as the key independent variable because there is only one observation of skill composition change within a MSA.

systematically to cities with high 1970 routine shares. Although it is still possible that these cities attract more immigrants with worse unobserved skills or more natives with better unobserved skills, it seems unlikely that the relationship would be different between observed and unobserved skills.[19]

As an additional test that my estimates are indeed measuring impacts of routinization, I use my data and empirical technique to test a standard result in the literature (Acemoğlu and Autor, 2011; Beaudry and Lewis, 2014): routinization yields higher skill wage premiums. The last column of Table 6 presents the regression results when I use changes in college/high-school adjusted relative wages between 1980 and 2000 as the dependent variable.[20] The positive and statistically significant estimated coefficient on the 1970 routine share variable implies that cities that were historically routine intensive also experienced growing skill wage premiums. While this result does not directly contribute to addressing the causal relationship question between routinization and native-immigrant wage gaps, it is nevertheless supportive evidence as it is difficult to argue that the routine intensive cities would cause any increase in returns to social-communication skills if it does not cause an increase in skill wage premium.

To summarize, I could not find any evidence suggesting that the observed wage gaps trend was caused by potential geographical sorting behaviors of native born and immigrants. All of the evidence presented in this section is still consistent with the argument that part of the increase in native-immigrant wage gaps was driven by routinization.

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[19] I also re-estimate model (1) with only workers who have not moved in the past 5 years to address the differential migration pattern concerns, the estimated coefficient of interest decreases marginally to 0.043, but it is still statistically significant at 10% level.
[20] A similar adjustment process is adopted, and it controls for age, age squared and racial composition.

C. Heterogeneous Effects

Having presented evidence that routinization led to increasing native-immigrant wage differentials, I now examine whether it is changes in the price of U.S.-specific communication skills that drove this relationship.

Even at the most basic level, U.S.-specific communication and social skills rely on English speaking abilities. Therefore, I start by directly comparing the wage trends of immigrants of different English language skills. In theory, if the positive estimated coefficient observed in the baseline regression indeed represents an increase in social skill prices, then the increase in wage gaps in routine intensive cities should be driven by immigrants who do not speak English well. The first two columns in Section A of Table 7 directly test this conjecture by comparing the changes in native-immigrant wage gaps between immigrants from non-English speaking countries and immigrants from English speaking countries. Recall that my original sample consists only of immigrants from non-English speaking countries, the first column of Table 7 is directly replicated from the results in the last column of Table 5. If I carry out the same regression with a sample of immigrants from English speaking countries, then the estimated coefficient on the routine employment share should not be as big as what is observed in the first column. Column 2 of Section A shows that the routine share estimate is negative and statistically significant when using the sample with only immigrants from English speaking countries. One explanation for why immigrants from English speaking countries experienced a *decrease* in wage gaps in routine intensive cities is that immigrants from English speaking countries might have better communication and social skills than native born as they are comfortable navigating at least two social and cultural environments. Given that they do not have language barriers, it is very

reasonable that these unobservable social and communication skills would be more valued in cities that underwent the routinization process more intensely.[21]

In the next two columns in Section A of Table 7, I separate the sample of immigrants from non-English speaking countries into two sub-categories: immigrants who identify themselves as speaking English well or very well, and immigrants who identify themselves as speaking English poorly or not at all. Following the same reasoning, I propose that more proficient English speakers should experience a less negative impact from routinization. The results suggest that each additional percentage point increase in routine employment share in a local labor market in 1970 would cause immigrants who did not speak English well to experience a 0.088 percentage point increase in wage gaps between 1980 and 2000, while immigrants who spoke English well would only experience a 0.040 percentage point increase.

Lastly, if routine intensive cities did experience a differential increase in returns to communication skills, then the wage gaps between immigrants with different levels of English mastery should also increase in these cities. I regress the changes in adjusted wage gaps between proficient English speaking immigrants and poor English speaking immigrants against routine employment shares, and present the results in Section B of Table 7. The positive estimated coefficient of 0.074 suggests that the wage gaps between immigrants of high and low English language skills also increased significantly in cities that were more likely to have undergone an extensive routinization process.

Communication in a work setting requires more than just a textbook ability to speak the dominant language. Sharing ideas about complex concepts and motivating and coordinating teams

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[21] It is also likely that immigrants from English speaking countries also have higher average human capital and therefore possess more abstract skills. Therefore, it is likely that the wage gap between these immigrants and the native-born would shrink in previously routine-intensive cities that now value these skills. Since the model presented in this paper has included many observable human capital characteristics and the shrinking wage gap still persists, I leave further explorations of this hypothesis in a future paper.

at work also requires a knowledge of the culture and social norms in the host country. I use measures of social assimilation beyond English language ability to separate immigrant groups, and present Table 8 to show impacts of 1970 routine shares on changes in native-immigrant wage gaps among immigrants of different levels of likely social integration. Throughout, the sample of natives is the same.

I first categorize immigrants' potential U.S.-specific social skills according to their age of arrival in the United States. Immigrants' social and language assimilation paths depend strongly on their age of arrival (Bleakley and Chin, 2010), and immigrants who migrated to the U.S. before the age of 18 could be considered "half-natives" because they grew up and went to school in the U.S. Therefore, they should have relatively better labor market outcomes, when compared to other immigrants, in areas that highly value social skills. In practice, I divide the sample into immigrants that migrated before or at the age of 18 and immigrants that migrated after the age of 18 and re-estimate the model. As can be seen in columns 1 and 2 of Table 8, immigrants migrating after the age of 18 suffered a higher increase in wage gaps when living in high routine share cities, while "half-natives" experienced a significantly tamer impact with only a marginally significant estimated coefficient.

