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ABSTRACT

Migrants from a Different Shore: Earnings and Economic Assimilation of Immigrants from China in the United States

Using data from 1980, 1990, and 2000 U.S. censuses, as well as the 2010 and 2019 American Community Surveys and the 1993–2019 National Survey of College Graduates, we investigate the performance of Chinese immigrants in the U.S. labor market over the past 40 years since China initiated its economic reforms and open-door policy in 1978. The results indicate that by 1990, Chinese immigrants' earnings surpassed those of immigrants from other countries, and by 2010, they exceeded the earnings of U.S.-born workers. Our Oaxaca-Blinder and Quantile decomposition analyses suggest that a significant portion of the earnings advantage held by Chinese immigrants, compared to other immigrant groups and U.S.-born workers over time, can be attributed to differences in observable characteristics, with education being the most crucial factor, both at the mean and across the earnings distribution. By employing national surveys that provide data on college graduates, we demonstrate that attaining the highest degree earned in the U.S. is associated with higher earnings for Chinese immigrants compared to all other immigrants. Furthermore, the difference in returns to U.S.-earned highest degrees can account for this earnings advantage.

JEL Classification: J31, J61, J24

Keywords: immigration, China, the U.S., economic assimilation, Oaxaca-Blinder decomposition, quantile decomposition

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1. Introduction

Most narratives on early immigration waves to the U.S. predominantly emphasize European settlers (Archdeacon 1983; Bodnar 1985; Gabaccia 1999; Handlin 2002). Chinese immigrants, nevertheless, also constituted a significant group, initially drawn by the economic opportunities arising from the California Gold Rush in the late 1840s (Chang 2003; Pfaelzer 2007). Following the Civil War, the expansion of railroads, specifically the construction of the Central Pacific Railroad, led to an increased demand for laborers, which was largely met by Chinese immigrants (Saxton 1971; Ting 1995). In 1882, the Chinese Exclusion Act was enacted, banning Chinese immigration to the U.S. and preventing naturalization for those already in the country. This legislation remained in effect until 1943. It was only in 1965, with the passage of the Immigration and Nationality Act, that Chinese immigration to the U.S. was legalized. Since then, immigration from China has grown rapidly. With the initiation of China's economic reform and open-door policy in 1978, Chinese citizens gained increased freedom to travel. The number of legal immigrants from China admitted to the U.S. has consistently risen, with an average of 500,000 individuals arriving each decade since 1990.[1] By 2019, there were 2.32 million Chinese immigrants in total (Table 1), making them the third-largest immigrant group in the U.S. and constituting 4.83% of the total 48 million immigrant population.[2]

[Insert Table 1 here]

Although numerous economic studies on immigration indicate a general decline in the economic outcomes of immigrants compared to the U.S.-born population since the 1960s, significant variation exists among different immigrant groups (Borjas 1999; Duleep & Regets 1999, 2002; Zimmermann & Constant 2004; Hanson 2006; Epstein & Gang 2010). Borjas (1999) analyzes four waves of cross-sectional data from the U.S. Census (1960, 1970, 1980, and 1990) and discovers that, in 1990, the earnings of immigrant workers originating from Europe and Canada—which constituted 21% of the total number of immigrant workers—were 18% higher than those of U.S.-born workers. Rivera-Batiz (2007) examines the 1980 U.S. Census

[1] Our analysis focuses on immigrants from mainland China and excludes those from Hong Kong, Macau, and Taiwan. We use "immigrants from China" and "Chinese immigrants" interchangeably throughout the paper.

[2] The largest immigrant group is from Mexico, which has 11 million individuals residing in the U.S. and accounted for 23.42% of the total immigrant population in 2019. Mexico (23.42%), India (5.67%), China (4.83%), the Philippines (4.51%), El Salvador (3.06%), Vietnam (2.95%), Cuba (2.90%), Dominican Republic (2.59%), Guatemala (2.41%), Germany (2.38%), South Korea (2.30%), and are the top 11 immigrant-sending countries, each having more than 1 million migrants in the U.S. in 2019.

and the 2005 American Community Survey (ACS) and demonstrates that immigrants from Latin America and the Caribbean (LAC) earned substantially lower wages than other immigrants, with this gap persisting over time. Lin (2013) presents evidence that labor market outcomes for immigrants from mainland China, Hong Kong, and Taiwan improved relative to those of other immigrants between 1990 and 2010.[3] These findings align with the assertion in Borjas (1999) that the country of origin plays a crucial role in immigrants' economic outcomes. Furthermore, Duleep *et al.* (2022) emphasize the importance of the inverse relationship between immigrants' entry earnings and their subsequent earnings growth. They demonstrate that economists tend to underestimate the earnings growth of immigrants who begin with low earnings compared to their U.S.-born counterparts of similar age and education when assessing economic assimilation.

Our paper aligns with the aforementioned literature in that its primary objective is not to establish causality. Instead, it presents facts and offers explanations for the earnings differentials between Chinese immigrants and both all other immigrants and U.S.-born workers. Our work contributes to the economics of immigration literature in several aspects: First, our study uniquely examines a 40-year span of data, providing insights into the long-term economic assimilation of immigrants from China in the U.S. This longitudinal perspective is essential for understanding how immigrant outcomes evolve over an extended period of time. By analyzing consistent findings from U.S. Census and ACS data over several decades, our work adds a contemporary perspective to the literature that helps encapsulate the trends and shifts in immigration dynamics more comprehensively.

Second, we employ a combination of decomposition techniques—specifically, Oaxaca-Blinder decompositions for fundamental analysis at the mean and unconditional quantile decompositions across the earnings distribution for a comprehensive and in-depth exploration. These methodological approaches enable us to disentangle the factors contributing to earnings differentials across groups, attributing differences in labor market outcomes to observable individual characteristics, such as education, and to unobservable factors.

[3] Our contribution to the existing literature is distinct from Lin (2013) in several key aspects. First, we examine immigrants from mainland China over a 40-year span, from 1980 (when the country first initiated its economic reforms and open-door policy) to 2019 (the most recent survey year before the pandemic), and assess their earnings and economic assimilation beyond the mean—across the earnings distribution—using the quantile method. Second, we analyze not just the earnings gap between Chinese immigrants and other immigrants, but also the gap between Chinese immigrants and U.S.-born workers. Third, while Lin (2013) employs a method based on migration status and educational attainment to determine whether an immigrant obtained their highest degree in the U.S., we provide direct evidence from the National Survey of College Graduates spanning the 1993–2019 period. We demonstrate that possessing a U.S.-earned highest degree results in higher earnings for Chinese immigrants than all other immigrants.

Third, our findings carry significant policy implications with regard to selection, training, and integration of immigrants to the U.S. In particular, we highlight the pivotal role of education, particularly U.S.-earned degrees, in the labor market outcomes of Chinese immigrants. We detail policies that facilitate access to higher education, recognize foreign credentials, and support education and training, all of which are likely to improve the economic assimilation of not only Chinese immigrants but also other immigrant groups. This aspect of our study not only informs the current policy debates but also provides empirical support for specific interventions aimed at enhancing the integration and success of immigrants in the U.S. labor market.

In Figure 1, we display the GDP per capita ratio of selected immigrant-sending countries relative to the U.S. The graph illustrates that the income gap between China and the U.S. has significantly narrowed over the past four decades—the ratio rose from 0.021 in 1980 to 0.255 in 2019. Furthermore, Figure 1 reveals that China's GDP per capita relative to the U.S. surpassed that of India in 1992, while the corresponding figures for Mexico and the LAC region declined during the same timeframe.

[Insert Figure 1 here]

With regard to labor market outcomes, Figure 2 demonstrates that Chinese immigrants earned lower wages than U.S.-born workers in 1980, and the wage ratio—Chinese immigrants relative to U.S.-born workers—remained unchanged in 1990. However, by 2000, the gap had nearly closed (0.995), and the wage ratio continued to rise in favor of Chinese immigrants, increasing to 1.042 in 2010 and reaching 1.351 in 2019. This illustrates that in recent years, Chinese immigrants earned 35% more than U.S.-born workers. In contrast, the black line indicates that the wage ratio of all other immigrants to U.S.-born workers declined from 0.938 in 1980 to 0.806 in 2010, then increased to 0.935 in 2019.

[Insert Figure 2 here]

Table 2 presents labor force participation rates and unemployment rates for Chinese immigrants, all other immigrants, and U.S.-born workers by gender, spanning from 1980 to 2019. The table reveals that both female and male Chinese immigrants experience lower unemployment rates compared to both U.S.-born workers and all other immigrants. Meanwhile, the labor force participation rate for female Chinese immigrants has steadily increased, rising from 65% in 1980 to 68% in 2019, while the rate for male Chinese immigrants decreased from

88% in 1980 to 77% in 2019. In summary, the labor market outcomes for Chinese immigrants have significantly improved relative to those of all other immigrants and U.S.-born workers over the past 40 years.

[Insert Table 2 here]

What accounts for Chinese immigrants' improved labor market outcomes, enabling them to surpass all other immigrants and U.S.-born workers? Which factors are primarily responsible for their progressive labor market performance over time? To explore these questions, we use five nationally representative datasets, from 1980, 1990, and 2000 Censuses and the 2010 and 2019 ACS, to identify the contributing factors and assess their relative importance. Our findings indicate that Chinese immigrants earned less than all other immigrants in 1980, but the gap closed by 1990, and the earnings advantage of Chinese immigrants grew subsequently. We also discover that, between 1980 and 2000, the earnings of Chinese immigrants were lower than those of U.S.-born workers. Nevertheless, the wage gap narrowed in 2010 and continued to favor Chinese immigrants in 2019.

To gain insight into the superior performance of Chinese immigrants in the U.S. labor market, we employ the Oaxaca-Blinder decomposition to analyze the mean earnings gap. Our findings reveal that a significant portion of the differentials between Chinese immigrants and other immigrant groups, as well as between Chinese immigrants and U.S.-born workers, can be attributed to differences in observable endowments—specifically, the characteristics effect. This constitutes our primary explanation for the growing earnings gap favoring Chinese immigrants. Further detailed decompositions demonstrate that educational endowments, primarily the differences in years of schooling favoring Chinese immigrants, account for a substantial portion of the earnings differentials from 1980 to 2019.

We proceed to investigate the earnings gap at various points in the earnings distribution by employing quantile decomposition. For the upper end of the distribution, our findings align with the assimilation narrative of Chinese immigrants, wherein their earnings advantage consistently grew over time. Observable characteristics account for the majority of the increase in the earnings gap, and their importance continued to rise during the 1980–2019 period. Similarly, our results for the earnings gap between Chinese immigrants and U.S.-born workers at the lower end of the distribution also reveal a consistent pattern. However, a distinct pattern emerges when examining the earnings gaps between Chinese immigrants and immigrants from all other countries at the lower end of the earnings distribution. In this case, the gaps between the two groups remain relatively stable, indicating divergent stories for the earnings disparities at the lower end of the distribution.

To supplement our analysis, we employ national surveys that provide data on the nation's college graduates between 1993 and 2019. Our results indicate that Chinese immigrants who obtain a highest degree from a U.S. institution earn substantially more than those with a non-U.S.-earned degree. This finding further reinforces the conclusions derived from our previous analysis based on Census and ACS data, highlighting the critical role that education from the host country plays in determining the earnings of immigrants. Overall, our paper's findings suggest that observable characteristics, particularly U.S.-earned degrees, play a pivotal role in assimilating Chinese immigrants into the U.S. labor market.

2. Recent Trends in Migration from China to the U.S.

2.1. Legal Migration Flows

The initial significant influx of Chinese immigrants did not commence until the 1980s. As demonstrated in Table 1, approximately 300,000 legal Chinese immigrants resided in the U.S. in 1980. As of 2019, 85% of the total Chinese immigrant population in the U.S. arrived after 1981. The number of legal Chinese immigrants escalated to 542,717 in 1990 and exceeded one million by 2000. In 2010, 1.63 million Chinese immigrants resided in the U.S., and this figure rose to 2.32 million in 2019, constituting 4.83% of the total immigrant population.

2.2. Occupation and Industrial Sectors

The response of firms and workers to immigration constitutes a critical aspect of the immigration debate and bears significant policy implications. Native workers may either complement or compete with immigrant workers as they adapt to the economic shifts induced by immigration. Both domestic and foreign-owned firms capitalize on these changes. Immigrants typically enter occupations and industries that differ from those pursued or occupied by native workers (Borjas 1999). Moreover, immigration often alters the skill composition of the workforce in the immigrant-receiving area, as well as transforming the region's industrial structure (Borjas *et al.* 1997).

Compared to other immigrants and U.S.-born workers in 1980, 1990, 2000, 2010, and 2019, Chinese immigrants were disproportionately represented in white-collar occupations, as illustrated in Figure 3. For instance, in 2019, 46% of Chinese immigrants held managerial and professional occupations (up from 35% in 1980), while 24% occupied technical, sales, and administrative support roles (up from 16% in 1980). Conversely, they were under-represented in precision production, craft and repair, farming, forestry, fishing, operators, fabricators, laborers, and the military.

[Insert Figure 3 here]

Figure 4 displays the industrial sectors where Chinese immigrants, all other immigrants, and U.S.-born workers were employed from 1980 to 2019. The figure reveals that few Chinese immigrants worked in agricultural, forestry, fishing, and mining sectors. However, an exception to this trend is the retail sector, where Chinese immigrants were more likely to work compared to all other immigrants or U.S.-born workers.

[Insert Figure 4 here]

2.3. Educational Attainment

Social science research has consistently demonstrated that human capital has a robust and indisputable influence on social and economic outcomes, encompassing higher earnings, improved economic assimilation, reduced criminal activity, diminished drug abuse, and increased life expectancy (Borjas 1999). Specifically, the literature on immigration, including seminal works by Chiswick (1978) and Borjas (1985), has indicated that the skill composition of the immigrant population in the U.S. plays a crucial role in determining their earnings outcomes and economic assimilation into the labor market.

Since 1960, the relative educational attainment and economic performance of the immigrant population in the U.S. have undergone changes. The literature indicates that in the 1960s, immigrant workers, on average, received higher wages than U.S.-born workers. However, the educational attainment and wages of immigrants have fallen behind those of native-born workers since 1990 (Borjas 1999; Katz & Autor 1999; Rivera-Batiz 2007).

Chinese immigrants are disproportionately represented among those holding master's, professional, and doctoral degrees compared to all other immigrants and U.S.-born workers, as depicted in Figure 5. The proportion of such Chinese immigrants rose from 23% in 1980 to 44% in 2019. In contrast, the percentage of those who had not graduated from high school declined substantially, dropping from 34% in 1980 to 9% in 2019. The percentage of high school diploma holders remained stable at 18% in both 1980 and 2019, while the proportion of bachelor's degree holders increased notably, from 13% in 1980 to 21% in 2019.

[Insert Figure 5 here]

2.4. English Language Proficiency

Upon arrival in the U.S., immigrants may enhance their human capital through various means. They may enroll in university degree programs or on-the-job training programs to acquire new skills and valuable labor market information. Arguably, the most critical aspect of the assimilation process is the improvement in English language proficiency (Borjas 1999). The literature has demonstrated that immigrants who understand and speak English proficiently earn more than those who do not (McManus *et al.* 1983; Rivera-Batiz 1990; Chiswick & Miller 1992, 1995; Rivera-Batiz 2007). For instance, after adjusting for differences in education and other socioeconomic factors, McManus (1985) finds that Hispanic immigrants who speak English well earn 17% more than those who do not.

Table 4 indicates that, based on the index[4], the average English language proficiency of immigrants from China increased from 2.02 in 1980 to 2.24 in 2019. Similarly, the proficiency of all other immigrants improved from 2.27 in 1980 to 2.42 in 2019. Figure 6 presents English language proficiency classified into four categories: "does not speak English," "does not speak English well," "speaks English well," and "speaks English very well." The proportion of Chinese immigrants who do not speak English decreased from 6% in 1980 to 5% in 2019, and the percentage of those who do not speak English well decreased from 23% in 1980 to 19% in 2019. Furthermore, the percentage of those who speak English well decreased from 32% in 1980 to 27% in 2019. However, the proportion of Chinese immigrants who speak English very well increased significantly from 38% in 1980 to 49% in 2019, exceeding the proportion of all other immigrants. In summary, while Chinese immigrants possessed inferior English language skills compared to other immigrants, their proficiency has significantly improved since 1980.

[Insert Figure 6 here]

[4] The language proficiency index ranges from 0 to 4, with the following categories: 0-Does not speak English; 1-Yes, but not well; 2-Yes, well; 3-Yes, very well; 4-Yes, speaks only English. The last category, which indicates that the individual speaks only English, is omitted for immigrants in the surveys.

3. The Relative Earnings of Immigrants from China

3.1. Data

In this study, we analyze the labor market performance of immigrants over the past four decades using five datasets—the 1980, 1990, and 2000 U.S. Censuses, along with the 2010 and 2019 ACS from IPUMS USA (Integrated Public Use Microdata Series), published by the Minnesota Population Center (Ruggles *et al.* 2019). The 1980, 1990, and 2000 datasets consist of a 5% national random sample of the population (Census), while the 2010 and 2019 ACS datasets comprise a 1-in-100 random sample of the population. In Section 5, where we examine the impact of U.S.-earned degrees on immigrant earnings, we use six waves of National Survey of College Graduates (NSCG) datasets for the years 1993, 2003, 2010, 2013, 2015, 2017, and 2019, capturing data from as early as possible to the year of 1990.

[Insert Table 3 here]

Each wave of the U.S. Censuses, ACS, and NSCG datasets includes a specific set of variables, while lacking others that we are interested but unavailable for our analyses. We provide detailed sources, definitions, and imputations of these variables in Table 3. For the variables in the 1980, 1990, and 2000 U.S. Censuses as well as the 2010 and 2019 ACS, we use harmonized variables provided by IPUMS USA, which are consistently coded across all years, ensuring comparability in our main analysis.

Across all waves of the U.S. Censuses, ACS, and NSCG datasets, we incorporate independent variables essential for explaining earnings, aligned with the economics of immigration literature (Chiswick 1978; Borjas 1985; Rivera-Batiz 2007). These include years of schooling, usual hours worked per week, marital status (spouse present), and year of immigration (used to calculate U.S. and non-U.S. experience).

Note several caveats due to data definition and availability differences between our primary analysis using the U.S. Census and ACS datasets and Section 5 that employs the NSCG datasets. First, in our primary analysis, the key dependent variable "earnings" (total personal annual earned income), which is consistently coded within IPUMS USA. In the NSCG datasets, the most comparable variable is the basic annual salary from the principal job before deductions. We employ this variable definition in Section 5 to examine the relationship between U.S.-earned degrees and immigrant earnings. Second, as noted in Section 1, because the U.S. Census and

ACS datasets do not include information on whether degrees were earned in the U.S., we use the NSCG datasets to study this effect in Section 5. Third, we are unable to include English language proficiency in our models in Section 5 due to its absence in the NSCG datasets.[5]

3.2. Summary Statistics

We define an individual as an immigrant if they were born in a foreign country; all other individuals are classified as U.S.-born.[6] Our analysis is restricted to men aged 18–64 who are full-time workers (typically working 35 hours or more per week for 50 to 52 weeks in the reference year), have positive earnings, are not self-employed, do not reside in group quarters, are not members of the military, and are not full-time students. To ensure the comparability of our samples, we exclude Chinese immigrants from the category of all other immigrants, adjust the earnings variable for inflation and express it in 2010 dollars. We apply sampling weights to all calculations throughout the paper.

Table 4 presents the descriptive statistics of the variables used in our analysis and reveals that, since 1990, the average annual earnings of Chinese immigrants have surpassed those of all other immigrants, with the earnings differential continuing to grow thereafter. Furthermore, their earnings exceeded those of U.S.-born workers in 2010. Educational attainment, indicated by the number of completed years of schooling, is the primary explanatory variable in our earnings equation. In 1980, Chinese immigrants had an average of 13.3 years of schooling, higher than the 11.58 years for all other immigrants. The educational attainment trend further favored Chinese immigrants, as their years of schooling exceeded those of all other immigrants by 1.61 years in 1990, increasing to 2.81 years in 2000, and 2.83 years in 2010, before slightly declining to 2.42 years in 2019. Using the pooled data, the results show that the average earnings of Chinese immigrants are about 11,000 dollars higher than those of all other immigrants and 7,000 dollars higher than those of U.S.-born workers. Similarly, the average years of schooling for Chinese immigrants are also about 2.5 years higher than those of all other immigrants and 1.21 years greater than those of U.S.-born workers.

[Insert Table 4 here]

[5] Despite this limitation, we estimate our primary models without controlling for English language proficiency. We find that the results are largely unchanged, indicating that our findings remain robust. These results are detailed in Appendix B.

[6] Naturalized citizens are defined as immigrants. We exclude individuals who were born in American Samoa, Guam, Puerto Rico, the U.S. Virgin Islands, an unknown location, or at sea from the analysis.

Since the data do not provide the actual amount of labor market experience, we follow the approach used by Green and Worswick (2010) and Boudarbat and Lemieux (2014), calculating an individual's potential work experience as their age minus years of schooling minus six and then dividing immigrants' total years of experience into U.S. experience and non-U.S. experience. To calculate U.S. and non-U.S. work experience, we first determine the age of arrival for each immigrant by subtracting the difference between the year of the survey and the year of immigration from the person's age at the time of the survey. Non-U.S. work experience is then calculated as the age at arrival minus an assumed school-leaving age, which varies depending on the level of schooling of the immigrant. U.S. work experience is subsequently calculated by subtracting non-U.S. experience from total years of potential experience. Table 4 indicates that, with the exception of 1990, Chinese immigrants had less U.S. experience than all other immigrants, but this increased from 1980 to 2019 with Chinese immigrants having a slightly smaller of 0.44 years using the pooled data[7] Typically, the U.S. labor market does not value non-U.S. experience as highly as U.S. experience, and Table 4 reveals that Chinese immigrants' non-U.S. experience steadily decreased from 9.73 years in 1980 to 7.66 in 2010, and further to 6.03 in 2019.

In terms of English language proficiency, Chinese immigrants were, on average, less proficient than all other immigrants in the pooled data and across all years; however, their proficiency has improved since 1990, as discussed in Section 2.4. With respect to marital status, Chinese immigrants were more likely to be married (spouse present) compared to both all other immigrants and U.S.-born workers. Additionally, Chinese immigrants tended to be late arrivals, as evidenced by their years since migrating to the U.S. In summary, despite working a similar number of hours per week as all other immigrants, having lower English proficiency, and shorter years since migrating to the U.S., Chinese immigrants have demonstrated progressive labor market performance and more rapid economic assimilation compared to their counterparts from other countries, which warrants a thorough investigation.

3.3. Empirical Models

The empirical model employs the standard Mincer earnings equation (Mincer 1974), which

[7] The average age of Chinese immigrants in the survey years exhibits a minor increase, rising from 41 in 1980 to 43 in 2019. Over the same period, the age of all other immigrants also grows, from 38 to 43. We illustrate this trend in Appendix Figure F1.

was originally used by Chiswick (1978) and Borjas (1985) in the context of immigration studies:

$$Y_{ist} = X'_{ist}\beta + S_s + \varepsilon_{ist} \ , \qquad (1)$$

where the dependent variable Y_{ist} is the log of the earnings of worker *i* in state *s* in year *t*.[8] X_{ist} is a vector of demographic and human capital characteristics that may affect worker *i*'s earnings in state *s* in year *t*. β is a vector of regression coefficients, S_s is the state fixed effects, and ε_{ist} is the error term. The variables included in *X* are as follows: First, educational attainment—measured as completed years of schooling—serves as the human capital variable and has been demonstrated to positively affect workers' earnings. Second, following Boudarbat and Lemieux (2014) and Green and Worswick (2010), our human capital measurement contains total experience (EXP), which is divided into U.S. work experience (EXP_{US}) and non-U.S. work experience (EXP_{NonUS}). Specifically, Equation (1) incorporates both U.S. work experience and its square term (EXP_{US}^2), as well as non-U.S. work experience and its square term (EXP_{NonUS}^2).

Furthermore, we include an interaction term between years of U.S. experience and non-U.S. experience to capture the impact of changes in U.S. experience on immigrant earnings, which could be influenced by non-U.S. experience. In a standard quadratic model for experience, let α represent a fraction of non-U.S. experience. The earnings equation, excluding other earnings determinants, can be written as follows:

$$\begin{aligned} Y &= \beta_1 EXP + \beta_2 EXP^2 \\ &= \beta_1 (EXP_{US} + \alpha EXP_{NonUS}) + \beta_2 (EXP_{US} + \alpha EXP_{NonUS})^2 \\ &= \beta_1 EXP_{US} + \beta_2 EXP_{US}^2 + \gamma_1 EXP_{NonUS} + \gamma_2 EXP_{NonUS}^2 + \delta EXP_{US} \times EXP_{NonUS}, \end{aligned}$$

where $\gamma_1 = \beta_1\alpha$, $\gamma_2 = \beta_2\alpha^2$, and $\delta = 2\beta_2\alpha$. This quadratic model helps to capture the returns to workers' skills, which typically increase and then decline due to factors like aging and extended time in the labor market. Hence, we expect the signs of β_1 and γ_1 to be positive, and those of β_2 and γ_2 to be negative. Regarding the interaction term, as demonstrated in Boudarbat and Lemieux (2014) and Green and Worswick (2010) that Canadian and non-Canadian experiences are substitutes for each other, we anticipate a negative coefficient (δ) for the

[8] We also use the log of the hourly wage as the dependent variable, and find that the results closely mirror those obtained using log earnings in Equation (1). Given the consistency across outcomes, and to demonstrate robustness, we have included these results in Appendix A.

interaction term between U.S. and non-U.S. experiences.

Existing literature has demonstrated that English language proficiency positively impacts labor market outcomes, such as earnings (Rivera-Batiz 1990; Chiswick & Miller 1999; Rivera-Batiz 2007). Specifically, job searches can be significantly hindered if English language skills are inadequate.[9] The usual hours worked variable is presumed to positively affect earnings, holding other factors constant (Rivera-Batiz 2007). With respect to marital status, research in sociology and economics has provided evidence that married men are more likely to participate in the labor force, invest more in human capital, maintain better health, and have higher incomes (Chiswick 1978).

3.4. Decomposing the Earnings Gap

To assess the relative contributions of factors influencing the earnings gap between Chinese immigrants and all other immigrants, as well as between Chinese immigrants and U.S.-born workers, we employ the Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) in Equation (2). This allows us to calculate the portions of the gap that can be explained and cannot be explained, as outlined below:

$$Gap_t = \overline{Y}_t^{CN} - \overline{Y}_t^{RG} = \underbrace{(\overline{X}_t^{CN} - \overline{X}_t^{RG})\hat{\beta}_t^{CN}}_{\substack{\text{Characteristics effects} \\ \text{(Explained gap)}}} + \underbrace{(\hat{\beta}_t^{CN} - \hat{\beta}_t^{RG})\overline{X}_t^{RG}}_{\substack{\text{Coefficient effects} \\ \text{(Unexplained gap)}}} \qquad (2)$$

where $\widehat{Gap}$ is the estimated mean earnings gap, the overbar represents the sample mean, *t* is the year, and superscripts *CN* and *RG* denote Chinese immigrants and the reference group (U.S.-born workers and all other immigrants). The two right-hand components of Equation (2) show the portion of $\widehat{Gap}$ that is "explained by differences in observables characteristics" (characteristics or endowment effects) and the portion that is unexplained or "explained by differences in coefficients" (coefficient effects), which measures the earnings gap attributable to differences in returns to observable characteristics. Then we go a step further to sub-decompose the first and second terms of Equation (2) along each variable *X*—a method referred to as the detailed decomposition—to quantify the contribution of each variable to the earnings gap (Lin 2015).[10]

[9] Table 4 reports the average of the index, while Table 5 presents the regression estimates for the four dummies, using "Speak English very well" as the reference category.

[10] Since the detailed decomposition result for coefficient effects of categorical variables is not invariant to the choice of the base

In addition to decomposing the mean earnings gap, Firpo *et al.* (2009) develop the unconditional quantile regression method, which decomposes the differentials at various quantiles across the earnings distribution. Let $q_t^{CN}(\tau)$ and $q_t^{RG}(\tau)$ be the τth quantile of the earnings distributions for Chinese immigrants and the reference group, respectively. We define the quantile gap, $Gap_t(\tau)$:

$$Gap_t(\tau) = q_t^{CN}(\tau) - q_t^{RG}(\tau). \tag{3}$$

Firpo *et al.* (2009) and Fortin *et al.* (2011) demonstrate that in unconditional quantile regressions, the quantile gaps can be decomposed by replacing the dependent variable with a re-centered influence function (RIF). Assuming that $q(\tau)$ is the quantile of interest, we can define the re-centered influence function $RIF_{it}(\tau)$ as

$$RIF_{it}(\tau) = q(\tau) + [I(Y_{it} \geq q(\tau)) - (1-\tau)]/f(q(\tau)), \tag{4}$$

where $I(\cdot)$ is the indicator function that equals 1 if $Y_{it} \geq q(\tau)$. $f(q(\tau))$ is the earnings density evaluated at the τth quantile. Then, $I(Y_{it} \geq q(\tau))$ is a binary variable indicating whether an earnings observation is greater than or equal to a given quantile τ, whereas the other terms are constant in Equation (4). Firpo *et al.* (2009) and Fortin *et al.* (2011) show that the RIF-regression equation is fundamentally the same as the OLS regression, as in Equation (5):

$$RIF_{it}(\tau) = X_{it}'\beta + \varepsilon_{it}. \tag{5}$$

In summary, Firpo *et al.* (2009) and Fortin *et al.* (2011) demonstrate that the RIF-regression for the mean is equivalent to a standard OLS regression, and the decomposition at the mean is a conventional Oaxaca-Blinder decomposition. The interpretations of the β coefficients in the RIF-regression are simply the effects of the independent variables on the unconditional quantiles.[11]

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category (Oaxaca & Ransom 1999; Horrace & Oaxaca 2001; Gardeazabal & Ugidos 2004; Yun 2005; Jann 2008), we apply the method outlined in Gardeazabal and Ugidos (2004) and Yun (2005) to address this issue.

[11] Besides the method of Fortin *et al.* (2011), Chernozhukov *et al.* (2013) develop a global inversion procedure for quantile decompositions. We use both methods and find that the results are qualitatively similar. Since the method by Fortin *et al.* (2011) can directly compare to the conventional Oaxaca-Blinder decomposition, we report the results based on unconditional quantile decompositions in Section 4.4.

4. Results and Discussion

4.1. The Earnings Equation Estimates

Table 5 presents the OLS estimates of the factors affecting earnings for three groups: Chinese immigrants in the first column, all other immigrants in the second column, and U.S.-born workers in the third column. To facilitate comparison of the effects of the determinants on earnings across groups and over time, the OLS estimates from the earnings equations are categorized by year and country of origin. The regression coefficients on the determinants exhibit similar signs across groups and are consistent with theoretical expectations. Nonetheless, there are some discernible variations in the coefficients' magnitude.

[Insert Table 5 here]

The OLS estimates indicate a significant increase in the rates of return to education for Chinese immigrants since 1980. In 1980, holding other variables constant, an additional year of schooling raised the earnings of Chinese immigrants by 4.9%, which was lower than the figures for all other immigrants (5.4%) and for U.S.-born workers (8.2%). By 2000, the rate of return to U.S. years of schooling for Chinese immigrants had increased to 7% and continued to grow to 7.8% in 2010 and 8.4% in 2019, with 6.5% using the pooled data. Meanwhile, the rate for all other immigrants rose from 7% in 2000 to 8.1% in 2010 and 8.2% in 2019, and with 6.8% using the pooled data. The rate for U.S.-born workers is 10% using the pooled data, and it increased gradually from 8.2% in 1980 to 11.1% in 2000, 12.7% in 2010, and 12.1% in 2019, and exceeded those of both all other immigrants and Chinese immigrants. Overall, the rate of return to U.S. education for Chinese immigrants has consistently risen over time.

The growth of the rate of return to education can be attributed to various factors. Acemoglu (2002) and Katz and Autor (1999) document that the rate of return to education in the U.S. has rapidly increased, with a significant rise in the return to more skilled workers since the early 1980s. This trend of skill-biased technological change, which continues to this day, has created more demand for skilled labor and increased their returns (Rivera-Batiz 2007).[12] As noted in

[12] Several studies have attempted to explain the changes that have led to rising income inequality and wage polarization in the U.S. labor market. Krueger (1993) and Levy and Murnane (2004) propose that the growing use of computers and the internet, which has created more demand for skilled labor, can largely account for the increase in the rates of return to education since the early 1980s. Bernard and Jensen (2000) suggest that other factors, such as unions, the minimum wage policy, and international trade, may also contribute to the changes.

Section 2.2, the growing skill premium has had a more significant impact on Chinese immigrants, who tend to have a higher level of educational attainment and are overrepresented in skilled occupations such as managerial and professional jobs. Consequently, Chinese immigrants have experienced a consistent increase in the rate of return to education over time.

Consistent with theoretical expectations, all estimated coefficients for both U.S. and non-U.S. experience are positive, while those for the squared terms are negative. This pattern indicates that initial years of experience lead to an increase in earnings, but the rate of return diminishes as experience accumulates. Since 1990, the returns on U.S. work experience for Chinese immigrants have substantially exceeded those for other immigrant groups. For instance, in 2019, holding other variables constant, a one-year increase in U.S. experience led to a 5.4% rise in earnings for Chinese immigrants, compared to a 4% increase for other immigrants.[13] In contrast, the returns on non-U.S. experience for Chinese immigrants have been relatively modest. Specifically, a one-year increment in non-U.S. experience resulted in earnings increases of 0.5% in 1980, 0.6% in 1990, and 2.2% in 2019. These figures indicate that non-U.S. experience played a minor role in explaining Chinese immigrants' earnings between 1980 and 2010, but its significance grew in 2019. Additionally, the estimated coefficients for the interaction terms between U.S. and non-U.S. experiences are negative and quantitatively small, and were insignificant in 1980. This pattern suggests that, on average, more U.S. experience is associated with lower returns than non-U.S. experience. This finding is consistent with the assumption that the two kinds of experience are substitutes, as reflected in the descriptive statistics presented in Table 4.

Chiswick and Miller (2009b), using the 2000 U.S. Census, demonstrate that extensive pre-immigration labor market experience often correlates with less optimal job matches in the U.S., primarily because such experience may be less relevant or less recognized in the new labor market context. Therefore, transferring work experience across international borders often presents practical challenges. Reflecting on these insights, our findings from 1990 onward indicate that Chinese immigrants have exhibited higher rates of return to U.S. work experience compared to all other immigrants. This is accompanied by a continuous decrease in their non-

[13] To interpret the estimated coefficient of the U.S. experience variable within our earnings equation—a quadratic model that includes both a quadratic term and an interaction term with non-U.S. experience—we compute the first derivative as follows: $\beta_1 + 2\beta_2 + \beta_3 \times$ non-U.S. Experience. Here, β_1 represents the coefficient of U.S. experience, β_2 is the coefficient for the square of U.S. experience, and β_3 is the coefficient for the interaction term. We calculate the marginal effect using the mean value of non-U.S. experience. We employ the same method to interpret the coefficient for non-U.S. experience.

U.S. (pre-immigration) work experience, which declined from 10.69 years in 1990 to 6.03 years in 2019, as detailed in Table 4. With shorter durations of non-U.S. experience, these trends suggest Chinese immigrants could experience increasingly better job matches in the U.S. labor market, potentially contributing to their increased earnings over time.

The estimated effects of usual hours worked per week on Chinese immigrants' earnings reveal that an additional hour worked per week had a minimal effect on their earnings, reducing them by 0.2% (insignificant) in 1980 and growing to 0.6% in 2019, with an average effect of 0.2% using the pooled data. This indicates that the return to usual hours worked per week had become more significant in explaining Chinese immigrants' earnings, although the effect remains small.

Despite Chinese immigrants having lower proficiency in English than other immigrant groups, the impact of English language skills on their earnings differs significantly, as shown in Table 5. The estimates indicate a considerable difference in the effect of "English well" and "English not well" on Chinese immigrants' earnings in all years. For instance, in 2000, the estimated effects on earnings for Chinese immigrants who speak "English well" (-0.186) and other immigrants (-0.181) are comparable. However, for Chinese immigrants who speak "English not well" or "English not at all," the estimated effect on earnings is much more negative, leading to a 53.4% and 57.3% decrease in earnings, respectively, compared to English-only speakers (29.8% and 34.7% for other immigrants). These findings suggest that English language skills are a significant barrier for Chinese immigrants working in the U.S. and highlight the importance of improving their language proficiency. Research indicates that once their English language skills improve, there is a rapid increase in the return on earnings (Rivera-Batiz 1990; Chiswick & Miller 1999).

In summary, our regression result indicates that the increasing returns to observable characteristics, especially human capital (such as education, work experiences in the U.S. and non-U.S., and English language skills), contribute to the earnings growth of Chinese immigrants in the U.S. over the past 40 years.[14] This finding is consistent with studies by Weiss *et al.* (2003) and Eckstein and Weiss (2004), who examine the economic assimilation of highly skilled

[14] Although we have provided an overview of the occupations of Chinese immigrants in Section 2.2, we do not include the occupation variable in the earnings regression. To check for this potential endogeneity issue, we replace the dependent variable with mean occupational earnings, as in Chiswick and Miller (2009a), and estimate both OLS and ordered probit models (Miller 1987). Our analysis indicates that the results are consistent with the main findings of our paper. Further details on the results are available in Appendix D.

immigrants from the former Soviet Union in Israel between 1990 and 2000. They find that the growing returns to skills and accumulated Israeli experience account for 3.4% and 1.5% in immigrants' wage growth, respectively. After addressing the sample selection issue,[15] we employ decomposition methods to provide insights into the economic assimilation of Chinese immigrants.

4.2. Results of the Oaxaca-Blinder Decomposition

We employ the Oaxaca-Blinder decomposition method (Blinder 1973; Oaxaca 1973) to quantify the underlying causes using Equation (2). To facilitate a clear understanding of the outcome across groups and time, we present the decomposition analysis results on the log of mean earnings gaps in Figure 7. This figure displays the differences in earnings between Chinese immigrants and two other selected groups, for the years 1980, 1990, 2000, 2010, 2019, and the pooled data, and shows the contributions of the characteristics effects and coefficients effects.

[Insert Figure 7 here]

In Panel A of Figure 7, it is evident that the initial negative earnings gap between Chinese immigrants and other immigrant groups closed in 1990 and subsequently became positive. This positive gap ranged between 0.18 and 0.26 log points during the 2000-2019 period, with 0.18 log points using the pooled data, which indicates that Chinese immigrants have fared better than all other immigrants since 1990. The increasing positive gap suggests that Chinese immigrants have had a more successful assimilation experience in the U.S. labor market compared to all other immigrants.

Our analysis also reveals that a significant proportion of the earnings gap can be explained by observable characteristics, and this proportion has continued to increase over time (although it fell in 2019). Additionally, we find that coefficient effects (differences in returns to observable characteristics) have become increasingly important in recent years. Specifically, the contribution of observable characteristics to the earnings gap between Chinese immigrants and all other immigrants increased from 0.09 log points in 1980 to 0.2 log points in 1990, and further

[15] To address the sample selection issue arising from the exclusion of female workers, we employ the two-step Heckit Model (Heckman 1976). In the first step, we include the number of preschool children in the family as a covariate in the selection equation. Our analysis shows that the insignificance of all inverse Mill's ratio coefficients (except for U.S.-born in 1980 and the pooled data) suggests that sample selection does not bias our results. Further details on the results are available in Appendix E.

increased to 0.24 log points in 2010 before declining to 0.17 log points in 2019, with an average of 0.21 log points using the pooled data. On the other hand, the contribution of coefficient effects increased from -0.11 log points in 1980 to 0.09 log points in 2019, with -0.03 log points using the pooled data. These findings underscore the importance of both characteristics and coefficient effects in improving Chinese immigrants' earnings performance. In summary, our findings suggest that much of the earnings advantage for Chinese immigrants can be attributed to characteristics effects.

Panel B of Figure 7 also examines the earnings gap between Chinese immigrants and U.S.-born workers. The figure reveals that the negative earnings gap decreased between 1980 and 2000, and became positive in 2010 (although the gap is -0.01 log point and statistically insignificant using the pooled data). The positive gap grew to 0.22 log points in 2019, and the decomposition results indicate that the growing gap is primarily due to characteristics effects. Specifically, the proportion of the earnings gap between Chinese immigrants and U.S.-born workers attributable to characteristics effects increased from -0.15 log points in 1980 to 0.18 log points in 2019, representing a 0.33 log-point increase, despite being -0.02 log points using the pooled data. In contrast, the proportion of the gap attributable to coefficient effects remained relatively constant, ranging between -0.02 and 0.04 log points over the same period. Therefore, it is evident from Figure 7 that the closing gap between Chinese immigrants and U.S.-born workers is primarily driven by characteristics effects. Our analysis implies that characteristics effects play a crucial role in the economic assimilation of immigrants into the U.S. labor market, as evidenced by both the closing gap between Chinese immigrants and U.S.-born workers and the widening gap between Chinese immigrants and all other immigrants.

4.3. Results of the Detailed Decomposition

Figure 8 provides detailed decomposition results, demonstrating that education significantly contributes to both characteristics and coefficient effects for all groups and years. However, the proportion of the earnings gap explained by coefficient effects varied in determining the gaps between Chinese immigrants and U.S.-born workers, as well as between Chinese immigrants and all other immigrants. Specifically, the years of schooling in the characteristics effects consistently and positively contribute to the growing earnings gap between Chinese immigrants and all other immigrants, as well as that between Chinese immigrants and U.S.-born workers. In contrast, differences in returns to years of schooling (coefficient effects) contribute negatively to the gap between Chinese immigrants and U.S.-born workers, while those between Chinese immigrants and all other immigrants are continually small and statistically insignificant, except for the -0.18 log points in 1990. Therefore, the detailed decomposition results in Figure 8 suggest that the characteristics effects from years of schooling, which favor Chinese immigrants, play a significant role in explaining their economic assimilation.