Next, I compare how the relationship between 1970 routine shares and changes in native-immigrant wage gaps differs by how long the immigrants have lived in the United States. Similar to the argument above, long-time immigrants have had more time to acclimate themselves into the host country's social and cultural settings than new immigrants, so they should experience a less negative impact from routinization. The third and fourth columns present the regression results when I separate the sample into immigrants who have lived in the U.S. for at least 15 years and those who have lived in the U.S. for less than 15 years. The larger and more statistically significant

estimated coefficient for new immigrants is consistent with the conjecture that the increase in returns to U.S.-specific social skills could explain part of the widening native-immigrant wage gaps.

In the same vein, immigrants who are married to natives, often termed *intermarried immigrants*, should not experience significantly negative effects from routinization because they are more socially assimilated into the host country than immigrants married to other immigrants (Furtado and Theodoropoulos, 2010; Furtado and Song, 2015). Furtado and Song (2015) find that intermarriage wage premiums have increased from 1980 to 2000 even when allowing the value of education and English-speaking ability to vary over time and suggest that the patterns might be driven by an increase in demand for social and management skills in the U.S. labor market. I follow this reasoning and separate intermarried immigrants from other married immigrants in calculating the native-immigrant wage gaps, and present the results of the two regressions in the columns 5 and 6 of Table 8, respectively. The estimated coefficient for intermarried immigrants is statistically insignificant as expected while immigrants that are married to other immigrants experienced a significantly larger wage gap increase.[22]

The last four columns of Table 8 categorize immigrants by their potential contact with their ethnic peers.[23] It is likely that immigrants who live in large ethnic enclaves and have more frequent interactions with their ethnic peers would have less exposure to the U.S. culture and social norms, and therefore lack U.S.-specific social skills. I use the population share of co-ethnics within an MSA to measure the ethnic enclave size, and I use the isolation index of an ethnic group within an

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[22] Restricting the sample of native born to only married natives in these two estimations neither changes the sign and significance of the estimated coefficients nor the interpretation.
[23] I define ethnic groups by immigrants' country of origin.

MSA to measure the potential contact probability between two co-ethnics.[24] I consider immigrants with above-median ethnic enclave size or above-median isolation index as immigrants with less potential U.S.-specific social skills. While I acknowledge that immigrants who live in larger ethnic enclaves or have more frequent interactions with their ethnic peers might not depend on their U.S.-specific social skills as much as their counterparts, results show that these immigrants still suffered wider native-immigrant wage gaps than immigrants who did not have significant ties with their ethnic peers.

To summarize, in Table 8, I construct various samples to parse out the potential U.S.-specific social skills among immigrants. I test whether immigrants who are more likely to have better social and communication skills experienced less negative impacts from routinization. The empirical results consistently show that they did, and therefore should be considered as more evidence suggesting that the increasing returns to U.S.-specific social skills brought about by routinization were a factor causing the growing native-immigrant wage gaps.

D. Alternative Explanations and Robustness Checks

Having shown several pieces of evidence supporting routinization as driving the increase in native-immigrant wage gaps, I address several alternative explanations for the results. First, suppose that in 1970 some cities experienced a random positive demand shock for goods produced by routine intensive industries and that immigrants were over-represented in these industries. After 1970,

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[24] I calculate the isolation index as $ISO_{gct} = \frac{\sum_i \frac{group_i}{group_{total,c}} \times \frac{group_i}{population_i} - \frac{group_{total,c}}{population_{total,c}}}{min\left(1, \frac{group_{total,c}}{population_{smallest,c}}\right) - \frac{group_{total,c}}{population_{total,c}}}$, where $group_i$ is the population of immigrants from ethnic group g living in tract i; $group_{total,c}$ is the population of immigrants from ethnic group g living in MSA c; $population_i$ is the total population in tract i; $population_{total,c}$ is the total population in MSA c; $population_{smallest,c}$ is the population of the tract with the least residents in MSA c. Hence ISO_{gct} is the MSA-level isolation index according to country of origin, calculated based on tract-level data. The calculation method is referenced from Glaeser et al. (2008), and I use the tract level information in Table PCT019 of Summary Tape File 3 of 2000 Census to construct the isolation index (U.S. Census Bureau, 2016).

local economies would tend to converge back to the pre-shock equilibrium. Subsequently, demand and relative wages of immigrant workers would decrease in those cities as well. This scenario would cause a false positive relationship between 1970 routine employment shares and changes in native-immigrant wage gaps afterward.

Another potential concern is that changes in native-immigrant wage differentials are driven by changes in labor market discrimination. While I account for the state-wide discrimination against immigrants by including state fixed effects, there may still be within-state discrimination changes over time. For example, Austin and Dallas might have drastically different cultures, even though they are both located in Texas. Discrimination and prejudice may have evolved in different ways in these two cities between 1980 and 2000, in a way that was systematically related to their 1970 routine shares.

In order to address these two concerns at the same time, I perform a placebo regression estimating the relationship between changes in native-immigrant wage gaps from 1970 to 1980 and the 1970 routine employment shares. If the two scenarios above were true, I should observe a similar positive relationship between the wage gap growth and routine employment share. On the other hand, if my results are driven by routinization induced by technological change, which started in 1980, then 1970 routine shares should not lead to increases in wage gaps before 1980. I replicate the original 1980 – 2000 results to column 1 in Panel A of Table 9 for ease of comparison, and I present the placebo regression results in column 2 in Panel A. The statistically insignificant estimated coefficient suggests that the positive relationship between the wage gap trend after the 1980s and the routine employment share in 1970 was not caused by random shocks or discrimination.

To further put the spurious relationship concerns to rest, I estimate the relationship between changes in adjusted native-immigrant wage gaps from 1950 to 1970 and the 1970 routine employment shares. Again, since the significant technological changes started in the 1980s, the routine intensity of cities in 1970 should not retroactively predict wage gap changes before 1970. The statistically insignificant estimated coefficient in the third column of Panel A in Table 9 is offered as confirmation.