[Insert Figure 8 here]

In addition, Figure 8 indicates that differences in the return to hours of work per week between Chinese immigrants and U.S.-born workers, as well as between Chinese immigrants and all other immigrants, negatively contribute to the earnings gap. We also find that differences in both characteristics effects and coefficient effects related to U.S. and non-U.S. work experience, marital status, and English language proficiency play a less important role in explaining the earnings gaps between Chinese immigrants and U.S.-born workers and that between Chinese immigrants and all other immigrants.

In conclusion, our analysis using the Oaxaca-Blinder decomposition method in Section 4.2 shows that observable characteristics that favor Chinese immigrants explain much of their relatively successful economic assimilation experience in the U.S. labor market. The detailed decomposition analysis further highlights that differences in years of schooling have become the most significant factor in explaining the closing earnings gap between Chinese immigrants and U.S.-born workers, as well as the growing gap between Chinese immigrants and all other immigrants. In the next section, we delve deeper into how our findings may differ for the lower and upper ends of the earnings distribution.

4.4. Decomposing the Gap Across the Earnings Distribution

We employ the RIF-regression in Equation (5) to study earnings differences across each decile. As our findings are qualitatively similar above and below the median, we present outcomes from the 10th percentile to represent the lower end of the earnings distribution and those from the 90th percentile to represent the upper end of the distribution.

[Insert Figure 9 here]

In Panel A of Figure 9, we present the results of the quantile decomposition of earnings gaps between Chinese immigrants and all other immigrants. At the lower end of the earnings distribution (10th percentile), the earnings gap was -0.11 log points in 1980, improved to -0.04 log points in 2000, and closed in 2010, but then became negative (-0.05 log points) in 2019, with -0.02 log points using the pooled data. Nearly two-thirds of the closing gap at the lower end (reduced from -0.11 to 0.07, a 0.18 log points change from 1980 to 2010) can be attributed to improved coefficient effects: increased from -0.16 to -0.04, a 0.12 log points change over the same period. Similar to the mean, we find the same result for the median, as the proportion of the earnings gap explained by coefficient effects increased from -0.16 log points in 1980 to 0.28 log points in 2019. At the upper end of the earnings distribution (90th percentile), the results indicate that the earnings gap rose from 0.04 log points in 1980 to 0.3 log points in 2019, with 0.23 log points using the pooled data. Differences in observable characteristics that favor Chinese immigrants account for much of the increased earnings advantage at the upper end of the earnings distribution.

Panel B of Figure 9 displays the outcomes of the quantile decomposition analysis for Chinese immigrants and U.S.-born workers and offers a distinct picture at the lower end of the earnings distribution. The result for the 10th percentile indicates that the gap has decreased by half, declining from -0.32 log points in 1980 to -0.16 log points in 2019 (-0.34 log points using the pooled data), with observable characteristics accounting for the reduction. This finding differs from that of Chinese immigrants and all other immigrants, where coefficient effects played a more significant role in closing the earnings gap.

Our analysis reveals a consistent trend in the results for both median and mean earnings. Specifically, the improvement in observable characteristics among Chinese immigrants explains the narrowing of the earnings gap. Notably, Chinese immigrants surpassed U.S.-born workers in median earnings in 2010. However, our findings for the 90th percentile indicate a substantial increase in the earnings gap, from 0.03 log points in 1980 to 0.39 log points in 2019, with 0.27 log points using the pooled data. We conclude that the observable characteristics that favor Chinese immigrants largely contribute to their earnings advantage at the upper end of the earnings distribution.

[Insert Figure 10 here]

[Insert Figure 11 here]

We conducted a detailed analysis of the earnings differentials between Chinese immigrants and other immigrant groups, as well as U.S.-born workers, at the 10th, 50th, and 90th percentiles of the earnings distribution. We present the findings in Figure 10 and Figure 11. Our results confirm the findings of the Oaxaca-Blinder decomposition, indicating that differences in years of schooling are the primary factor in explaining the earnings gaps across the lower, middle, and upper ends of the earnings distribution over time. Specifically, at the lower end, the differences in returns to years of schooling become increasingly important. At the upper end, the earnings advantage of Chinese immigrants can be largely attributed to differences in characteristics resulting from years of schooling, although differences in returns to years of schooling work in the opposite way.

In summary, our findings indicate that at the lower end of the earnings distribution, coefficient effects contribute significantly to the narrowing of the earnings gap between Chinese immigrants and all other immigrants, while characteristics effects largely explain the reduced earnings gap between Chinese immigrants and U.S.-born workers. At the upper end of the earnings distribution for both groups, differences in observable characteristics are the primary factor driving Chinese immigrants' increased earnings advantage.

5. Underlying Mechanism: U.S.-earned Degrees and Their Impact on Immigrant Earnings

Our paper presents two major findings. First, the widening earnings gap between Chinese immigrants and all other immigrants is primarily explained by observable characteristics, specifically differences in years of schooling.[16] Our detailed decomposition analysis reveals that the contribution of years of schooling to the earnings gap is substantial over time. Second, the earnings gap between Chinese immigrants and U.S.-born workers closed in 2010. We demonstrate that much of the gap closing can be attributed to characteristics effects, with differences in years of schooling favoring Chinese immigrants playing a significant role in their economic assimilation experience. This leads us to investigate whether U.S.-earned degrees led to higher earnings for immigrants, and to what extent such differences account for the disparate

[16] Our finding is consistent with previous studies. Rivera-Batiz (2007)) examines the wage gap between immigrants from LAC and other immigrants in the U.S. He finds that the widening wage gap between LAC immigrants and other immigrants was primarily due to the slow increase in the educational attainment of LAC workers and their lower rate of return to a college education. Zavodny (2003) used census data from 1980 and 1990, as well as data from the Current Population Survey from 1994 to 2000, to examine the earnings of Cuban immigrants in the U.S. labor market. She finds that non-white male Cuban immigrants earned 15% less than white U.S.-born workers, and attributed a significant portion of the wage gap to differences in education endowments and U.S. experience. Chiswick *et al.* (2008) also finds that years of schooling and labor market experience had a greater impact on earnings at higher deciles of the earnings distribution in both the U.S. and Australian labor markets.

economic assimilation experiences between Chinese immigrants and all other immigrants.

Given that the Censuses and ACS lack information on the location of the school where the degree was earned, we used seven waves of the NSCG dataset from 1993 to 2019 to examine this issue. The summary statistics presented in Table 6 indicate that, among immigrants with a college degree or higher, Chinese immigrants' earnings have grown steadily and surpassed those of all other immigrants by 2010, being approximately 7,000 dollars higher using the pooled data. Notably, the proportion of Chinese immigrants who obtained a U.S.-earned highest degree exceeded that of all other immigrants by 11 percentage points in 1993 (0.73 vs. 0.62) and further increased to 21 percentage points in 2019 (0.77 vs. 0.56), with 0.17 percentage point difference (0.73 vs. 0.56) using the pooled data. To answer our research questions, we estimate the following equation:

$$Y_{ist} = \delta EDUS_{ist} + X'_{ist}\beta + S_s + \varepsilon_{ist} \quad , \tag{6}$$

where *EDUS* is a dummy that equals 1 if the immigrant obtained their highest degree in the U.S. All other variables have the same definitions as in Equation (1), except for the fact that we did not distinguish between U.S. and non-U.S. experiences. This is because the NSCG data differs from Censuses and ACS in terms of the available information about the year of migration to the U.S. Additionally, we did not include hours of work per week as an independent variable because it was not available in the 1993 dataset.[17] Nevertheless, the results of including hours of work per week are quantitatively similar.[18]

[Insert Figure 12 here]

Figure 12 presents the estimates of U.S.-earned highest degrees on the earnings of Chinese immigrants and all other immigrants. The graph illustrates that, among Chinese immigrants, holding other factors constant, having a U.S.-earned highest degree is associated with 18% to 44% higher earnings than those who earned their highest degree outside of the U.S. between 1993 and 2019, with an average increase of 33% using the pooled data. Over the same period, the estimates for all other immigrants range from 5% to 18% and are consistently smaller than those for Chinese immigrants. These findings reinforce our previous conclusions based on

[17] The most relevant variable in the NSCG data is the year first came to U.S. and stayed for six months or longer. We use this variable in our analysis and find that the results are robust.

[18] We have included these results in Appendix C as a robustness check.

Census and ACS data and further underscore the vital role that education from the U.S.—the host country—plays in determining the earnings of immigrants.

[Insert Figure 13 here]

[Insert Figure 14 here]

To examine the earnings gap between college graduates of Chinese immigrants and all other immigrants, we employ the same decomposition method outlined in Section 3.4 and present the results of the overall Oaxaca-Blinder decomposition over time in Figure 13 and the detailed decomposition over time in Figure 14. The results in Figure 13 indicate that, on average, Chinese immigrants earned less than all other immigrants in 1993, but the gap closed (though insignificantly) in 2003. It then grew to 0.16 log points in 2010, 0.18 log points in 2013 and 2015, and slightly decreased to 0.14 log points in 2017 and 2019, including the pooled data. The decomposition results reveal that differences in observed characteristics explain over 85% of the gap each year. While the estimates are insignificant between 2010 and 2019 as well as the pooled data, we find that improving differences in the return to characteristics—the coefficient effects—can contribute to Chinese immigrants' progressive labor market performance. Detailed decomposition results in Figure 14 support these findings. The graph illustrates that, among statistically significant coefficients, differences in the return to U.S.-earned highest degrees significantly contribute to the earnings advantage of Chinese immigrants. The estimate was 0.17 in 1993, increased to 0.19 in 2013, rose to 0.29 in 2015, then decreased to 0.23 in 2017, and fell to 0.15 in 2019, with a consistent effect of 0.16 using the pooled data.

In summary, the results from NSCG data support our main findings based on Censuses and ACS, and provide further evidence that obtaining a U.S.-earned highest degree leads to higher earnings for Chinese immigrants than for all other immigrants.

6. Conclusion and Policy Implications

Migration from China to the U.S. has experienced a substantial upsurge since the initiation of China's reform and opening-up policy in the late 1970s. The findings of our empirical analysis demonstrate that the earnings of Chinese immigrants have experienced a notable upward trajectory as they have assimilated into the U.S. labor market, compared to other immigrant groups in the country. Most of this earnings advantage can be attributed to differences in observable characteristics, with a particular emphasis on higher levels of education completed within the U.S., predominantly contributing to the earnings advantage enjoyed by Chinese immigrants.

Our findings remain consistent across various specifications and reference groups; however, some limitations exist. First, as migration decisions are not random, the endogeneity issue may introduce potential biases in the results. Second, our data does not account for return migration. Due to the unavailability of emigration data, addressing these issues necessitates making unverifiable statistical and institutional assumptions (Borjas 1985). Consequently, if we were to adopt the improbable assumption that all individuals who do not succeed in the U.S. return to their countries of origin, our results would exhibit an upward bias.

Our study sheds light on the economic assimilation of immigrants from China in the U.S., a group that has demonstrated distinct labor market trajectories over the past forty years compared to other immigrants and U.S.-born workers. Understanding these patterns is important as it helps policymakers and scholars identify unique factors contributing to the economic success of this group —factors essential for developing targeted economic and immigration policies for the future. Our detailed exploration of these outcomes enhances our understanding of the unique patterns of labor market integration of immigration by country of origin, offering a nuanced view of how various immigrant groups fare in the U.S. labor market.

Human capital characteristics have emerged as significant factors influencing the earnings growth of immigrants from China over the past forty years. Particularly, our analysis identifies educational attainment as a key driver of economic success for immigrants from China. This insight is vital for policymakers and scholars, emphasizing the need to prioritize educational attainment in the process of selecting and supporting immigrants for smooth assimilation in the U.S. labor market.

Notably, our findings that education is pivotal align with those of Rivera-Batiz (2007) who uses the 1980 U.S. Census and the 2005 ACS to study the wage gap between immigrants from LAC and all other immigrants in the U.S. He finds that the slow increase in the educational attainment of LAC workers and their lower rate of return to a college education could primarily explain the widening wage gap between LAC immigrants and other immigrants.

Another distinct finding of our study reveals the importance of the location of earned degrees using data from the National Survey of College Graduates spanning 1993 to 2019. Our results show that Chinese immigrants who obtained their highest degree from U.S. institutions tend to achieve higher earnings compared to those with degrees from outside the U.S. This suggests that the quality and relevance of U.S.-based education significantly enable better job matches and labor market outcomes.

Our findings underscore the pivotal role of education, particularly U.S.-earned degrees, in the economic outcomes of immigrants from China. Policies that facilitate access to U.S. higher education, recognize foreign qualifications, and support education and training are likely to improve the economic assimilation of not only immigrants from China but also other immigrant groups.

Additionally, the economic outcomes of immigrants from China, as highlighted in our study, also reflect the broader implications of different immigrant policies. Countries like Canada employ a point-based immigration system, where potential immigrants are admitted based on factors such as education and work experience. This system tends to favor immigrants with higher educational qualifications and skills that are directly transferable to the labor market (Baker & Benjamin 1994). Consequently, immigrants from China who enter Canada through this point system often exhibit higher labor market success from the outset due to the pre-selection of individuals with attributes that align with the country's economic needs (Benjamin *et al.* 2021).

In contrast, the U.S. immigration system has traditionally emphasized family unification and accepting refugee claimants since the Immigration and Nationality Act of 1965, allowing immigrants to sponsor family members and admitting refugees, regardless of their immediate economic potential. While such policies foster strong family support networks that can aid in the social integration of immigrants, they do not necessarily prioritize economic selection criteria, such as education or work experience. As a result, immigrants from China arriving through family unification may encounter initial disadvantages in the labor market if their qualifications or skills are not well-aligned with U.S. labor market demands.

Our findings suggest that the economic success of immigrants to the U.S. could be enhanced by policies that integrate elements of the point system, such as recognizing and prioritizing educational attainment and professional skills in immigrant selection decisions. This could involve reforms to the current family unification policy to incorporate additional selection criteria that assess the economic potential of future immigrants, similar to Canada's point-based system.

Furthermore, policies that support the recognition of foreign credentials and qualifications, along with providing pathways for upskilling or reskilling, could help bridge the gap for immigrants entering the U.S. under less selective policies, such as family reunification or as refugee claimants. By adopting a hybrid approach that leverages the strengths of both family-based and point-based systems, the U.S. could potentially enhance the economic outcomes for all immigrant groups, including those from China.

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Table 1. Changes in the number of immigrants from China and other countries and in what percentage of the U.S. population they form

Year	The U.S. born	All immigrants = (1) + (2)		All other immigrants (1)		Immigrants from China (2)	
	Number	Number	% of the U.S. population	Number	% of the U.S. population	Number	% of all immigrants
2019	278,078,457	48,022,409	14.73	45,704,887	13.92	2,317,522	4.83
2010	265,214,606	42,386,752	13.78	40,753,302	13.17	1,633,450	3.85
2000	246,765,636	33,055,462	11.81	32,043,657	11.39	1,011,805	3.06
1990	225,200,798	20,626,488	8.39	20,083,771	8.09	542,717	2.63
1980	210,632,200	14,149,840	6.29	13,852,060	6.11	297,780	2.10

Note: The table includes all observations from each survey. The U.S. population is the sum of the U.S. born and all immigrants.
Source: 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

Table 2. Labor market status of U.S.-born workers, immigrants from China, and all other immigrants

Unit: %	Year	Immigrants from China		All other immigrants		U.S. born	
		Men	Women	Men	Women	Men	Women
Labor force participation rate	Pooled	85.24	64.37	85.24	64.37	82.31	70.13
	2019	77.19	68.10	87.89	68.72	80.09	74.11
	2010	80.28	66.82	87.16	66.44	79.60	72.92
	2000	79.46	63.41	77.86	58.66	81.70	71.53
	1990	83.70	65.93	86.84	63.46	85.36	69.96
	1980	87.89	65.49	86.30	57.14	86.08	60.18
Unemployment rate	Pooled	4.72	5.12	6.17	7.68	6.79	6.19
	2019	2.86	3.17	3.11	4.52	4.86	4.37
	2010	8.08	8.47	9.58	10.92	11.61	9.55
	2000	4.08	4.78	5.67	7.85	5.28	5.14
	1990	4.50	4.86	6.82	8.34	5.88	5.61
	1980	2.73	4.39	5.83	7.31	6.10	6.08

Note: Observations are between 18 and 64 years of age. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

Table 3. Variable data sources, definitions, and imputations

Variable	Data sources	Definition
Earnings	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019. • NSCG: 1993, 2003, 2010, 2013, 2015, 2017, and 2019.	Earnings are calculated for the sample of men and women who did not reside in group quarters, were employed in the civilian labor force, were not enrolled in full-time education, reported positive annual earnings, weeks worked, and weekly hours, and were not self-employed. The annual earnings for 1980, 1990, 2000, and 2019 were then adjusted for inflation and converted to 2010 constant dollars. In NSCG datasets, earnings are defined as the basic annual salary from the principal job before deductions. This definition excludes bonuses, overtime pay, and any additional compensation for summertime work.
Usual hours worked per week	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019. • NSCG: 2003, 2010, 2013, 2015, 2017, and 2019.	In the 2010 and 2019 American Community Surveys (ACS), the number of weeks worked in the calendar year prior to the survey is reported as a categorical variable. We impute the number of weeks worked for each worker using the following assignments: ▪ 7 weeks for those who worked 13 weeks or less, ▪ 20 weeks for 14–26 weeks, ▪ 33 weeks for 27–39 weeks, ▪ 43.5 weeks for 40–47 weeks, ▪ 48.5 weeks for 48–49 weeks, ▪ 51 weeks for 50–52 weeks. In the NSCG datasets, we use the variable "Hours per week typically worked," which indicates the number of hours a person works during a typical week on the principal job. Note that the 1993 NSCG survey does not include this variable.
Years of schooling	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019. • NSCG: 1993, 2003, 2010, 2013, 2015, 2017, and 2019.	Due to variations in the coding of the education variable across surveys, we adopted specific coding strategies for calculating completed years of education. For the 1980 and 1990 censuses, the following assignments were made: 2.5 years for grades 1 through 4; 6.5 years for grades 5 through 8; 12 years for completing grade 12 or obtaining a high school diploma or GED. In the 2000 census, the assignments were: 2.5 years for nursery school through grade 4; 5.5 years for grades 5 and 6; 7.5 years for grades 7 and 8; and 12.5 years for some college attendance without completing a year. For all census data and the ACS, the coding was as

		follows: 13 years for completing some college but not earning a degree; 14 years for earning an associate's degree. In both the censuses, ACS, and the NSCG, educational attainment was coded at 16 years for a bachelor's degree, 18 years for a master's degree, 19 years for a professional degree beyond a bachelor's degree, and 20 years for a doctoral degree.
Experience	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019. • NSCG: 1993, 2003, 2010, 2013, 2015, 2017, and 2019.	We define experience as the worker's age at the time of the survey minus years of completed education minus 6. Our analysis is limited to individuals who have between 1 and 45 years of experience.
U.S. and non-U.S. experience	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019.	First, we calculate an immigrant's age of arrival by subtracting the number of years between the immigration year and the survey year from the person's age at the time of the survey. Non-U.S. experience is calculated by subtracting an assumed age of leaving school—which varies based on the immigrant's level of education—from the age of arrival. We then calculate U.S. experience by subtracting the non-U.S. experience from the total experience.
U.S-earned highest degree	• NSCG: 1993, 2003, 2010, 2013, 2015, 2017, and 2019.	We use the variable "Location of school awarding highest degree (U.S./non-U.S.)", coding it as 1 if the highest degree was earned in the U.S., and 0 if obtained outside the U.S.
English language proficiency	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019.	English language proficiency is defined as a categorical variable: it is assigned a value of 0 if the individual does not speak English; 1 if the individual speaks English but not well; 2 if the individual speaks English well; and 3 if the individual speaks English very well.
Married, spouse present	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019. • NSCG: 1993, 2003, 2010, 2013, 2015, 2017, and 2019.	"Married, spouse present" is defined as a binary variable: it is assigned a value of 1 if the individual's marital status is "married" and their spouse is present. In all other cases (including married with spouse absent, widowed, divorced, separated, or never married), the variable is assigned a value of 0.
Year of immigration	• U.S. Census: 1980, 1990, and 2000. • ACS: 2010 and 2019.	The year a foreign-born individual first entered the U.S. is recorded based on their responses in the 1980 and 1990 Censuses, where they were asked to indicate a range of years that included their year of arrival—for

	example, stating "1990" for arrivals between 1987 and 1990. We impute the specific year of migration for each worker using midpoint estimates for these ranges: for instance, 1988.5 for 1987–1990. The variable "Year Since Migration" is then calculated as the difference between the year of the survey and the imputed year of immigration.

Source: U.S. Censuses and American Community Survey (ACS) are from IPUMS USA. National Survey of College Graduates (NSCG) data are public use data files from National Science Foundation.

Table 4. Descriptive statistics

Variables	Year	Immigrants from China		All other immigrants		U.S. born	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Annual earnings (2010 dollars)	Pooled	61,378	61,201	49,981	54,107	54,254	47,281
	2019	89,626	88,396	67,817	76,296	65,979	67,571
	2010	69,504	63,069	54,360	60,395	62,695	58,670
	2000	57,212	56,043	48,812	56,533	58,047	56,096
	1990	51,086	46,584	46,273	43,679	52,528	41,225
	1980	43,090	31,343	43,327	31,363	47,149	28,932
Years of schooling	Pooled	14.48	4.80	12.00	4.60	13.27	2.63
	2019	15.84	4.22	13.42	4.12	14.02	2.53
	2010	15.44	4.50	12.61	4.30	13.90	2.46
	2000	14.64	4.73	11.83	4.58	13.45	2.41
	1990	13.28	4.79	11.67	4.74	13.23	2.54
	1980	13.30	5.19	11.58	4.70	12.78	2.92
U.S. work experience	Pooled	13.23	9.15	13.67	9.57	19.99	11.52
	2019	14.96	9.94	17.97	11.01	21.15	12.17
	2010	14.08	8.73	16.16	10.05	23.16	11.52
	2000	12.38	8.66	13.19	9.25	20.76	10.80
	1990	13.71	9.65	12.47	8.87	19.12	10.99
	1980	11.98	8.61	12.11	8.84	18.73	12.34
Non-U.S. work experience	Pooled	8.73	9.80	6.80	8.19		
	2019	6.03	8.27	5.96	7.90		
	2010	7.66	9.02	6.26	7.89		
	2000	8.87	9.45	6.52	7.98		
	1990	10.69	10.71	6.90	8.28		
	1980	9.73	10.82	8.36	8.78		
English language proficiency	Pooled	2.04	.96	2.24	.96		
	2019	2.24	.89	2.42	.86		
	2010	2.09	.96	2.22	.96		
	2000	2.02	.97	2.17	1.00		
	1990	1.92	.98	2.26	.95		
	1980	2.02	.93	2.27	.93		
Usual hours worked per week	Pooled	44.55	8.86	44.19	8.58	44.76	8.42
	2019	43.27	7.39	43.99	8.26	44.98	8.55
	2010	44.00	8.30	43.65	8.02	44.95	8.51
	2000	45.03	9.08	44.72	8.72	45.52	8.57
	1990	45.43	9.98	44.23	9.11	44.84	8.71
	1980	44.07	8.47	43.22	7.75	43.74	7.70
Married, spouse present	Pooled	.78	.42	.65	.48	.68	.47
	2019	.73	.44	.66	.47	.59	.49
	2010	.78	.42	.65	.48	.65	.48
	2000	.77	.42	.61	.49	.65	.48
	1990	.81	.39	.66	.47	.70	.46
	1980	.81	.40	.74	.44	.73	.44

Years since migrating to the U.S.	Pooled	14.99	10.36	16.80	11.67	
	2019	17.50	10.82	21.99	13.46	
	2010	15.89	9.77	19.62	12.62	
	2000	13.83	9.98	16.27	11.62	
	1990	15.34	11.19	15.69	10.80	
	1980	13.79	9.35	14.38	9.52	
Observations	Pooled	22,220		758,460		6,548,850
	2019	3,774		82,299		433,395
	2010	2,697		74,857		391,415
	2000	8,136		303,696		2,017,059
	1990	4,400		183,280		1,914,349
	1980	3,213		114,328		1,792,632

Note: Observations are men between 18 and 64 years of age full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The earnings have been adjusted for inflation and are expressed in 2010 dollars. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. English language proficiency is a categorical variable that equals 0 if the person does not speak English; equals 1 if the person speaks English but not well; equals 2 if the person speaks English well; equals 3 if the person speaks English very well.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

Table 5. Determinants of earnings of immigrants from China and selected groups: OLS estimates

Dependent variable: log earnings	Year	Immigrants from China		All other immigrants		U.S. born	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of schooling	Pooled	.065***	.002	.068***	.000	.100***	.000
	2019	.084***	.004	.082***	.001	.121***	.000
	2010	.078***	.005	.081***	.001	.127***	.001
	2000	.070***	.003	.070***	.000	.111***	.000
	1990	.052***	.003	.065***	.000	.103***	.000
	1980	.049***	.004	.054***	.001	.082***	.000
U.S. work experience	Pooled	.053***	.002	.054***	.000	.050***	.000
	2019	.049***	.005	.044***	.001	.044***	.000
	2010	.064***	.006	.048***	.001	.053***	.000
	2000	.051***	.004	.045***	.001	.045***	.000
	1990	.071***	.005	.062***	.001	.052***	.000
	1980	.052***	.006	.070***	.001	.052***	.000
U.S. work experience squared /100	Pooled	-.099***	.006	-.091***	.001	-.079***	.000
	2019	-.087***	.013	-.073***	.002	-.068***	.001
	2010	-.119***	.015	-.078***	.003	-.088***	.001
	2000	-.094***	.011	-.072***	.001	-.074***	.000
	1990	-.130***	.012	-.099***	.002	-.082***	.000
	1980	-.105***	.017	-.129***	.003	-.082***	.000
Non-U.S. work experience	Pooled	.007***	.002	.030***	.000		
	2019	.039***	.008	.042***	.002		
	2010	.016**	.007	.038***	.001		
	2000	.008**	.004	.034***	.001		
	1990	.020***	.005	.040***	.001		
	1980	.005	.006	.040***	.001		
Non-U.S. work experience squared /100	Pooled	-.003	.006	-.051***	.001		
	2019	-.089***	.022	-.087***	.005		
	2010	-.003	.017	-.072***	.004		
	2000	-.007	.011	-.069***	.002		
	1990	-.032**	.013	-.074***	.002		
	1980	-.004	.014	-.072***	.003		
U.S. and non-U.S. work experience interaction	Pooled	-.001***	.000	-.001***	.000		
	2019	-.001***	.000	-.001***	.000		
	2010	-.001***	.000	-.001***	.000		
	2000	-.001***	.000	-.001***	.000		
	1990	-.001***	.000	-.001***	.000		
	1980	-.000	.000	-.001***	.000		
Usual hours worked per week	Pooled	.002***	.001	.011***	.000	.011***	.000
	2019	.006***	.002	.014***	.000	.016***	.000
	2010	.004**	.002	.015***	.000	.016***	.000
	2000	.003***	.001	.012***	.000	.013***	.000

	1990	.000	.001	.009***	.000	.009***	.000
	1980	-.002	.002	.007***	.000	.006***	.000
Married, spouse present	Pooled	.160***	.013	.212***	.002	.259***	.001
	2019	.180***	.030	.223***	.005	.273***	.002
	2010	.110***	.034	.194***	.006	.247***	.002
	2000	.142***	.021	.205***	.003	.246***	.001
	1990	.104***	.029	.226***	.004	.259***	.001
	1980	.189***	.034	.214***	.005	.258***	.001
English well	Pooled	-.229***	.012	-.202***	.002		
	2019	-.297***	.030	-.304***	.007		
	2010	-.226***	.029	-.260***	.007		
	2000	-.186***	.019	-.181***	.003		
	1990	-.193***	.027	-.129***	.004		
	1980	-.213***	.031	-.133***	.005		
English not well	Pooled	-.560***	.017	-.315***	.003		
	2019	-.655***	.045	-.348***	.008		
	2010	-.566***	.048	-.363***	.008		
	2000	-.534***	.028	-.298***	.004		
	1990	-.493***	.034	-.257***	.005		
	1980	-.457***	.043	-.269***	.008		
English not at all	Pooled	-.653***	.026	-.369***	.004		
	2019	-.700***	.071	-.336***	.013		
	2010	-.774***	.069	-.390***	.012		
	2000	-.573***	.044	-.347***	.006		
	1990	-.534***	.050	-.368***	.008		
	1980	-.671***	.076	-.354***	.012		
Constant	Pooled	4.499***	.046	3.924***	.007	3.461***	.002
	2019	4.132***	.178	3.645***	.033	2.763***	.015
	2010	4.247***	.171	3.501***	.031	2.659***	.014
	2000	4.438***	.105	3.769***	.015	3.081***	.006
	1990	4.595***	.142	3.690***	.019	3.254***	.006
	1980	4.867***	.117	4.093***	.019	3.888***	.004
Observations	Pooled	22,220		758,460		6,548,850	
	2019	3,774		82,299		433,395	
	2010	2,697		74,857		391,415	
	2000	8,136		303,696		2,017,059	
	1990	4,400		183,280		1,914,349	
	1980	3,213		114,328		1,792,632	
Adjusted R^2	Pooled	.438		.358		.315	
	2019	.408		.342		.349	
	2010	.495		.394		.352	
	2000	.424		.356		.325	
	1990	.448		.397		.338	
	1980	.398		.296		.265	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Observations are men between 18 and 64 years of age who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The earnings have been adjusted for inflation and are expressed in 2010 dollars. The group “All other immigrants” excludes the group “Immigrants from China” from the entire immigrant population. The reference category of English language proficiency is “English only” and “English very well”. All regressions include state fixed effects and the pooled estimations additionally control for year fixed effects.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author’s tabulations.

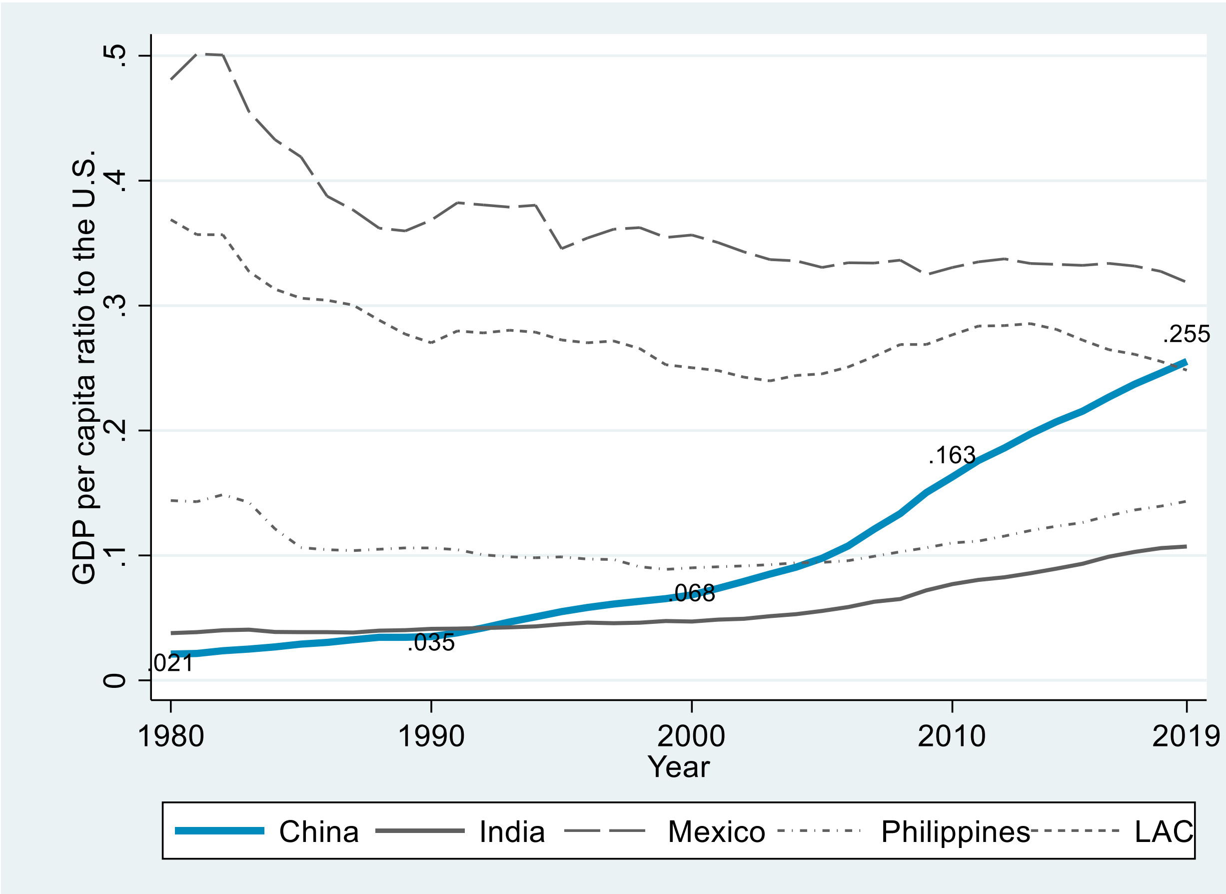
Table 6. Descriptive statistics of immigrant college graduates

Variables	Year	Immigrants from China		All Other Immigrants	
		Mean	S.D.	Mean	S.D.
Earnings* (2010 dollar)	Pooled	95,288	45,906	88,309	54,965
	2019	100,017	48,486	90,990	54,993
	2017	98,592	47,054	91,278	55,571
	2015	97,875	47,273	88,048	54,926
	2013	91,756	42,787	83,037	53,228
	2010	92,972	41,521	86,958	56,549
	2003	87,565	42,550	89,918	55,172
	1993	77,776	44,819	83,967	50,656
U.S.-earned highest degree	Pooled	.73	.44	.56	.50
	2019	.77	.42	.56	.50
	2017	.73	.44	.57	.49
	2015	.76	.43	.56	.50
	2013	.70	.46	.57	.50
	2010	.69	.46	.51	.50
	2003	.71	.45	.55	.50
	1993	.73	.44	.62	.49
Years of schooling	Pooled	17.99	1.17	17.15	1.32
	2019	17.99	1.18	17.14	1.30
	2017	17.97	1.18	17.13	1.30
	2015	18.00	1.12	17.14	1.30
	2013	18.01	1.16	17.12	1.31
	2010	17.99	1.19	17.13	1.32
	2003	18.05	1.14	17.19	1.37
	1993	17.79	1.34	17.37	1.48
Potential experience (year)	Pooled	18.661	9.89	20.78	10.08
	2019	16.94	10.51	20.78	10.26
	2017	18.17	10.46	20.93	10.58
	2015	17.94	9.98	20.44	10.46
	2013	19.22	8.57	21.47	9.80
	2010	21.23	9.37	20.89	9.75
	2003	19.06	8.69	20.50	9.42
	1993	21.91	9.26	19.41	9.02
Married, spouse present	Pooled	.82	.38	.78	.41
	2019	.74	.44	.77	.42
	2017	.80	.40	.77	.42
	2015	.81	.40	.77	.42
	2013	.89	.32	.78	.41
	2010	.88	32	.81	.40
	2003	.91	.28	.82	.39
	1993	.93	.26	.81	.39
Hours per week typically worked	Pooled			44.32	11.12
	2019	42.66	10.45	42.78	11.98
	2017	43.27	9.18	44.05	10.74

	2015	42.91	9.12	44.03	10.73
	2013	42.60	11.77	44.28	10.62
	2010	44.10	9.00	45.52	11.06
	2003	44.22	9.62	46.39	11.07
	1993				
Observations	Pooled	5,979		55,544	
	2019	1,397		8,969	
	2017	965		7,604	
	2015	886		7,693	
	2013	870		8,037	
	2010	644		6,850	
	2003	810		8,539	
	1993	407		7,852	

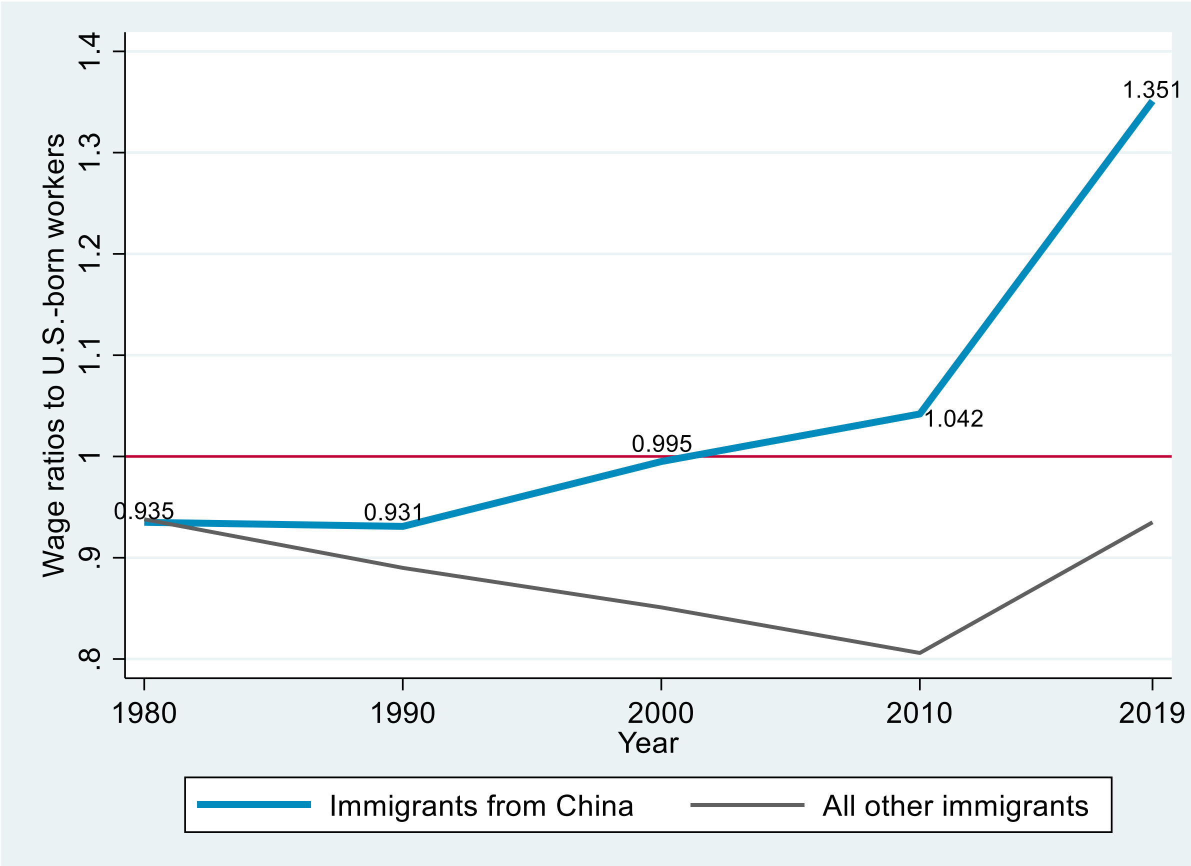
Note: * Earnings is the basic annual salary on the principal job before deductions, which do not include bonuses, overtime, or additional compensation for summertime. Final survey-specific weights are used in all calculations. The variable hours per week typically worked is not available in 1993.
Source: National Survey of College Graduates.

Figure 1. Income gaps between selected countries and the U.S.



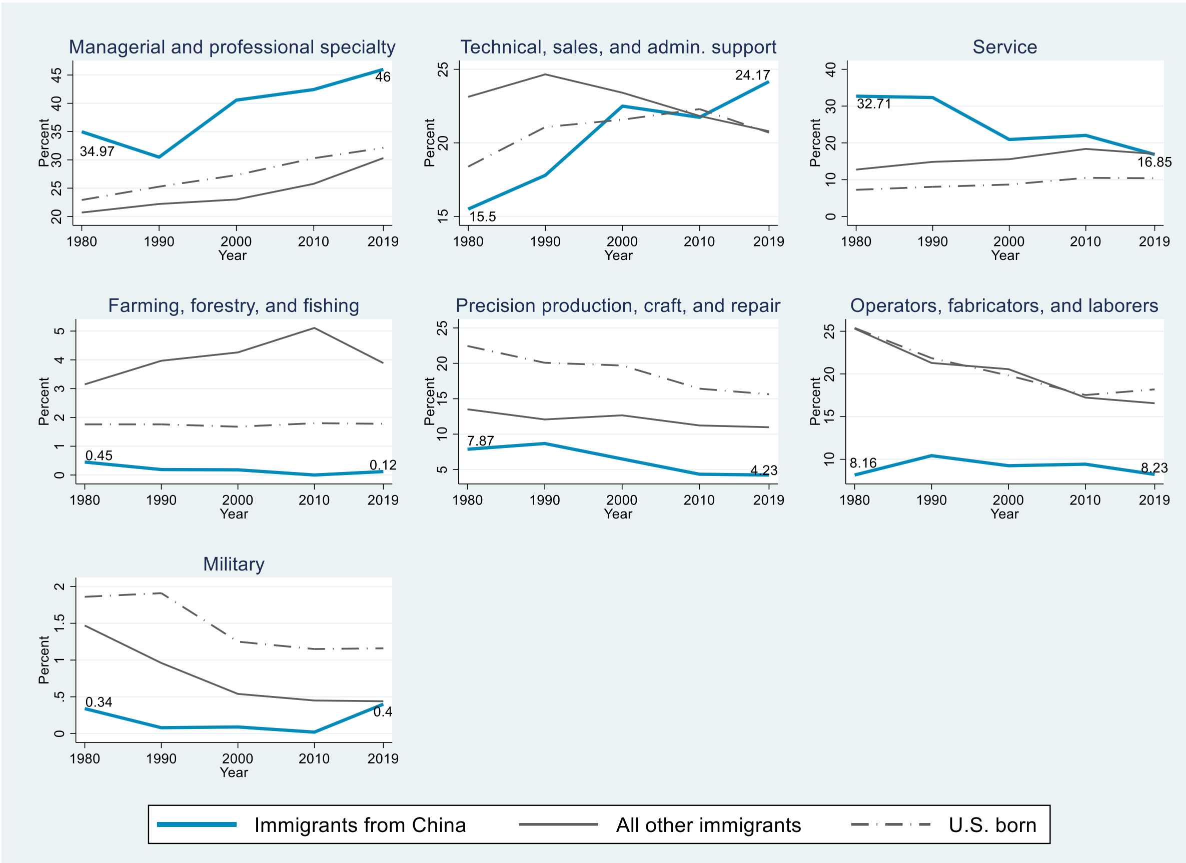
Note: Numbers are ratios of GDP per capita of selected countries to those of the U.S. The data are PPP–adjusted and expressed in constant 2017 international dollars. LAC denotes Latin America and the Caribbean.
Source: World Economic Outlook Database, IMF (2021).