Estimations thus far have only focused on the wage gap changes from 1980 to 2000. One could argue that it was a coincidental positive relationship between changes in native-immigrant wage gaps and routinization. I can re-estimate the model using additional years of data to address this concern. In practice, I use the five percent sample for the 1990 Census, the merged 3-year 1 percent samples of American Community Survey for 2005-2007, and the merged 3-year 1 percent samples of American Community Survey for 2008-2010. In Panel A of Table 10, I estimate the relationship between 1970 routine employment shares and changes in adjusted native-immigrant wage gaps for the periods from 1980 to 2005 – 2007, from 1980 to 2008 – 2010, and from 1990 to 2008 – 2010. The positive and statistically significant estimated coefficients are robust in all time periods after 1980, suggesting that the positive relationship observed for the 1980 – 2000 period is not a coincidence.

In order to ensure that the findings so far are not driven by the choice of measurement on routinization, I develop an additional measure by taking nation-wide routine intensity levels of industries into consideration. According to Autor and Dorn (2013), areas that were historically specialized in routine task intensive *industries* should adopt technology and displace routine labor more quickly. It is possible that the same industry might have different routine intensity in different geographic regions before the technology boom, but it is also reasonable to suppose that an

industry, no matter where they are located, might have a similar tendency to adopt the same technology to replace routine labors during the technology boom. Therefore, $RShare_{ec,1970}$ could potentially be a noisy measure in that the same industry adopting the same amount of technology could have different values of $RShare_{ec,1970}$ in different cities. I could sidestep this potential problem by first measuring the general routine intensity of an industry calculated from its nation-wide routine employment share. I first separate 231 industries into ten broad industry groups: construction; manufacturing; transport and utilities; wholesale trade; retail trade; finance, insurance and real-estate; business services; personal services and entertainment; professional services; and public administration. Then, I calculate each industry group's nation-wide routine employment share in 1970 as $RS_{j,1970} = \left(\sum_i L^r_{ij,1970}\right) \cdot \left(\sum_i L_{ij,1970}\right)^{-1}$, where the numerator is the total number of hours worked by people in "routine occupations" in industry j in 1970, and the denominator is the total number of hours employed in industry j in 1970. Thus, an industry that requires more routine labor input would have a bigger $RS_{j,1970}$.

$RS_{j,1970}$ is then assigned to each individual according to the industry group they belong to, and then I take the average of $RS_{j,1970}$ by MSA and education group and call this variable routine intensity index $RIndex_{ec,1970}$ for education group e in MSA c. For example, suppose in 1970 there are only two cities c and d and two industries j and k in an economy. Industry j is more routine intensive and requires 80 percent of total labor input to be routine labor ($RS_j = 0.8$), while industry k is less routine intensive and requires only 20 percent of routine labor input ($RS_k = 0.2$). Suppose city c employs five people from education group e with two working in industry j and the rest working in industry k, while city d has five workers in education group e with one working in industry j and four working in industry k. Then $RIndex_{ec,1970} = (0.8 \times 2 + 0.2 \times 3)/5 = 0.44$, and $RIndex_{ed,1970} = 0.8 \times 1 + 0.2 \times 4)/5 = 0.32$. Intuitively,

$RIndex_{ec,1970}$ uses national level routine intensity of industries to measure the routine intensity of a MSA-education group, and therefore estimates the general routinization tendency of industries.

In Panel B of Tables 9 and 10, I test the robustness of the empirical results over all the previously estimated time periods using $RIndex_{ec,1970}$. Despite magnitude differences due to different scales, I consistently find the same positive relationship between $RIndex_{ec,1970}$ and the various wage gap changes after 1980 without observing any meaningful relationship for the wage gap changes before 1980.

V. CONCLUSION

Motivated by the concurrent movement of native-immigrant wage gaps and technological advancement since the 1980s, this paper asks whether the increasing returns to social skills induced by technology's routinization process play a role in explaining recent increases in native-immigrant wage gaps. In particular, if the routinization process increased the returns to U.S.-specific social skills, and natives have a comparative advantage in these skills, then it may have increased native-immigrant wage gaps even holding constant human capital characteristics of both immigrants and natives.

Consistent with this hypothesis, I show that markets that were historically routine intensive, and therefore more likely to adopt technology to substitute routine labor, experienced more prominent increases in native-immigrant wage gaps. The positive relationship does not seem to be driven by selective migration between cities, and the basic result survives several mechanism checks, placebo regressions, and an alternative routinization measure. Taken together, the results in this paper provide rather strong evidence suggesting that indeed native workers have enjoyed

better labor market outcomes than immigrants because they are highly endowed with U.S.-specific social skills, which have become more highly rewarded in the labor market.

This paper has several implications for immigration policy. Concerns about the "quality" of recent immigrants and how they are not assimilating economically at the same speed as earlier cohorts have garnered significant media attention. Borjas (1985, 1995, 2015) suggests that part of the decline in economic assimilation in recent waves of immigrants is due to their slower rates of human capital accumulation, particularly slower English language skill acquisition. My results suggest that even if the recent cohorts acquired English language skills at the same speed as the earlier cohorts of immigrants, they would still have had lower wages and potentially slower wage growth due to structural changes in the U.S. labor market. To address this issue, the government's immigrant assistance programs might prioritize training for English language skills as well as other social and communication skills. Policies designed specifically to improve immigrants' social capital might be especially cost-effective if they decrease immigrants' need for safety net programs. Furthermore, such policies could reduce long-term inequality between natives and immigrants as immigrants become better able to invest in their children's education and health (Lassem and Sanders, 2013).

The results in this paper also have implications for policies unrelated to immigration. While a large literature has pointed to the increasing returns to schooling as a result of routinization, a growing literature has focused on the returns to cognitive and social skills (Deming, 2017). The results in this paper reinforce the idea that social skills have become increasingly important, suggesting that these skills should be given more priority in the education of all students, not just the foreign-born.

References

Acemoğlu, D., & Autor, D. (2011) Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics* (Volume 4 ed., pp. 1043). Ashenfelter O. and Card D. eds., Amsterdam: Elsevier.

Acemoğlu, Autor, Dorn, Hanson, & Price. (2016). Import Competition and the Great US Employment Sag of the 2000s. *Journal of Labor Economics*, 34, S141.

Alba, R. D., & Nee, V. (2003). *Remaking the American mainstream: Assimilation and contemporary immigration.* Cambridge, Mass: Harvard University Press.

Atkinson, A. (2008). The changing distribution of earnings in OECD Countries. *The Rodolfo De Benedetti Lecture Series*

Autor, D.H. (2015). Why are there still so many jobs? The history and future of workplace automation. *Journal of Economic Perspectives,* 29(3), 3-30.

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review, 103*(5), 1553-1597.

Autor, D. H., Dorn, D., & Hanson, G. (2015). Untangling trade and technology: Evidence from local labour markets. *Economic Journal, 125*(584), 621-646.

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics, 113*(4), 1169-1213.

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics, 118*(4), 1279-1333.

Baum, S., & Flores, S. (2011). Higher education and children in immigrant families. *The Future of Children, 21*(1), 171-193.

Beaudry, P., & Lewis, E. (2014). Do male-female wage differentials reflect differences in the return to skill? Cross-city evidence from 1980-2000. *American Economic Journal: Applied Economics, 6*(2), 178-194.

Bleakley, H., & Chin, A. (2004). Language skills and earnings: Evidence from childhood immigrants. *The Review of Economics and Statistics, 86*(2), 481-496.

Bleakley, H., & Chin, A. (2010). Age at arrival, English proficiency, and social assimilation among US immigrants. *American Economic Journal, 2*(1), 165-192.

Borjas, G. J. (1985). Assimilation, Changes in Cohort Quality, and the Earnings of Immigrants. Journal of Labor Economics. *3(4)*, 463-489.

Borjas, G. J. (1990). Self-selection and the earnings of immigrants: Reply. *American Economic Review, 80*(1), 305.

Borjas, G. J. (1991). Immigration and self-selection. In *Immigration, Trade, and the Labor Market* (pp. 29-76). Abowd J. M., and Freeman R.B. eds., University of Chicago Press

Borjas, G. J. (1995). Assimilation and Changes in Cohort Quality Revisited: What Happened to Immigrant Earnings in the 1980s? Journal of Labor Economics, *13(2)*, 201–245.

Borjas, G.J. (2015). The Slowdown in the Economic Assimilation of Immigrants: Aging and Cohort Effects Revisited Again. *Journal of Human Capital, 9*(4), 483-517.

Bound, J., & Johnson, G. (1992). Changes in the structure of wages in the 1980's: An evaluation of alternative explanations. *The American Economic Review, 82*(3), 371-392.

Butcher, K., & Dinardo, J. (2002). The Immigrant and Native-Born Wage Distributions: Evidence from United States Censuses. *Industrial and Labor Relations Review, 56*(1), 97-121.

Card, D., & Dinardo, J. (2002). Skill biased technological change and rising wage inequality: Some problems and puzzles. *Journal of Labor Economics*, 20(4), 733-783.

Card, D., & Lemieux, T. (2001). Can falling supply explain the rising return to college for younger men? A cohort-based analysis. *Quarterly Journal of Economics, 116*(2), 705-746.

Central Intelligence Agency. (2014). Languages. In The world factbook. Retrieved from https://www.cia.gov/library/publications/the-world-factbook/fields/2098.html, (accessed May 25, 2014).

Chiswick, B. R. (1978). The effect of Americanization on the earnings of foreign-born men. *Journal of Political Economy, 86*(5), 897.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *Quarterly Journal of Economics, 132(4)*, 1593-1640.

Ebenstein, A., Harrison, A., McMillan, M., & Phillips, S. (2014). Estimating the Impact of Trade and Offshoring on American Workers using the Current Population Surveys. *The Review of Economics and Statistics*, *96(4)*, 581-595.

Fitzenberger, B., & Kohn, K. (2006). Skill wage premia, employment, and cohort effects: Are workers in Germany all of the same type?. *University of Freiburg Working Paper*

Foged, M., & Peri, G. (2013). Immigrants' and native workers: New analysis on longitudinal data. *NBER Working Paper No. 1931. National Bureau of Economic Research, Inc.*

Furtado, D., & Song, T. (2015). Intermarriage and socioeconomic integration: Trends in earnings premiums among U.S. immigrants who marry natives. *The ANNALS of the American Academy of Political and Social Science, 662*(1), 207-222.

Furtado, D., & Theodoropoulos, N. (2009). I'll marry you if you get me a job: Marital assimilation and immigrant employment rates. *International Journal of Manpower* 30 (1-2): 116-26.

Glaeser, E., Cutler, D., & Vigdor, J. (2008). Is the melting pot still hot? Explaining the resurgence of immigrant segregation. *Review of Economics and Statistics*, 90(3), 478-497.

Katz, L. F., & Murphy, K. M. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics, 107*(1), 35.

Lazear, E. (1999). Culture and Language. *Journal of Political Economy, 107*(S6), S95-S126.

Lessem, R., & Sanders, C. (2013). Decomposing the native-immigrant wage gap in the United States. *2013 Meeting Papers No. 19206. Society for Economic Dynamics.*

Lewis, E. (2013). Immigrant-native substitutability and the role of language. In *Immigration, Poverty, and Socioeconomic Inequality*. Card D. and Raphael S. eds., New York: Russell Sage Foundation.