Figure 2. Wage ratios of immigrants from China and other countries to U.S.-born workers



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses, and ACS from 2010 and 2019; author's tabulations.

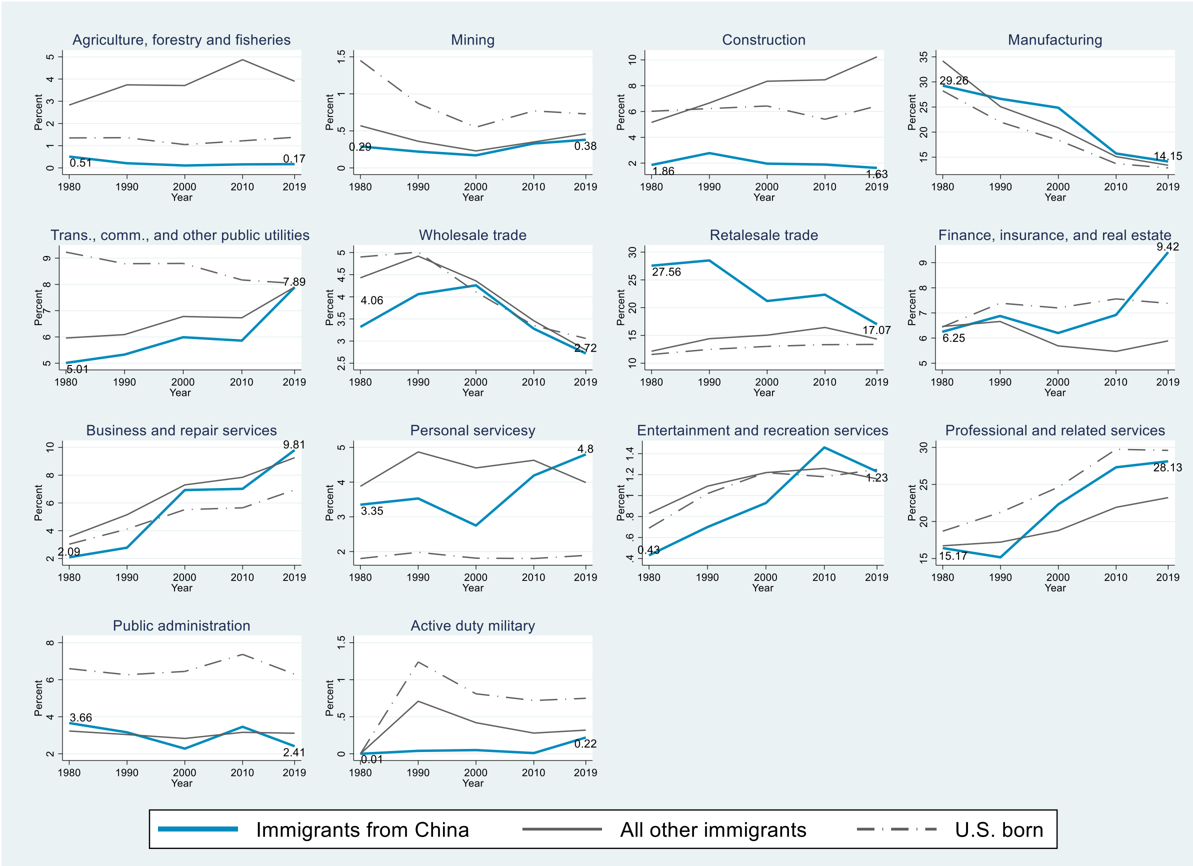
Figure 3. Occupation of immigrants from China and selected groups



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

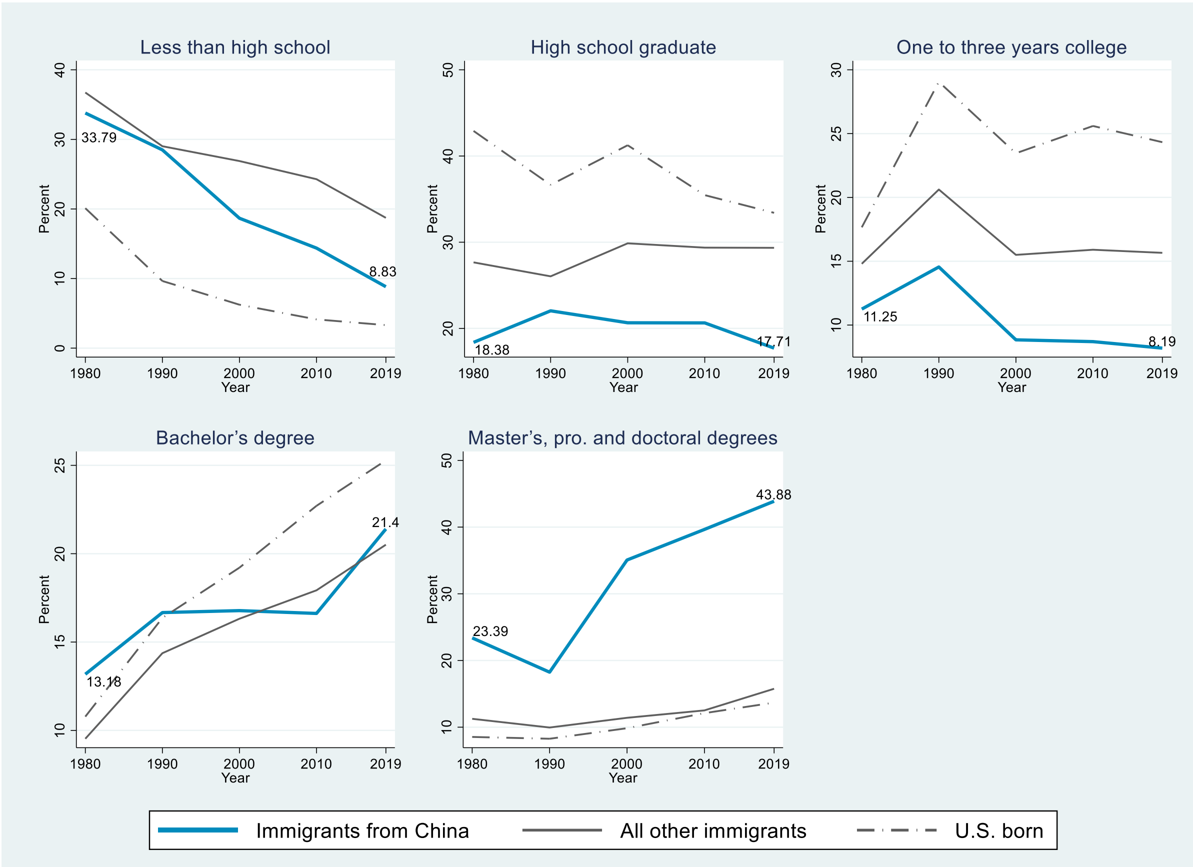
Figure 4. The industrial sector of immigrants from China and selected groups



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

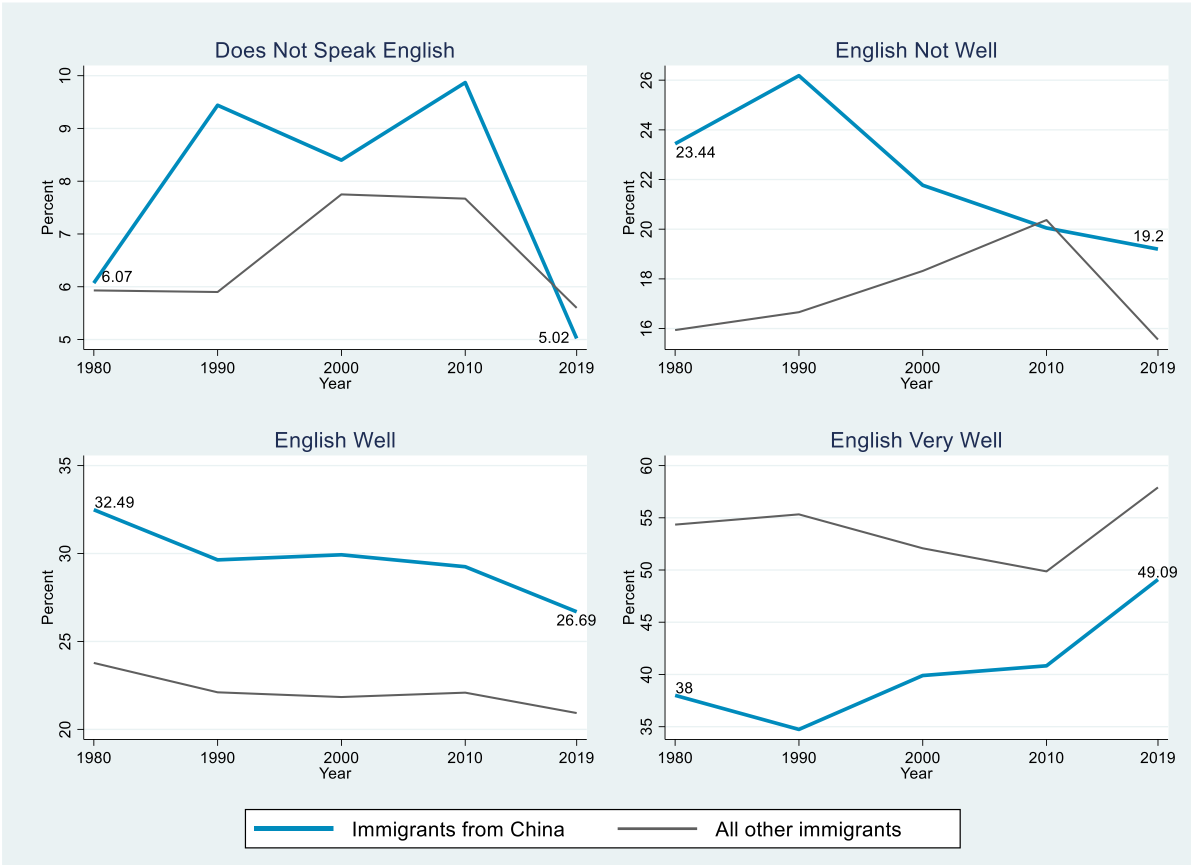
Figure 5. Educational attainment of immigrants from China and selected groups



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

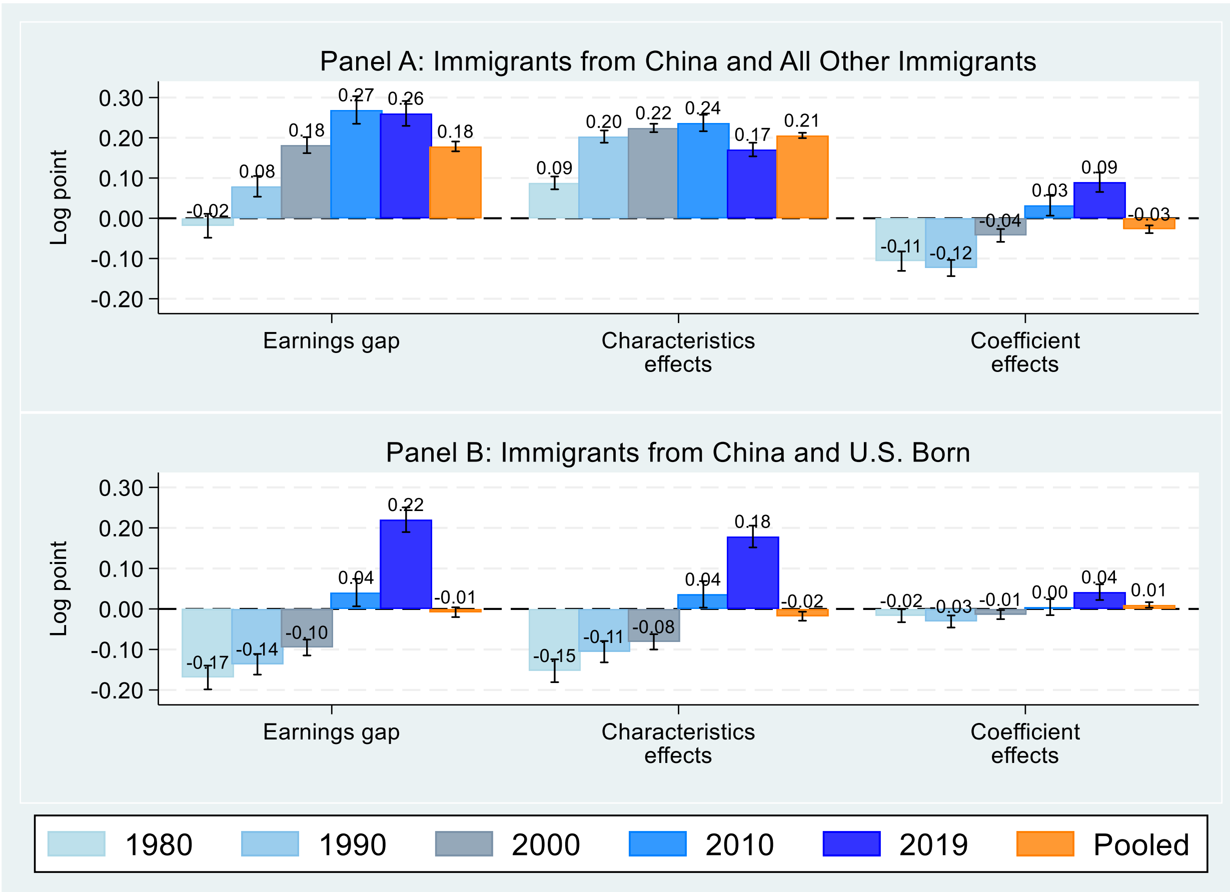
Figure 6. English language proficiency of immigrants from China and all other countries



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

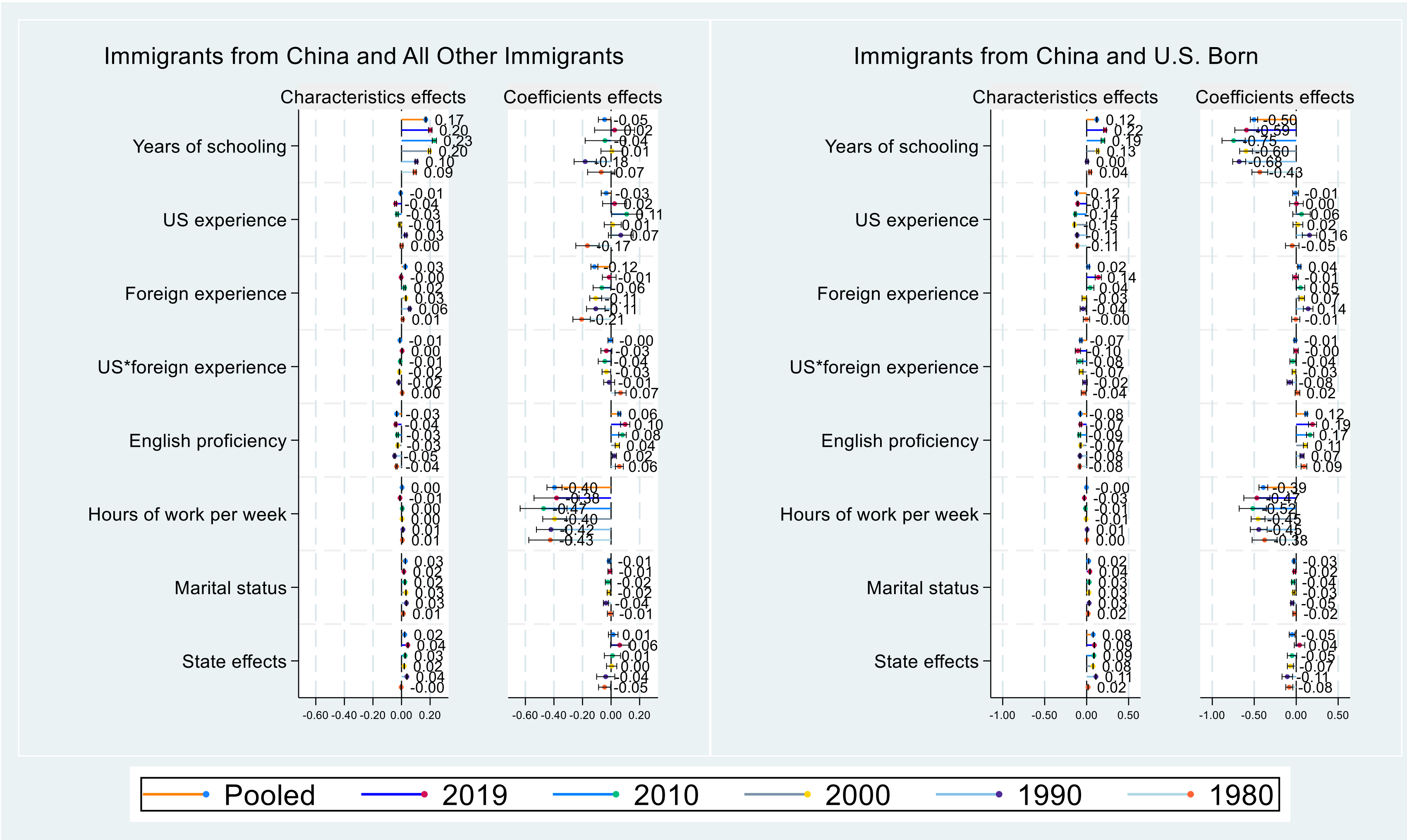
Figure 7. Oaxaca-Blinder decompositions: earnings gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

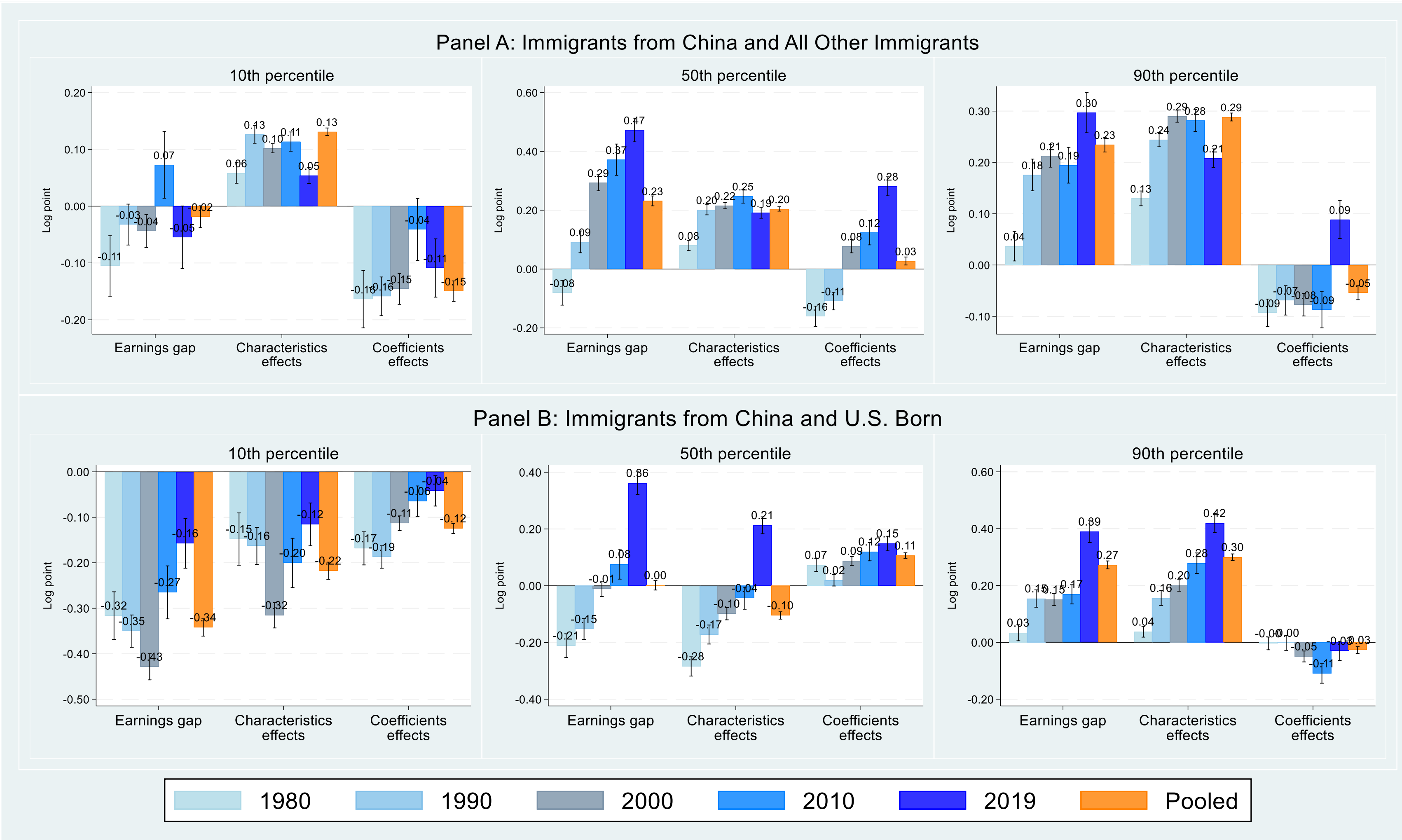
Figure 8. Detailed Oaxaca-Blinder decompositions: earnings gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