Lu, Y., & Ng, T. (2013). Import competition and skill content in U.S. Manufacturing industries. *Review of Economics and Statistics*, 95(4), 1404-1417

Mandelman, F. & Zlate, A. (2016). Offshoring, low-skilled immigration, and labor market polarization. *Boston Fed RPA Working Paper 16-03*

Orrenius, P. & Zavodny, M. (2010). Immigrants' employment outcomes over the business cycle. *IZA DP 5354. IDEAS Working Paper Series from RePEc*

Peri, G., & Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal, 1*(3), 135-169.

Plunkert, L. M. (1990). The 1980's: A decade of job growth and industry shifts. *Monthly Labor Review, 113*(9), 3.

RobotShop Distribution Inc. (2008). History of robotics: timeline. (2008). Retrieved from http://www.robotshop.com/media/files/PDF/timeline.pdf

Ruggles, J. S., Alexander, T., Genadek, K., Goeken R., Schroeder, M. B. and Sobek M. (2010) *Integrated Public Use Microdata Series: Version 5.0* [Machine-readable database]. Minneapolis: University of Minnesota.

U.S. Bureau of Economic Analysis (2016), "*Gross-Domestic-Product-(GDP)-by-Industry Data Table*", http://www.bea.gov/industry/gdpbyind_data.htm (accessed April 2, 2016).

U.S. Census Bureau; *Census 2000, Summary File 3, Table PCT019*; generated by Tian Lou and Tao Song, using American FactFinder, http://factfinder2.census.gov, (accessed 10 May, 2016)

Vigdor, J.L. (2015). The civic and cultural assimilation of immigrants to the United States. In *Immigration: From Social Science to Public Policy*. Powell B. ed., Oxford University Press.

Wallén, J. (2008). The History of the Industrial Robot. *Technical report from Automatic Control at Linköpings universitet*. LiTH-ISY-R, 2008.

FIGURE 1
Average native-immigrant relative wages, 1960 – 2010
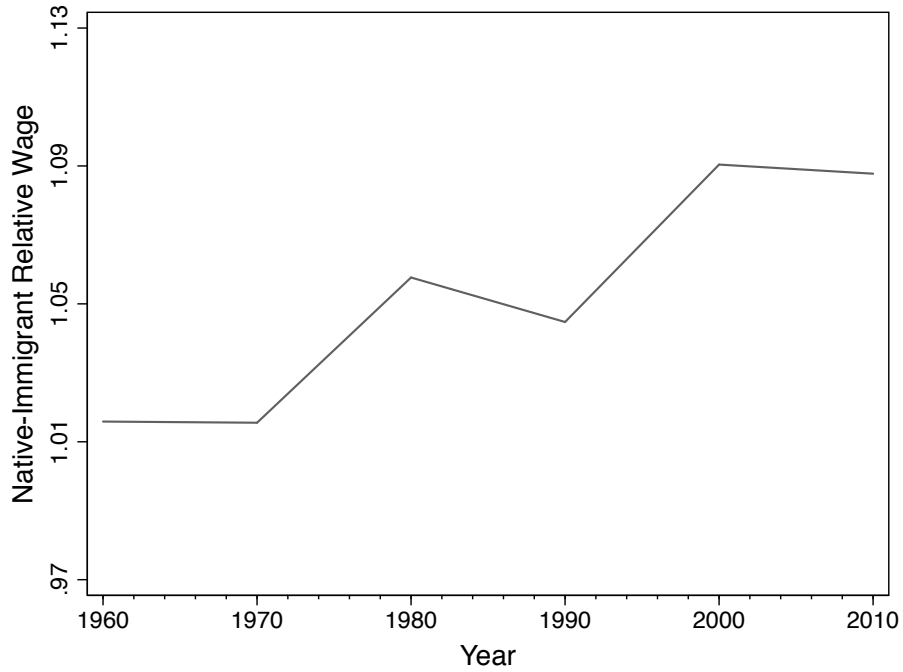
*Notes*: Simple average native-immigrant relative log hourly wages between 1960 and 2010.
Sources: The sample consists of 5% sample of 1960 Census, merged 2 version of 1% metro samples of 1970 Census, 5% sample of 1980 Census, 5% sample of 1990 Census, 5% sample of 2000 Census, and the 2008 – 2010 3-year sample of American Community Survey.

FIGURE 2
Technology boom – Share of IT industries output in GDP, 1960 – 2010
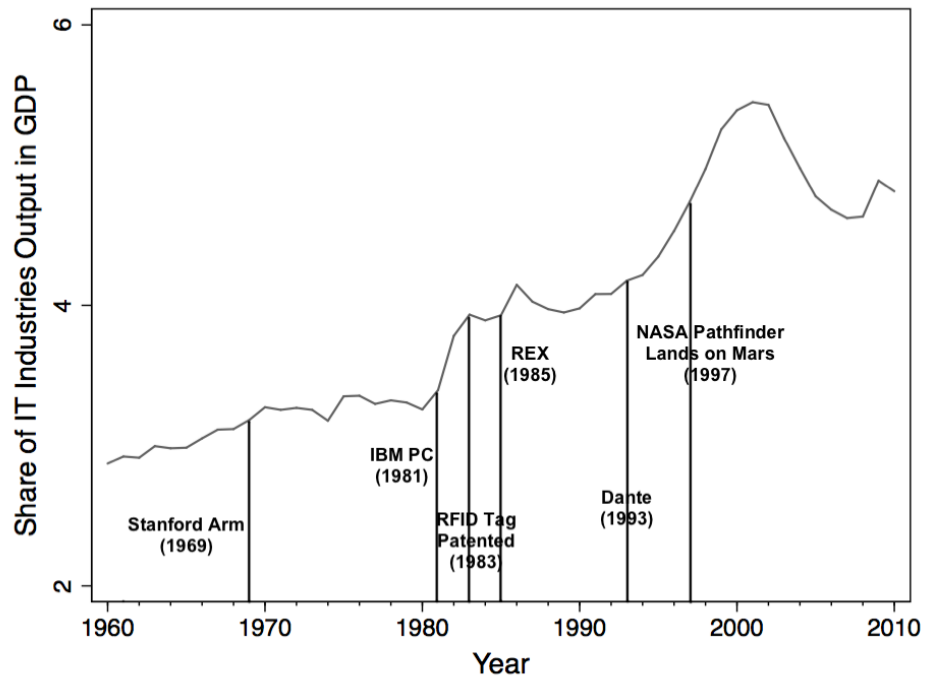
Sources: Share of IT industries output in GDP is calculated from the "Gross-Domestic-Product-(GDP)-by-Industry Data" Table from U.S. Bureau of Economic Analysis. Key technology events are referenced from Card and DiNardo (2002), Wallén (2008), and RobotShop Distribution Inc. (2008).

FIGURE 3
Routine employment share by MSA, 1970
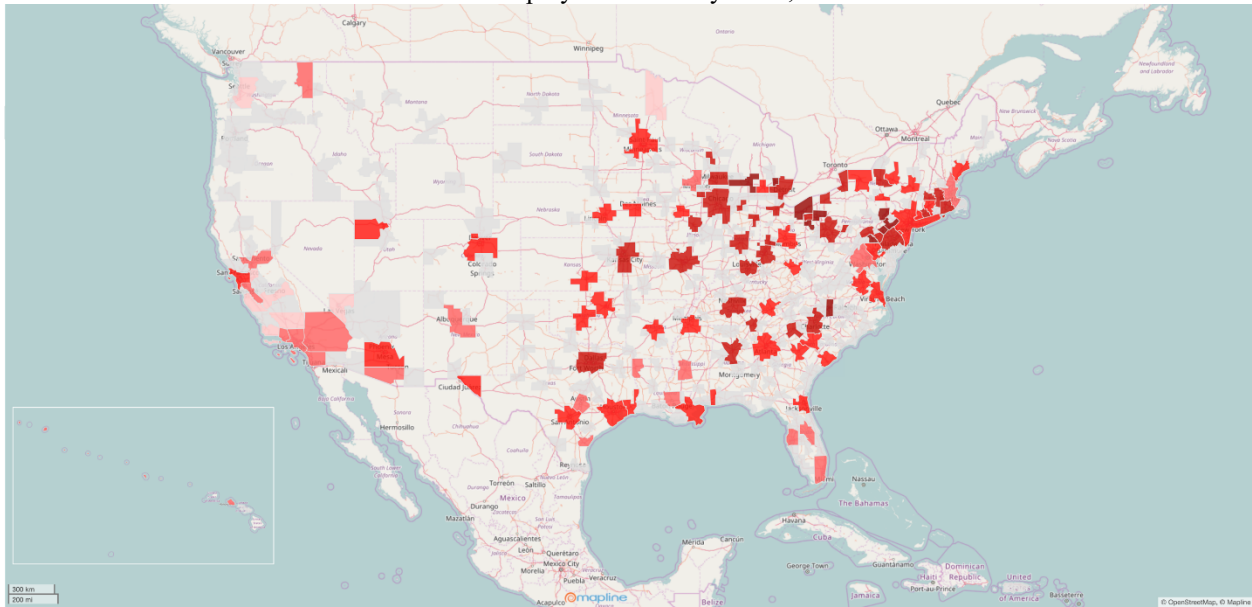
Notes: MSA level routine employment share in 1970 is calculated from the merged two versions of 1% samples of 1970 Census. Darker red colors represent higher routine employment share. The routine occupations classification is referenced from Autor and Dorn (2013) and categorized as follows: administrative support, retail sales, precision production, craft workers, machine operators, and assemblers are routine intensive occupations; while managers, technicians, financiers, public safety, transportation, construction, mining professions, farmers, and service occupations are considered non-routine occupations. This grouping method is developed through a procedure where the authors merge job task requirements from the fourth edition of the US Department of Labor's *Dictionary of Occupational Titles* (DOT) to the corresponding Census occupation classifications to measure each occupation's routine intensity, and then separate routine intensive occupations from non-routine intensive occupations accordingly. Data is not available the MSAs marked in grey and in Alaska due to inconsistencies of MSAs across sample periods. Figure is created using Mapline®.

TABLE 1

Change in native-immigrant wage gaps descriptive statistics, 1980 – 2000

	Unadj. Δ N-I Wage Gap	SE	Adj. Δ N-I Wge Gap	SE
Overall Sample	0.096	0.010	0.035	0.002
High school drop outs	0.083	0.023	0.073	0.003
High school diploma	0.114	0.023	0.042	0.003
Some college	0.123	0.017	0.023	0.004
At least college degree	0.066	0.021	0.003	0.003

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. The unadjusted Δ N-I Wage Gap is the change in average inflation adjusted wage gap between 1980 and 2000, and the adjusted Δ N-I Wge Gap is regression adjusted using age and age squared, education level controls, and race group controls. SE are standard errors obtained from regressing the wage gap against a constant.

TABLE 2

Routine employment share and changes in low skill service employment and in routine employment, 1980 – 2000

	$RShare_{c,\,1970}$
Δ Low skill service employment share	0.272[***]
	(0.023)
Δ Routine employment share	-0.668[***]
	(0.038)

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, and reside in an identifiable metropolitan area. Dependent variables are change in low skill service employment share from 1980 to 2000 and change in routine employment share from 1980 to 2000. $RShare_{c,\,1970}$ is routine employment share by MSA in 1970. Statistical significance levels are noted by the following: [*] significant at 10 percent; [**] significant at 5 percent; [***] significant at 1 percent.

TABLE 3

Top and bottom five MSAs by routine employment share

Top 5	Bottom 5
Jersey City, NJ	Las Vegas, NV
Wilkes-Barre-Hazelton, PA	Salinas-Sea Side-Monterey, CA
Lorain-Elyria, OH	Santa Barbara-Santa Maria-Lompoc, CA
Reading, PA	Fresno, CA
York, PA	West Palm Beach-Boca Raton-Delray Beach, FL

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars.