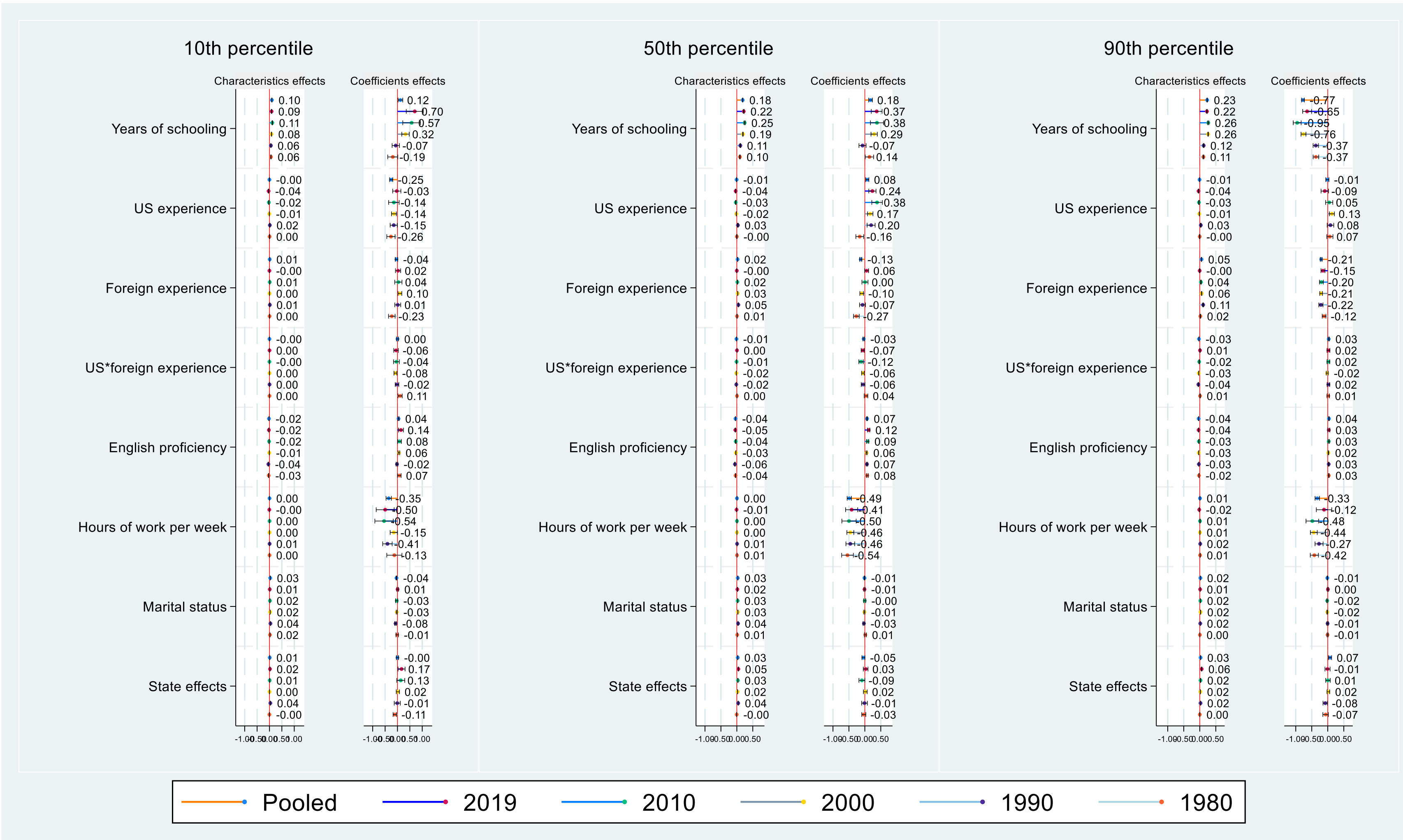
Figure 9. Quantile decompositions: earnings gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

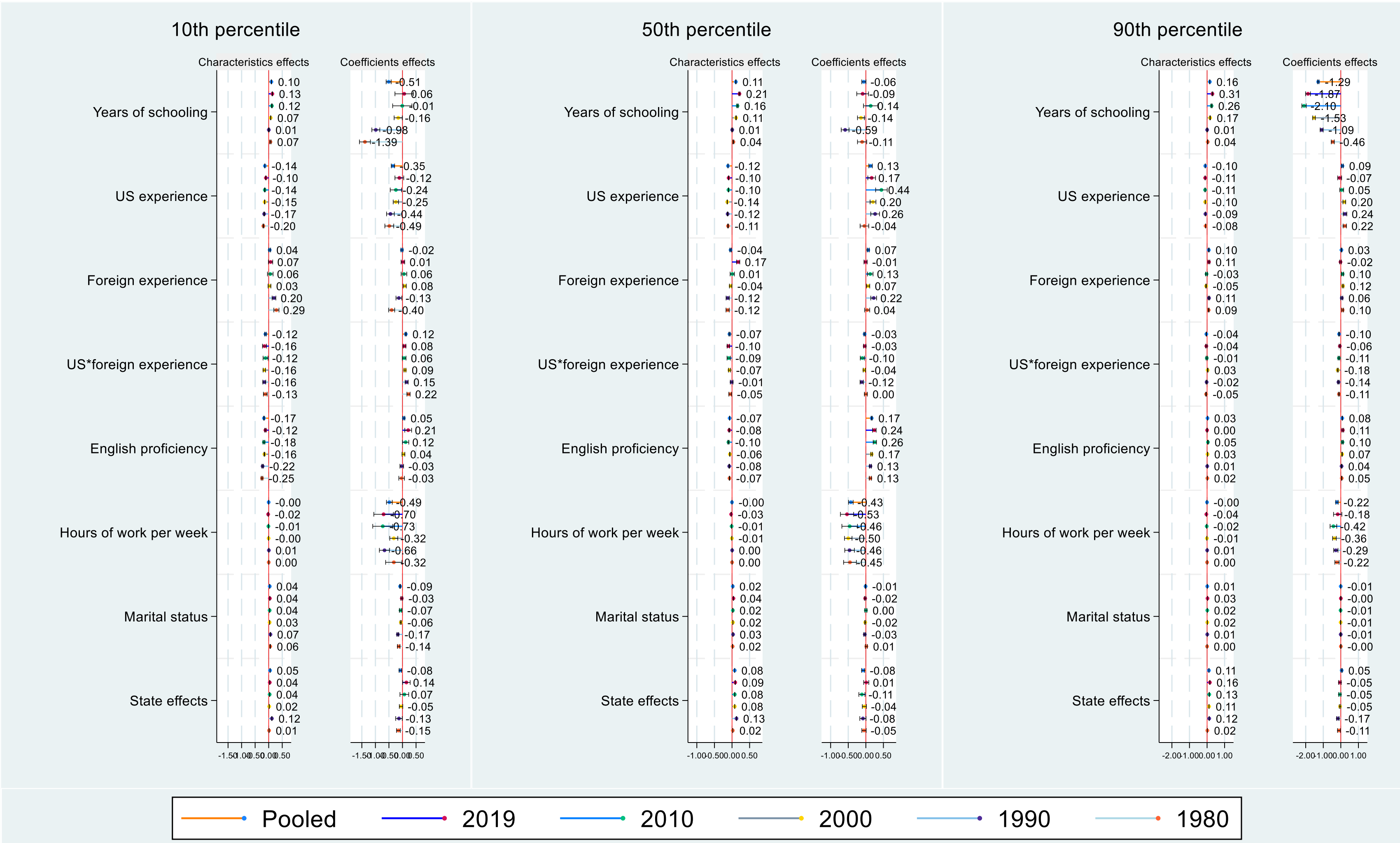
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure 10. Detailed quantile decompositions: earnings gaps between immigrants from China and all other immigrants



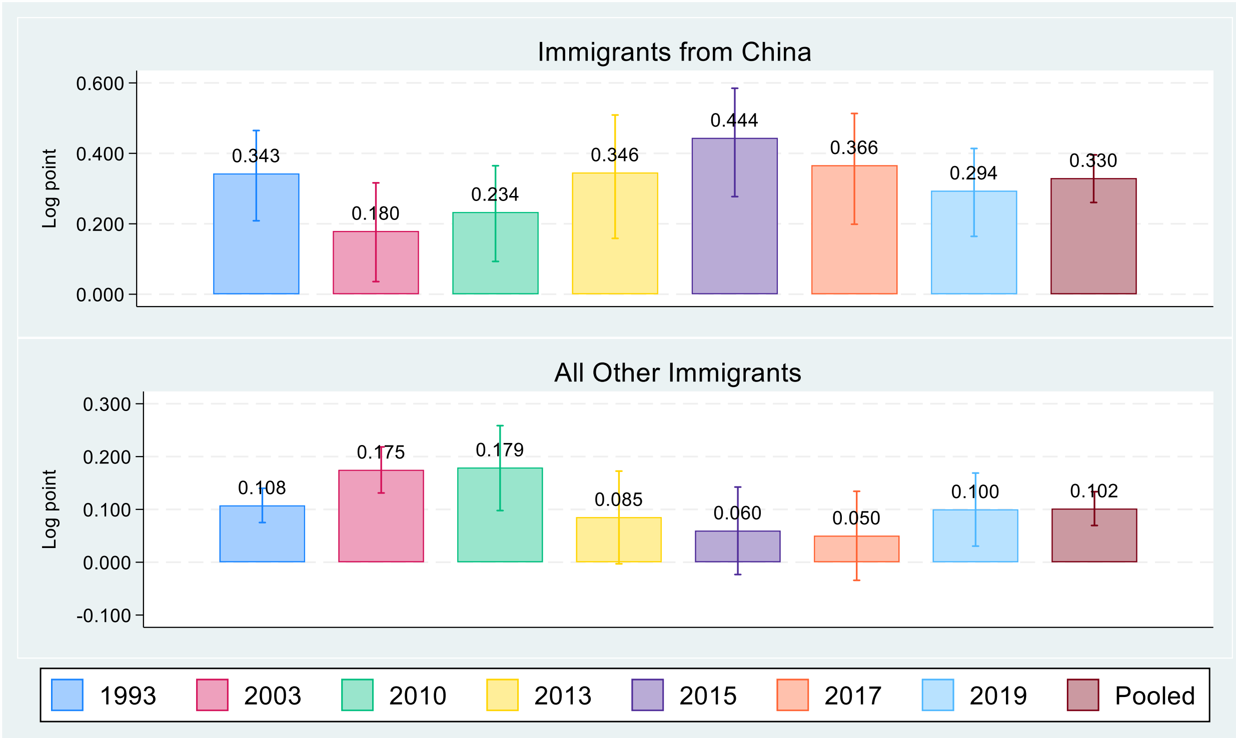
Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group “All other immigrants” excludes the group “Immigrants from China” from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure 11. Detailed quantile decompositions: earnings gaps between immigrants from China and U.S.-born workers



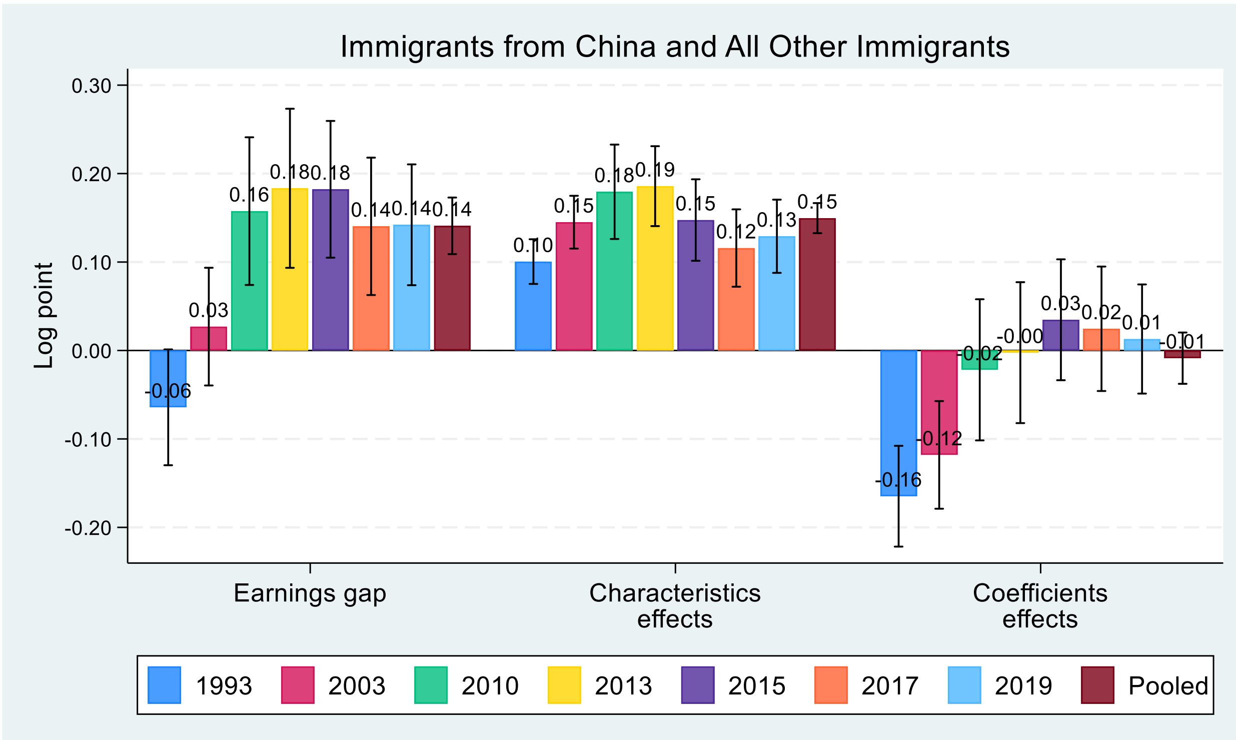
Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure 12. Effects of U.S.-earned highest degrees on immigrant earnings



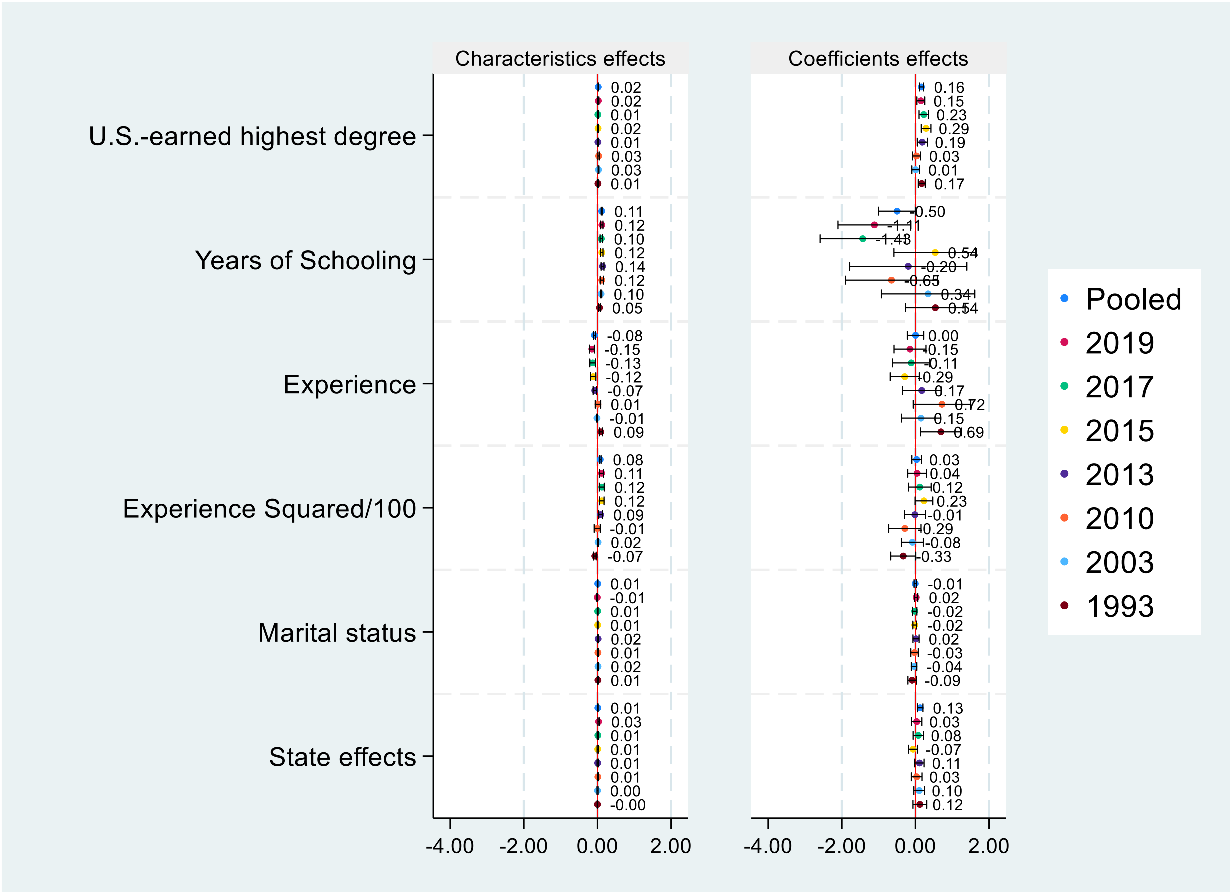
Note: The numbers in the graph are estimates of the dummy variable U.S.-earned highest degree that equals one if the person earned the highest degree in the U.S. Range bars are 95% confidence intervals. The dependent variable earnings is the log of basic annual salary on a principal job before deductions (excluding bonuses, overtime, or additional compensation). All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table 6. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: National Survey of College Graduates.

Figure 13. Oaxaca-Blinder decompositions: earnings gaps of college graduates between immigrants from China and all other immigrants



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of all other immigrants. Range bars are 95% confidence intervals. All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table 6. The group “All other immigrants” excludes the group “Immigrants from China” from the entire immigrant population.
Source: National Survey of College Graduates

Figure 14. Detailed decompositions: earnings gaps of college graduates between immigrants from China and all other immigrants



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of all other immigrants. Range bars are 95% confidence intervals. All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table 6. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: National Survey of College Graduates.

Appendix

Robustness Analyses

A. Results Using Log of Hourly Wage as the Dependent Variable

Tabe A1. Descriptive statistics

Variables	Year	Immigrants from China		All other immigrants		The U.S. born	
		Mean	S.D.	Mean	S.D.	Mean	S.D.
Hourly wage (2010 dollars)	Pooled	29.72	41.68	24.13	40.47	25.00	31.41
	2019	42.00	58.05	31.41	55.40	29.88	51.32
	2010	32.30	27.69	24.93	26.43	27.76	24.29
	2000	29.29	47.94	23.85	47.99	26.34	38.87
	1990	24.31	27.19	22.73	31.55	24.37	27.23
	1980	21.12	15.94	21.35	20.93	22.37	18.15
Years of schooling	Pooled	14.48	4.80	12.00	4.60	13.27	2.63
	2019	15.84	4.22	13.42	4.12	14.02	2.53
	2010	15.44	4.50	12.61	4.30	13.90	2.46
	2000	14.64	4.73	11.83	4.58	13.45	2.41
	1990	13.28	4.79	11.67	4.74	13.23	2.54
	1980	13.30	5.19	11.58	4.70	12.78	2.92
U.S. work experience	Pooled	13.23	9.15	13.67	9.57	19.99	11.52
	2019	14.96	9.94	17.97	11.01	21.15	12.17
	2010	14.08	8.73	16.16	10.05	23.16	11.52
	2000	12.38	8.66	13.19	9.25	20.76	10.80
	1990	13.71	9.65	12.47	8.87	19.12	10.99
	1980	11.98	8.61	12.11	8.84	18.73	12.34
Non-U.S. work experience	Pooled	8.73	9.80	6.80	8.19		
	2019	6.03	8.27	5.96	7.90		
	2010	7.66	9.02	6.26	7.89		
	2000	8.87	9.45	6.52	7.98		
	1990	10.69	10.71	6.90	8.28		
	1980	9.73	10.82	8.36	8.78		
English language proficiency	Pooled	2.04	.96	2.24	.96		
	2019	2.24	.89	2.42	.86		
	2010	2.09	.96	2.22	.96		
	2000	2.02	.97	2.17	1.00		
	1990	1.92	.98	2.26	.95		
	1980	2.02	.93	2.27	.93		
Married, spouse present	Pooled	.78	.42	.65	.48	.68	.47
	2019	.73	.44	.66	.47	.59	.49
	2010	.78	.42	.65	.48	.65	.48
	2000	.77	.42	.61	.49	.65	.48
	1990	.81	.39	.66	.47	.70	.46

	1980	.81	.40	.74	.44	.73	.44
Years since migrating to the U.S.	Pooled	14.99	10.36	16.80	11.67		
	2019	17.50	10.82	21.99	13.46		
	2010	15.89	9.77	19.62	12.62		
	2000	13.83	9.98	16.27	11.62		
	1990	15.34	11.19	15.69	10.80		
	1980	13.79	9.35	14.38	9.52		
Observations	Pooled	22,220		758,460		6,548,850	
	2019	3,774		82,299		433,395	
	2010	2,697		74,857		391,415	
	2000	8,136		303,696		2,017,059	
	1990	4,400		183,280		1,914,349	
	1980	3,213		114,328		1,792,632	

Note: Observations are men between 18 and 64 years of age full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. Hourly wages are calculated as the ratio of annual earnings to hours worked in the previous calendar year, with annual hours computed as the product of weeks worked last year and the usual hours worked per week. Hourly wages have been adjusted for inflation and are expressed in 2010 dollars. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. English language proficiency is a categorical variable that equals 0 if the person does not speak English; equals 1 if the person speaks English but not well; equals 2 if the person speaks English well; equals 3 if the person speaks English very well.

Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

Tabe A2. Determinants of earnings of immigrants from China and selected groups

Dependent variable: log hourly wage	Year	Immigrants from China		All other immigrants		U.S. born	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of schooling	Pooled	.065***	.001	.062***	.000	.090***	.000
	2019	.082***	.005	.078***	.001	.115***	.000
	2010	.078***	.004	.075***	.001	.116***	.000
	2000	.066***	.003	.063***	.000	.101***	.000
	1990	.054***	.003	.058***	.000	.092***	.000
	1980	.054***	.003	.050***	.001	.072***	.000
U.S. work experience	Pooled	.036***	.002	.039***	.000	.041***	.000
	2019	.036***	.005	.036***	.001	.039***	.000
	2010	.054***	.006	.039***	.001	.047***	.000
	2000	.029***	.004	.030***	.001	.037***	.000
	1990	.050***	.005	.048***	.001	.044***	.000
	1980	.031***	.006	.051***	.001	.042***	.000
U.S. work experience squared /100	Pooled	-.061***	.005	-.059***	.000	-.063***	.000
	2019	-.060***	.013	-.058***	.002	-.058***	.001
	2010	-.098***	.013	-.062***	.002	-.077***	.001
	2000	-.046***	.011	-.037***	.001	-.056***	.000
	1990	-.088***	.011	-.070***	.002	-.066***	.000
	1980	-.051***	.016	-.087***	.003	-.066***	.000
Non-U.S. work experience	Pooled	.007***	.002	.029***	.000		
	2019	.029***	.006	.034***	.001		
	2010	.010*	.006	.029***	.001		
	2000	.001	.004	.024***	.001		
	1990	.006	.005	.028***	.001		
	1980	.000	.005	.028***	.001		
Non-U.S. work experience squared /100	Pooled	-.002	.005	-.048***	.000		
	2019	-.063***	.017	-.068***	.004		
	2010	.005	.016	-.051***	.003		
	2000	007	.009	-.042***	.002		
	1990	.002	.011	-.043***	.002		
	1980	.008	.013	-.047***	.002		
U.S. and non-U.S. work experience interaction	Pooled	-.001***	.000	-.001***	.000		
	2019	-.001***	.000	-.001***	.000		
	2010	-.001***	.000	-.001***	.000		
	2000	-.001***	.000	-.001***	.000		
	1990	-.001***	.000	-.001***	.000		
	1980	-.000**	.000	-.001***	.000		
Married, spouse present	Pooled	.125***	.012	.169***	.002	.192***	.001
	2019	.167***	.030	.202***	.005	.233***	.002
	2010	.084***	.032	.173***	.005	.203***	.002
	2000	.104***	.020	.159***	.003	.189***	.001

	1990	.093***	.026	.170***	.003	.186***	.001
	1980	.114***	.030	.145***	.005	.172***	.001
English well	Pooled	-.213***	.011	-.181***	.002		
	2019	-.276***	.028	-.294***	.006		
	2010	-.230***	.029	-.255***	.006		
	2000	-.177***	.019	-.173***	.003		
	1990	-.196***	.024	-.134***	.004		
	1980	-.208***	.028	-.114***	.005		
English not well	Pooled	-.538***	.015	-.270**	.002		
	2019	-.617***	.042	-.337***	.008		
	2010	-.574***	.046	-.341***	.007		
	2000	-.535***	.026	-.270***	.003		
	1990	-.474***	.031	-.227***	.004		
	1980	-.423***	.039	-.208***	.007		
English not at all	Pooled	-.632***	.023	-.280***	.003		
	2019	-.725***	.069	-.292***	.012		
	2010	-.771***	.064	-.331***	.010		
	2000	-.576***	.039	-.272***	.005		
	1990	-.530***	.045	-.272***	.006		
	1980	-.549***	.064	-.256***	.010		
Constant	Pooled	1.757***	.033	1.649***	.005	1.181***	.002
	2019	1.542***	.133	1.516***	.027	.783***	.013
	2010	1.745***	.147	1.448***	.024	.713***	.011
	2000	1.962***	.085	1.683***	.011	1.026***	.005
	1990	1.855***	.133	1.573***	.013	1.077***	.004
	1980	1.931***	.074	1.716***	.019	1.422***	.003
Observations	Pooled	22,220		758,460		6,548,850	
	2019	3,774		82,299		433,395	
	2010	2,697		74,857		391,415	
	2000	8,136		303,696		2,017,059	
	1990	4,400		183,280		1,914,349	
	1980	3,213		114,328		1,792,632	
Adjusted R^2	Pooled	.441		.315		.271	
	2019	.409		.310		.295	
	2010	.519		.370		.317	
	2000	.422		.302		.268	
	1990	.445		.360		.312	
	1980	.387		.252		.223	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Observations are men between 18 and 64 years of age who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. Hourly wages are calculated as the ratio of annual earnings to hours worked in the previous calendar year, with annual hours computed as the product of weeks worked last year and the usual hours worked per week. Hourly wages have been adjusted for inflation and are expressed in 2010 dollars. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. The reference category of English language proficiency is "English only" and "English very well". All regressions include state fixed effects and the pooled estimations additional control for year fixed effects.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

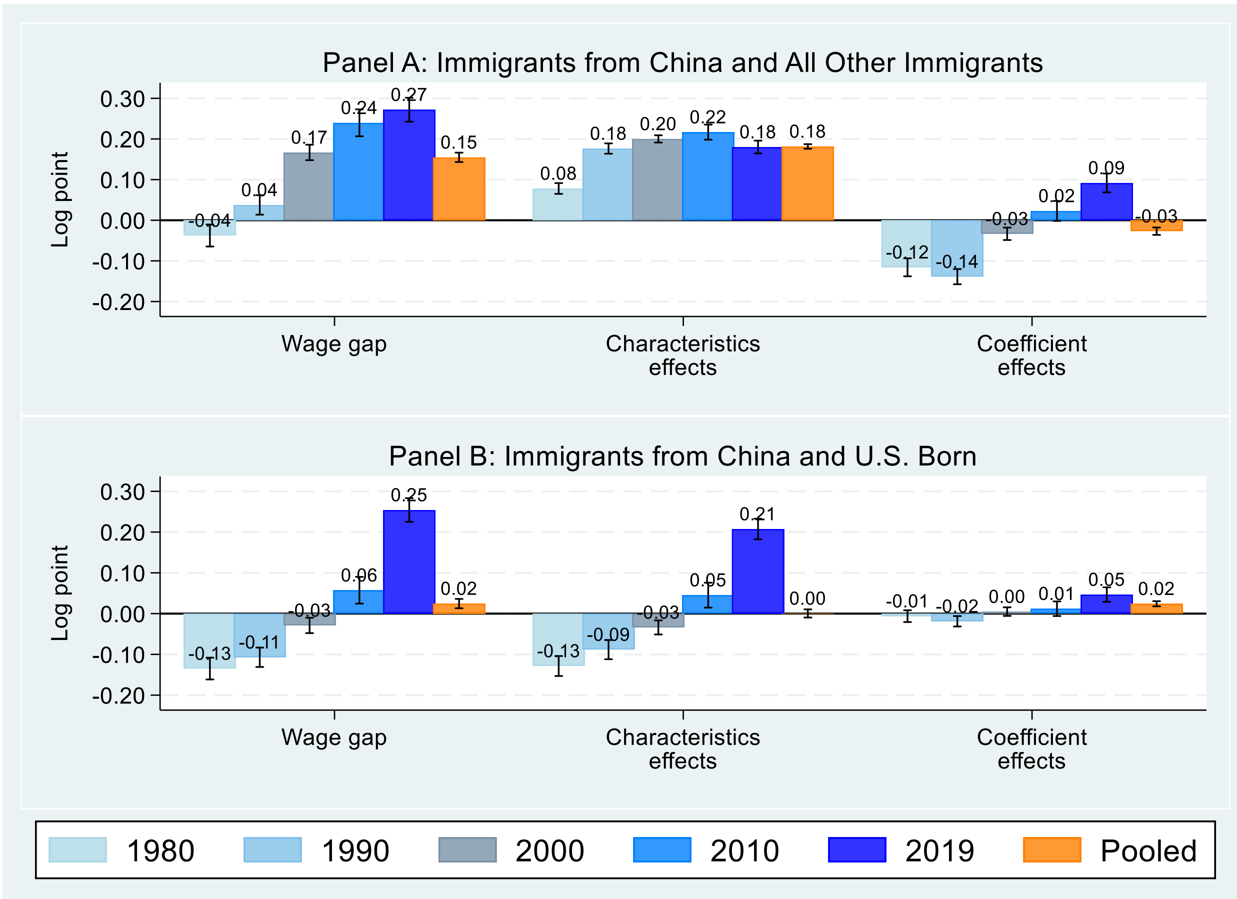
Tabe A3. Descriptive statistics of immigrant college graduates

Variables	Year	Immigrants from China		All Other Immigrants	
		Mean	S.D.	Mean	S.D.
Hourly wage* (2010 dollar)	Pooled	56.13	40.38	42.87	51.76
	2019	52.95	62.77	42.61	60.40
	2017	41.24	29.28	41.13	65.08
	2015	46.20	49.16	47.78	59.92
	2013	45.21	55.96	36.56	64.05
	2010	43.63	56.59	38.99	48.87
	2003	58.23	64.69	52.83	69.54
	1993				
U.S.-earned highest degree	Pooled	.73	.44	.56	.50
	2019	.77	.42	.56	.50
	2017	.73	.44	.57	.49
	2015	.76	.43	.56	.50
	2013	.70	.46	.57	.50
	2010	.69	.46	.51	.50
	2003	.71	.45	.55	.50
	1993	.73	.44	.62	.49
Years of schooling	Pooled	17.99	1.17	17.15	1.32
	2019	17.99	1.18	17.14	1.30
	2017	17.97	1.18	17.13	1.30
	2015	18.00	1.12	17.14	1.30
	2013	18.01	1.16	17.12	1.31
	2010	17.99	1.19	17.13	1.32
	2003	18.05	1.14	17.19	1.37
	1993	17.79	1.34	17.37	1.48
Potential experience (year)	Pooled	18.661	9.89	20.78	10.08
	2019	16.94	10.51	20.78	10.26
	2017	18.17	10.46	20.93	10.58
	2015	17.94	9.98	20.44	10.46
	2013	19.22	8.57	21.47	9.80
	2010	21.23	9.37	20.89	9.75
	2003	19.06	8.69	20.50	9.42
	1993	21.91	9.26	19.41	9.02
Married, spouse present	Pooled	.82	.38	.78	.41
	2019	.74	.44	.77	.42
	2017	.80	.40	.77	.42
	2015	.81	.40	.77	.42
	2013	.89	.32	.78	.41
	2010	.88	32	.81	.40
	2003	.91	.28	.82	.39
	1993	.93	.26	.81	.39
Hours per week typically worked	Pooled			44.32	11.12
	2019	42.66	10.45	42.78	11.98
	2017	43.27	9.18	44.05	10.74

	2015	42.91	9.12	44.03	10.73
	2013	42.60	11.77	44.28	10.62
	2010	44.10	9.00	45.52	11.06
	2003	44.22	9.62	46.39	11.07
	1993				
Observations	Pooled	5,572 / 5,979		47,692 / 55,544	
	2019	1,397		8,969	
	2017	965		7,604	
	2015	886		7,693	
	2013	870		8,037	
	2010	644		6,850	
	2003	810		8,539	
	1993	407		7,852	

Note: * Hourly wages are calculated as the ratio of annual earnings to hours worked in the previous calendar year, with annual hours computed as the product of weeks worked last year and the hours per week typically worked. Hourly wages have been adjusted for inflation and are expressed in 2010 dollars. Earnings is the basic annual salary on the principal job before deductions, which do not include bonuses, overtime, or additional compensation for summertime. Final survey-specific weights are used in all calculations. The variable hours per week typically worked is not available in 1993.
Source: National Survey of College Graduates.

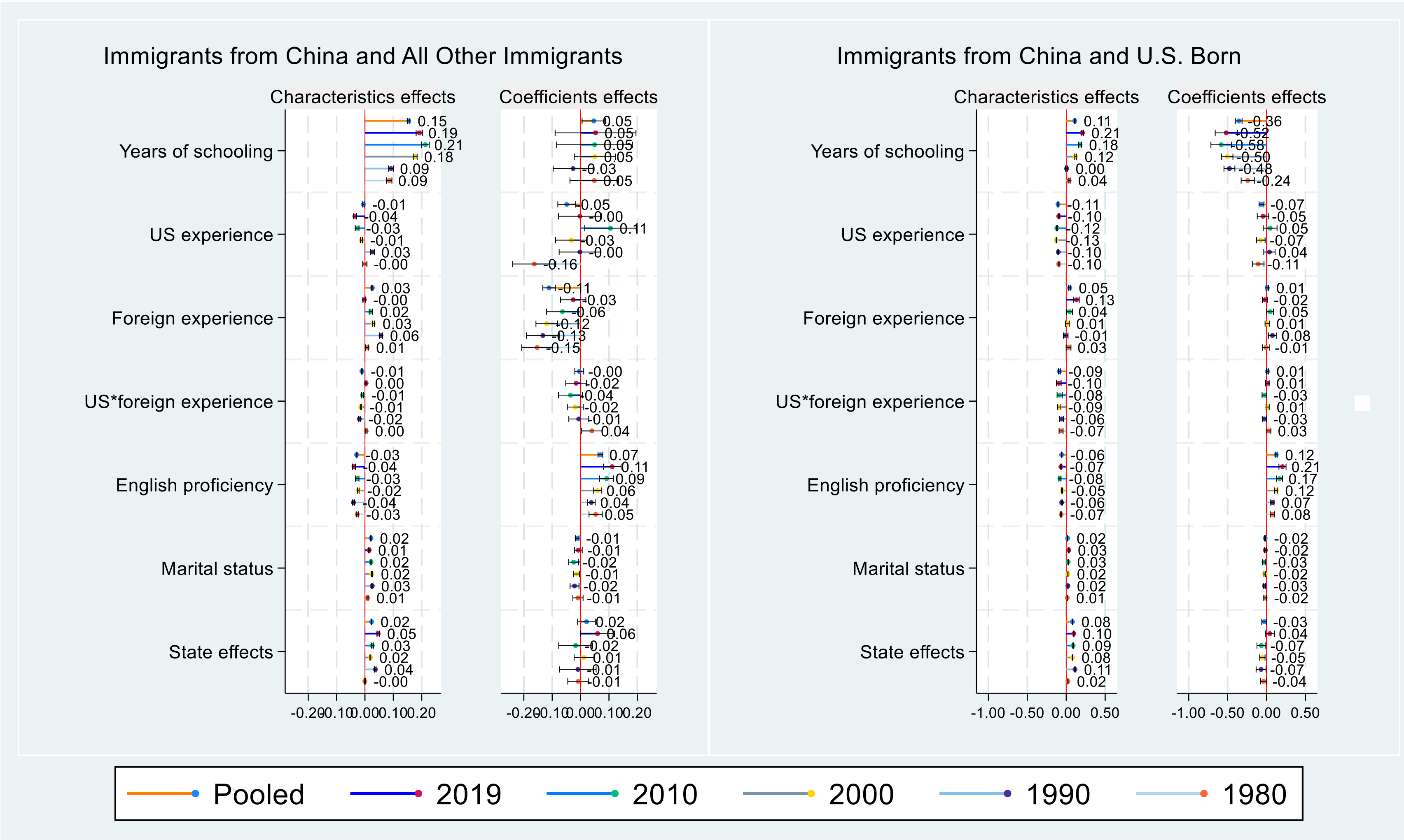
Figure A1. Oaxaca-Blinder decompositions: wage gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log hourly of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Table A1 and Table A2. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

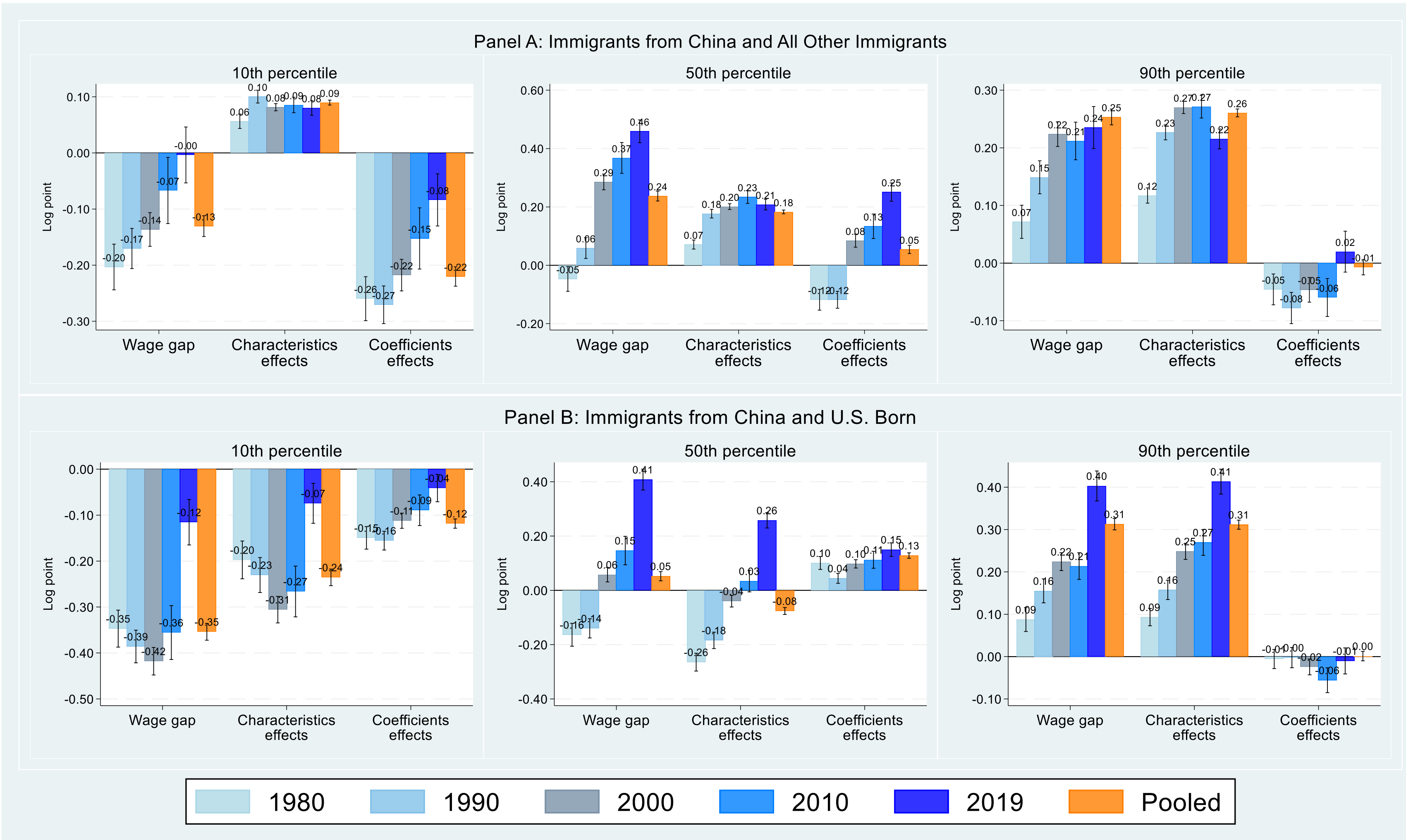
Figure A 2. Detailed Oaxaca-Blinder decompositions: wage gaps between immigrants from China and selected groups



Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Table A1 and Table A2. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure A3. Quantile decompositions: wage gaps between immigrants from China and selected groups