TABLE 4
Descriptive statistics

	1980		2000	
	Native	Immigrant	Native	Immigrant
Age	39.18	39.58	39.52	38.66
Log hourly wage	2.86	2.64	2.86	2.53
Less than high school	19.29	42.75	9.22	35.52
High school	37.49	23.88	32.47	25.41
Some college	18.67	12.87	28.68	17.91
College degree or more	24.55	20.50	29.63	21.16
White	89.45	85.00	90.16	80.64
Black	9.38	3.34	8.50	3.71
Asian	0.71	11.03	0.82	15.25
Hispanic	3.51	43.57	4.19	54.32
Number of observations	1,255,808	91,817	1,192,503	144,391

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars.

TABLE 5
Routine employment share and change in native-immigrant adjusted wage gaps within MSA-education groups, 1980–2000

Dependent Variable: Δ N-I Wage Gap	(1)	(2)	(3)	(4)
$RShare_{ec, 1970}$	0.115***	0.121***	0.123***	0.056***
	(0.010)	(0.009)	(0.009)	(0.014)
Compositional controls	No	Yes	Yes	Yes
State FE controls	No	No	Yes	Yes
Industry mix controls	No	No	No	Yes
R^2	0.283	0.308	0.373	0.403
Observations	469	469	469	469

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Δ N-I Wage Gap is the change in wage gap that is regression adjusted using age and age squared, education level controls, and race group controls. $RShare_{ec, 1970}$ is routine employment share by MSA and education group in 1970. Compositional controls include share of Hispanic workers, share of black workers, unemployment rate and size of immigrants along with its square form. State FE controls are state fixed effect dummies. Industry mix controls refer to shares of employment in durable and nondurable manufacturing industries, and shares of employment in high skill and low skill service sectors. The impact of the four sector share variables is allowed to vary by broad education group, which is defined as at least some college education versus at most high school graduates. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors that are clustered on MSA level are shown in brackets.

TABLE 6

Routine employment share and change in low skill immigrant share, change in high skill native born share, and change in college/high school relative wages within MSAs, 1980–2000

Dependent Variable	(1) Δ Low Skill Immi. Share	(2) Δ High Skill Native Share	(3) Δ College/High School Relative Wage
RShare$_{c, 1970}$†	0.023	0.319	0.016**
	(0.394)	(0.236)	(0.008)
R^2	0.549	0.598	0.869
Observations	118	118	118

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Wage gaps are regression adjusted using age and age squared, education level controls, and race group controls. Individuals with at most a high school degree are considered low skilled, and individuals with at least some college degree are considered high skilled. Compositional controls, industry mix controls, state fixed effect dummies are included in the model specification. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors are shown in brackets.
†: I use RShare$_{c, 1970}$ instead of RShare$_{ec, 1970}$ for the regressions in this table, as there is only one observation of each dependent variable in each MSA.

TABLE 7

Routine employment share and change in native-immigrant adjusted wage gaps (separated by immigrants' English language skills) and change in proficient-poor English speaking immigrant wage gaps within MSA-education groups, 1980–2000

(Section A: Adjusted native-immigrant wage gaps are separately estimated by immigrants' English speaking skills. Section B: Adjusted wage gaps between proficient and poor English speaking immigrants)

	A. Wage Gaps between Natives and Immigrants of Different English Speaking Skills				B. Wage Gaps between Proficient and Poor English Speaking Immigrants
	Non-English Country	English Country	Poor English Speaker	Proficient English Speaker	Proficient versus Poor English speakers
RShare$_{ec, 1970}$	0.056***	-0.042***	0.088***	0.040***	0.074***
	(0.014)	(0.023)	(0.036)	(0.008)	(0.032)
R^2	0.403	0.162	0.266	0.588	0.239
Observations	469	443	459	463	459

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Wage gaps are regression adjusted using age and age squared, education level controls, and race group controls. Immigrants who self-identify as speaking English well or very well are defined as proficient English speakers. Immigrants who self-identify as speaking English poor or not at all are defined as poor English speakers. RShare$_{ec, 1970}$ is routine employment share by MSA and education group in 1970. Compositional controls, industry mix controls, state fixed effect dummies are included in the model specification. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors that are clustered on MSA level are shown in brackets.

TABLE 8

Routine employment share and change in native-immigrant adjusted wage gaps (separated by immigrants' potential U.S. specific social skills) within MSA-education groups, 1980–2000

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Immigrated after the Age of 18	Immigrated before or at the Age of 18	Live in the U.S. for less than 15 Years	Live in the U.S. for at least 15 Years	Non-Intermarried	Intermarried	Live in Big Ethnic Enclaves	Live in Small Ethnic Enclaves	High Co-Ethnic Contact Likelihood	Low Co-Ethnic Contact Likelihood
$RShare_{ec,\ 1970}$	0.088**	0.034*	0.071***	0.031*	0.070***	0.012	0.066***	-0.035**	0.057***	0.029**
	(0.018)	(0.019)	(0.025)	(0.017)	(0.017)	(0.010)	(0.017)	(0.017)	(0.017)	(0.014)
R^2	0.437	0.480	0.293	0.409	0.376	0.363	0.386	0.209	0.311	0.368
Observations	464	457	454	466	465	457	469	364	469	454

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Wage gaps are regression adjusted using age and age squared, education level controls, and race group controls. A big ethnic enclave is defined as an ethnic enclave with above medium share of co-ethnic immigrants within an MSA. A small ethnic enclave is defined as an ethnic enclave with below medium share of co-ethnic immigrants within an MSA. Immigrants who immigrated after the age of 18, who have lived in the U.S. for less than 15 years, who are non-intermarried, who live in big ethnic enclaves, or who have high co-ethnic contact likelihood are considered to have low potential social skill; Immigrants who immigrated before or at the age of 18, who have lived in the U.S. for more than 15 years, who are intermarried, who live in small ethnic enclaves, or who have low co-ethnic contact likelihood are considered to have high potential social skill. $RShare_{ec,\ 1970}$ is routine employment share by MSA and education group in 1970. Compositional controls, industry mix controls, state fixed effect dummies are included in the model specification. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors that are clustered on MSA level are shown in brackets.

TABLE 9

Placebo Regressions: routine employment share and change in native-immigrant adjusted wage gaps within MSA-education groups, 1980 – 2000, 1970 – 1980, 1950 – 1970

(Panel A: independent variable: routine employment share of MSA-education group; Panel B: independent variable: routine intensity index of MSA-education group)

Dependent Variable: Δ N-I Wage Gap	$1980 - 2000$	$1970 - 1980$	$1950 - 1970$
Panel A			
$RShare_{ec,\ 1970}$	0.056***	0.000	-0.013
	(0.026)	(0.078)	(0.013)
R^2	0.403	0.199	0.264
Observations	469	438	267
Panel B			
$RIndex_{ec,\ 1970}$	0.185***	0.074	-0.027
	(0.037)	(0.135)	(0.032)
R^2	0.452	0.200	0.263
Observations	469	438	267

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Δ N-I Wage Gap is the wage gap that is regression adjusted using age and age squared, education level controls, and race group controls. $RShare_{ec,\ 1970}$ is routine employment share by MSA and education group in 1970. $RIndex_{ec,\ 1970}$ is routine employment index by MSA and education group in 1970, weighted by the national average level of routine intensity of industries. Compositional controls, industry mix controls, state fixed effect dummies are included in the model specification. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors that are clustered on MSA level are shown in brackets.

TABLE 10

Robustness Tests: routine employment share and change in native-immigrant adjusted wage gaps within MSA-education groups, 1980–2007, 1980 – 2010, 1990 – 2010

(Panel A: independent variable: routine employment share of MSA-education group; Panel B: independent variable: routine intensity index of MSA-education group)

Dependent Variable: Δ N-I Wage Gap	$1980 - 2007$	$1980 - 2010$	$1990 - 2010$
Panel A			
$Rshare_{ec,\ 1970}$	0.156***	0.239***	0.045***
	(0.028)	(0.033)	(0.013)
R^2	0.444	0.492	0.329
Observations	472	454	470
Panel B			
$Rindex_{ec,\ 1970}$	0.385***	0.495**	0.072**
	(0.069)	(0.059)	(0.032)
R^2	0.486	0.505	0.313
Observations	472	469	470

Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. Δ N-I Wage Gap is the wage gap that is regression adjusted using age and age squared, education level controls, and race group controls. $Rshare_{ec,\ 1970}$ is routine employment share by MSA and education group in 1970. $Rindex_{ec,\ 1970}$ is routine employment index by MSA and education group in 1970, weighted by the national average level of routine intensity of industries Compositional controls, industry mix controls, state fixed effect dummies are included in the model specification. Statistical significance levels are noted by the following: * significant at 10 percent; ** significant at 5 percent; *** significant at 1 percent. Heteroskedasticity-robust standard errors that are clustered on MSA level are shown in brackets.

Appendix

FIGURE A1

Regression adjusted native-immigrant relative wages, 1980 – 2010
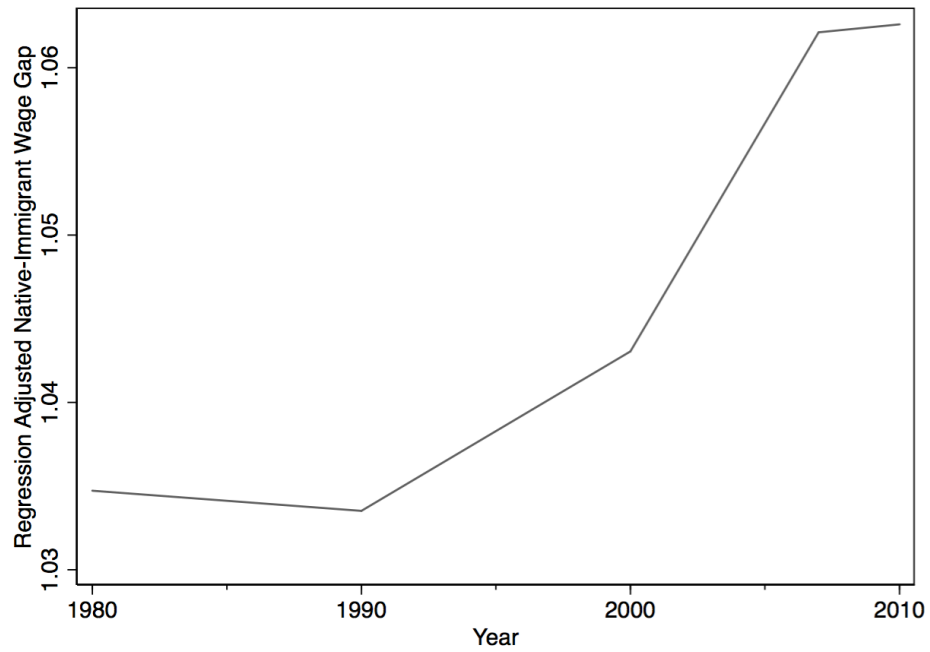
Notes: The sample consists of employed male workers between the ages of 18 and 64, who are not in school and work full time full year, reside in an identifiable metropolitan area, and earn an hourly wage between $2 and $200 in 1999 dollars. The wage gap is regression adjusted using age and age squared, education level controls, and race group controls. SE are standard errors obtained from regressing the wage gap against a constant.