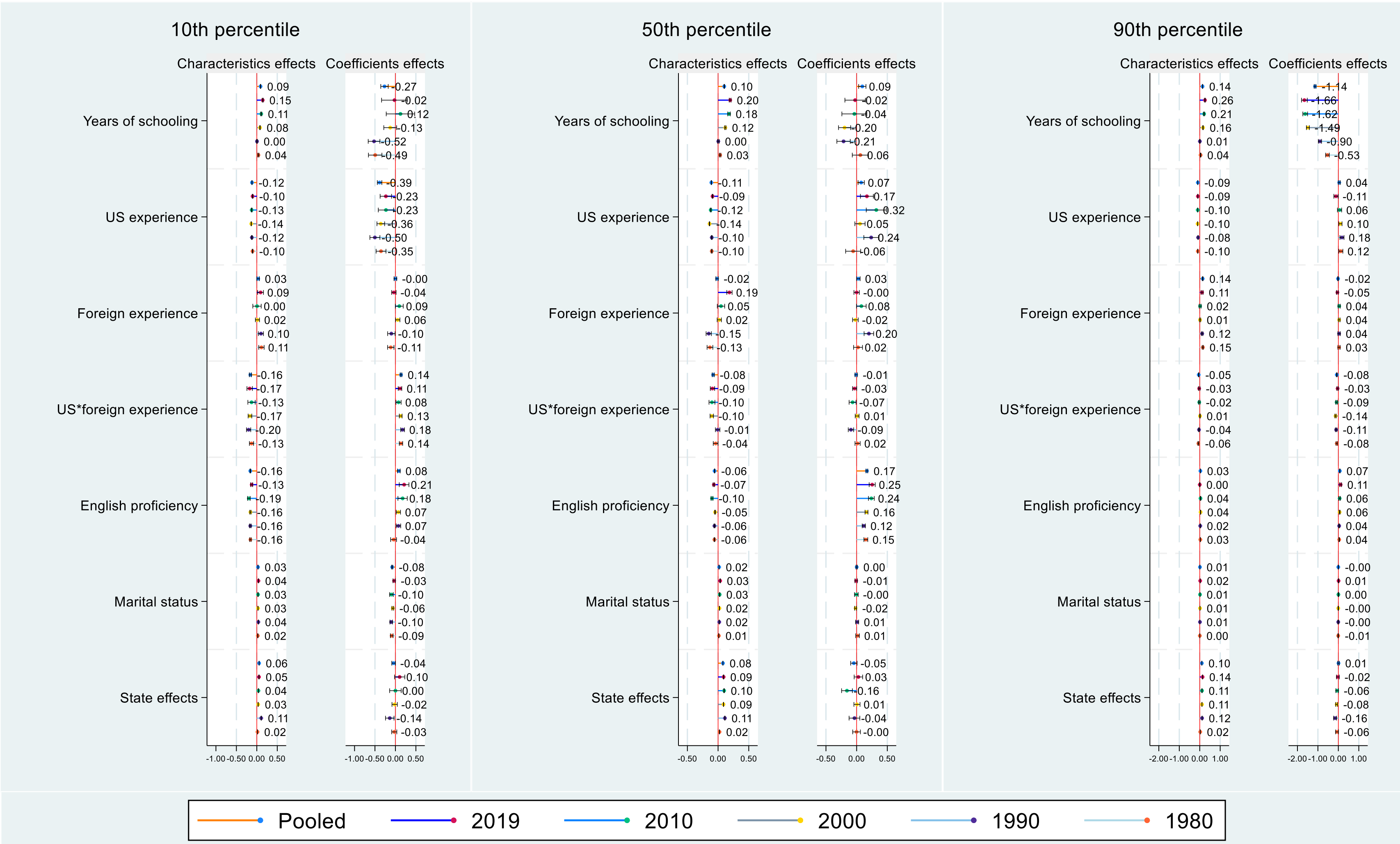


Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Table A1 and Table A2. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure A4. Detailed quantile decompositions: earnings gaps between immigrants from China and all other immigrants

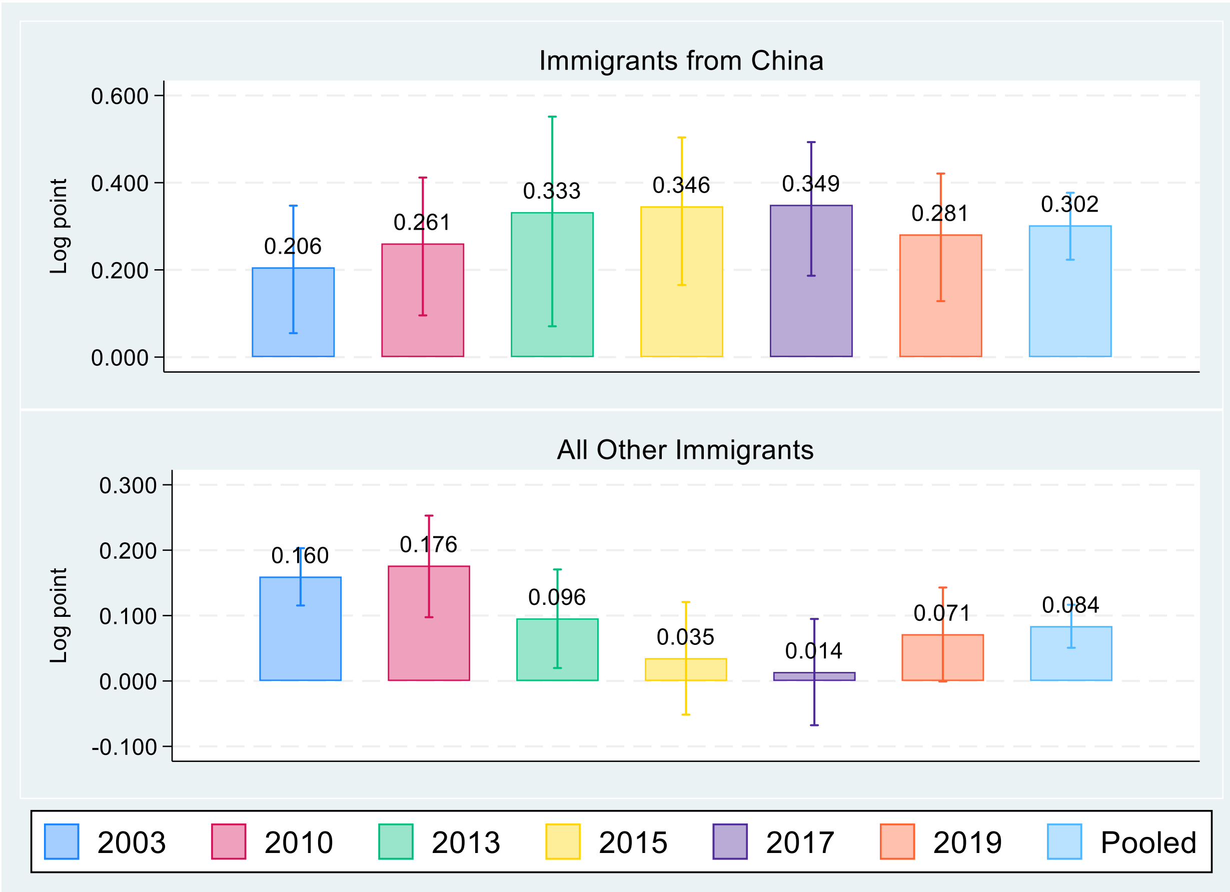
Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Table A1 and Table A2. The numbers of observations are identical to those in Tables 3 and 4. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure A5. Detailed quantile decompositions: wage gaps between immigrants from China and U.S.-born workers



Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Table A1 and Table A2.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

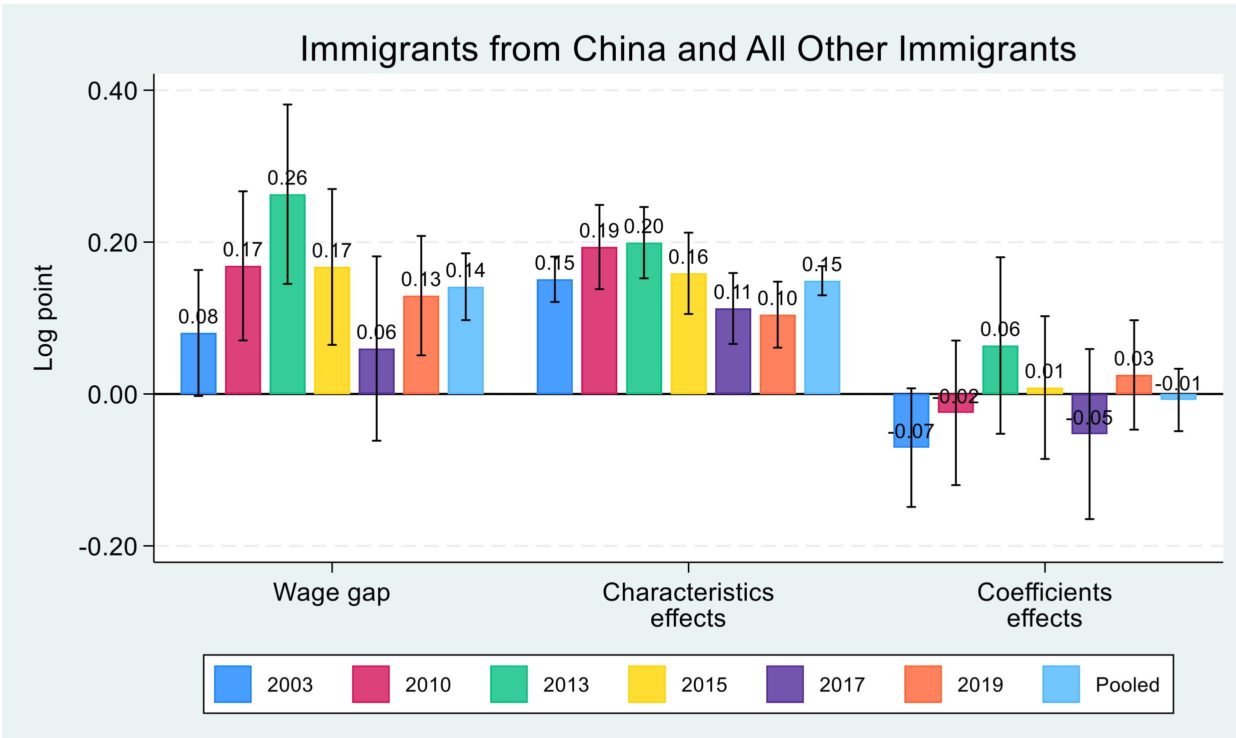
Figure A6. Effects of U.S.-earned highest degrees on immigrant wages



Note: The numbers in the graph are estimates of the dummy variable U.S.-earned highest degree that equals one if the person earned the highest degree in the U.S. Range bars are 95% confidence intervals. The dependent variable earnings is the log hourly wage on a principal job before deductions (excluding bonuses, overtime, or additional compensation). All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

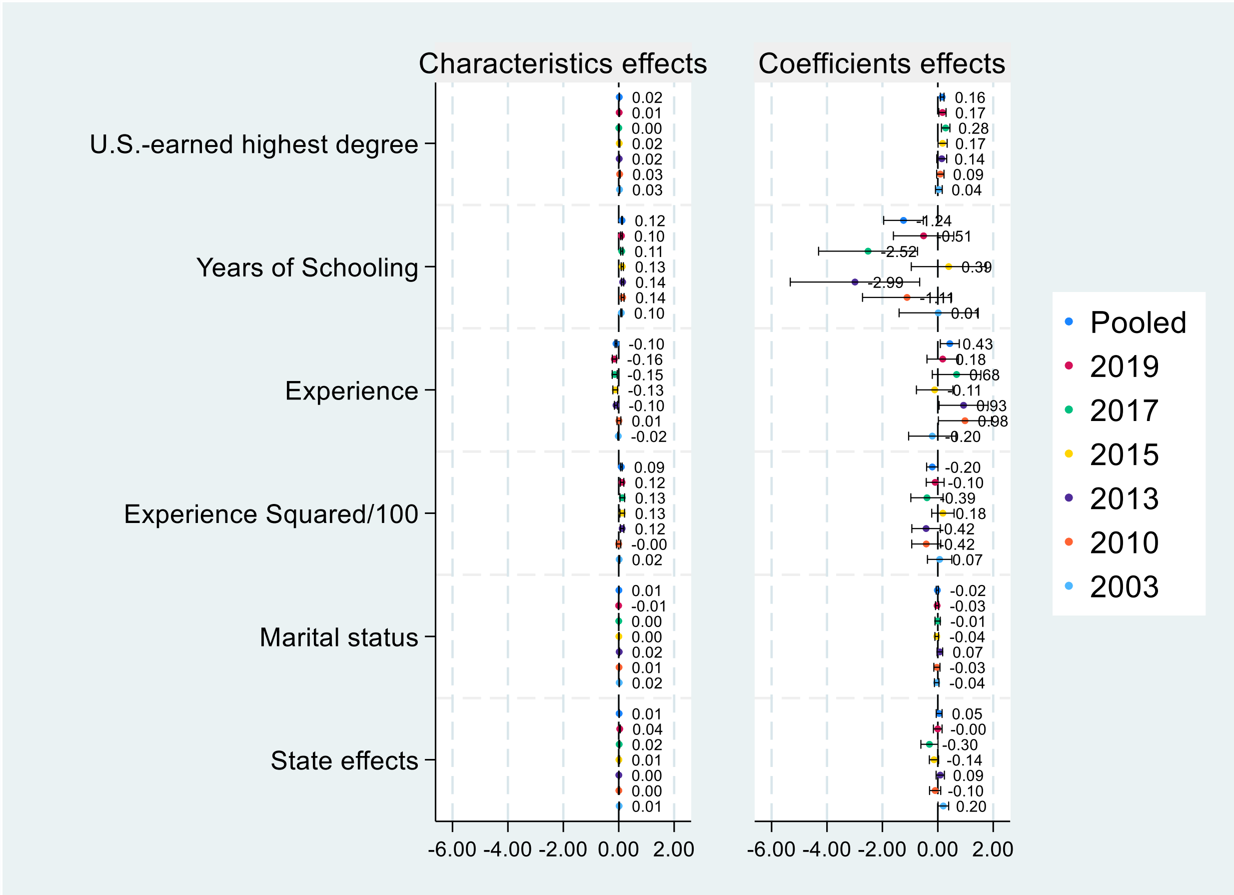
Source: National Survey of College Graduates.

Figure A7. Oaxaca-Blinder decompositions: wage gaps of college graduates between immigrants from China and all other immigrants



Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of all other immigrants. Range bars are 95% confidence intervals. All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: National Survey of College Graduates

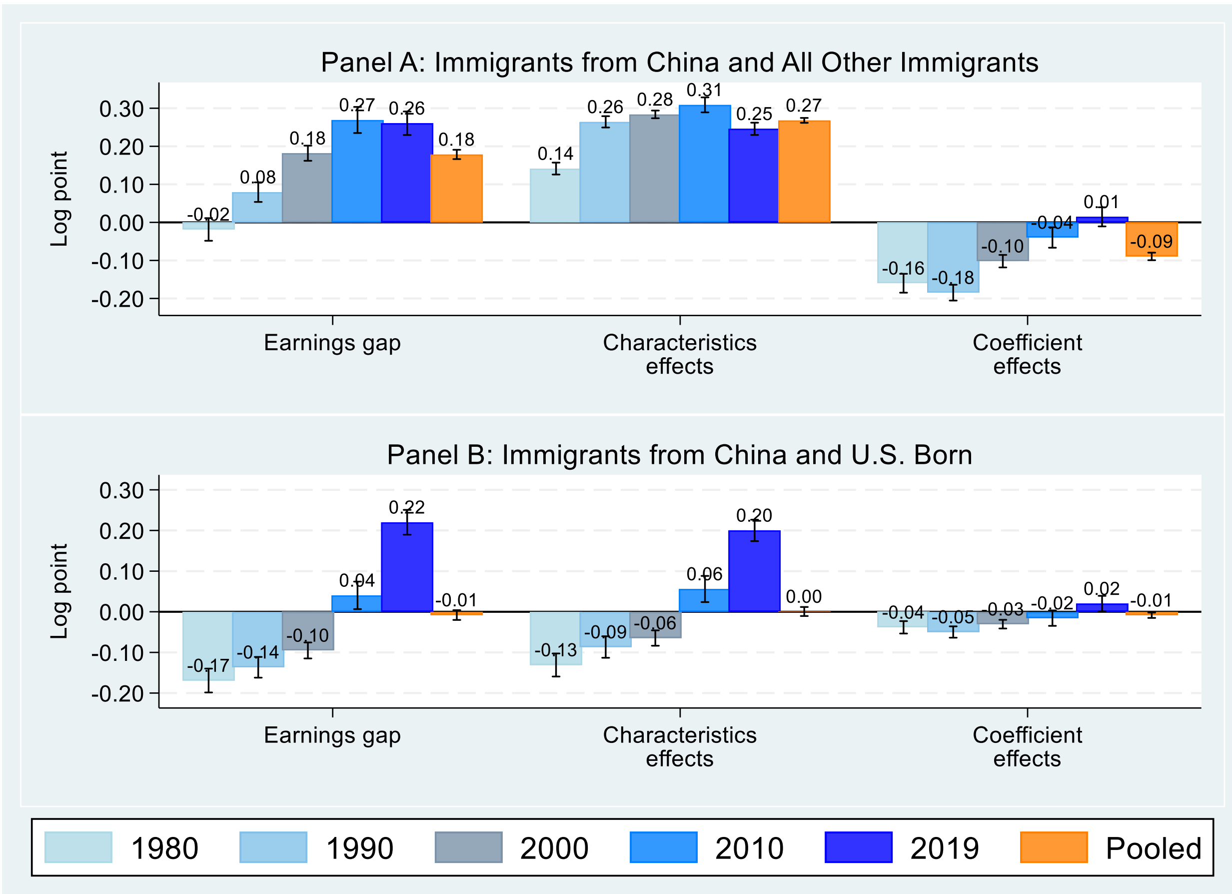
Figure A8. Detailed decompositions: wage gaps of college graduates between immigrants from China and all other immigrants



Note: The wage gap is equal to the log hourly wage of immigrants from China minus the log hourly wage of all other immigrants. Range bars are 95% confidence intervals. All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, and state effects. Sample observations are men, salaried workers, and aged 22 to 64 during the survey year. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: National Survey of College Graduates.

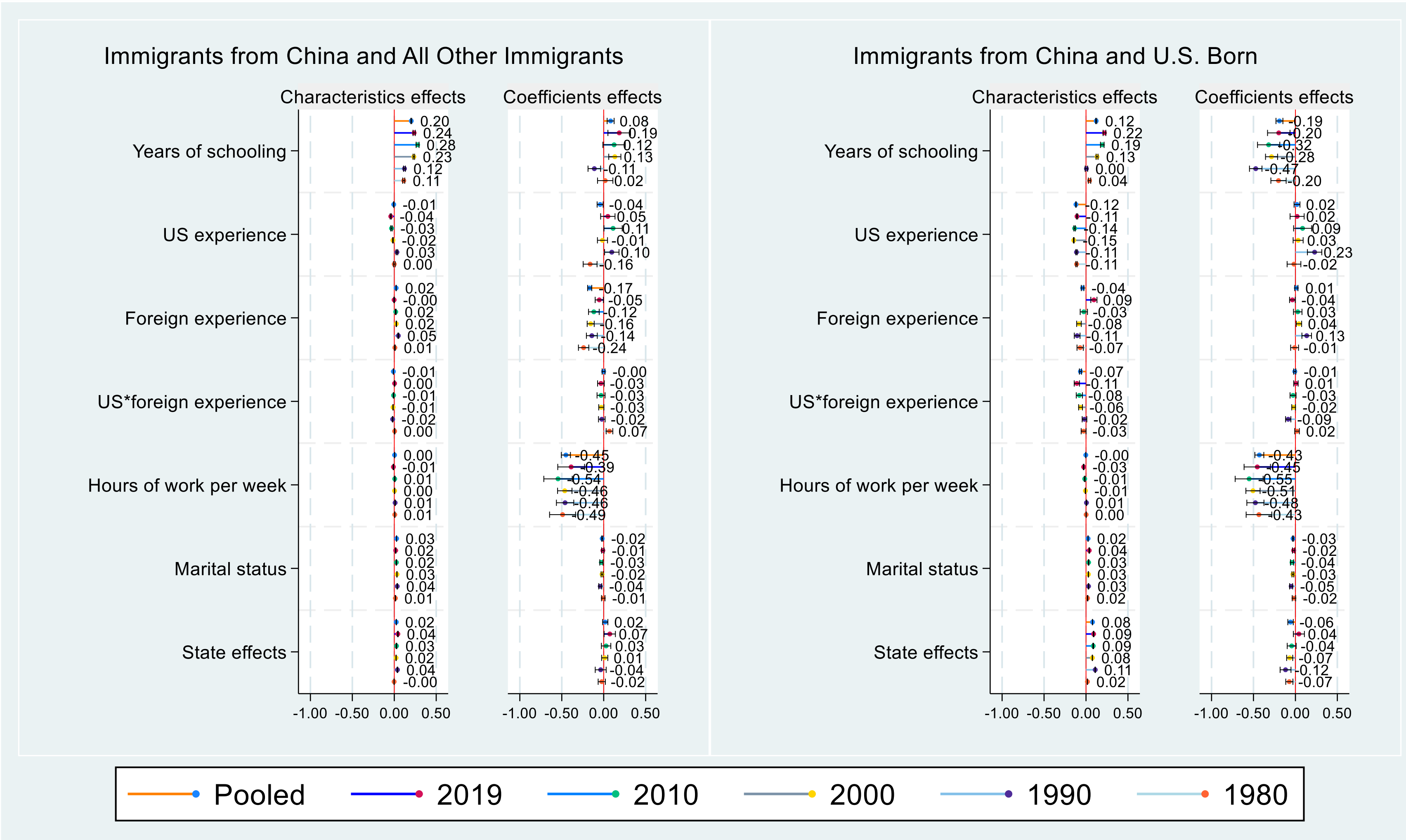
B. Results Excluding English Language Proficiency as an Independent Variable

Figure B1. Oaxaca-Blinder decompositions: earnings gaps between immigrants from China and selected groups



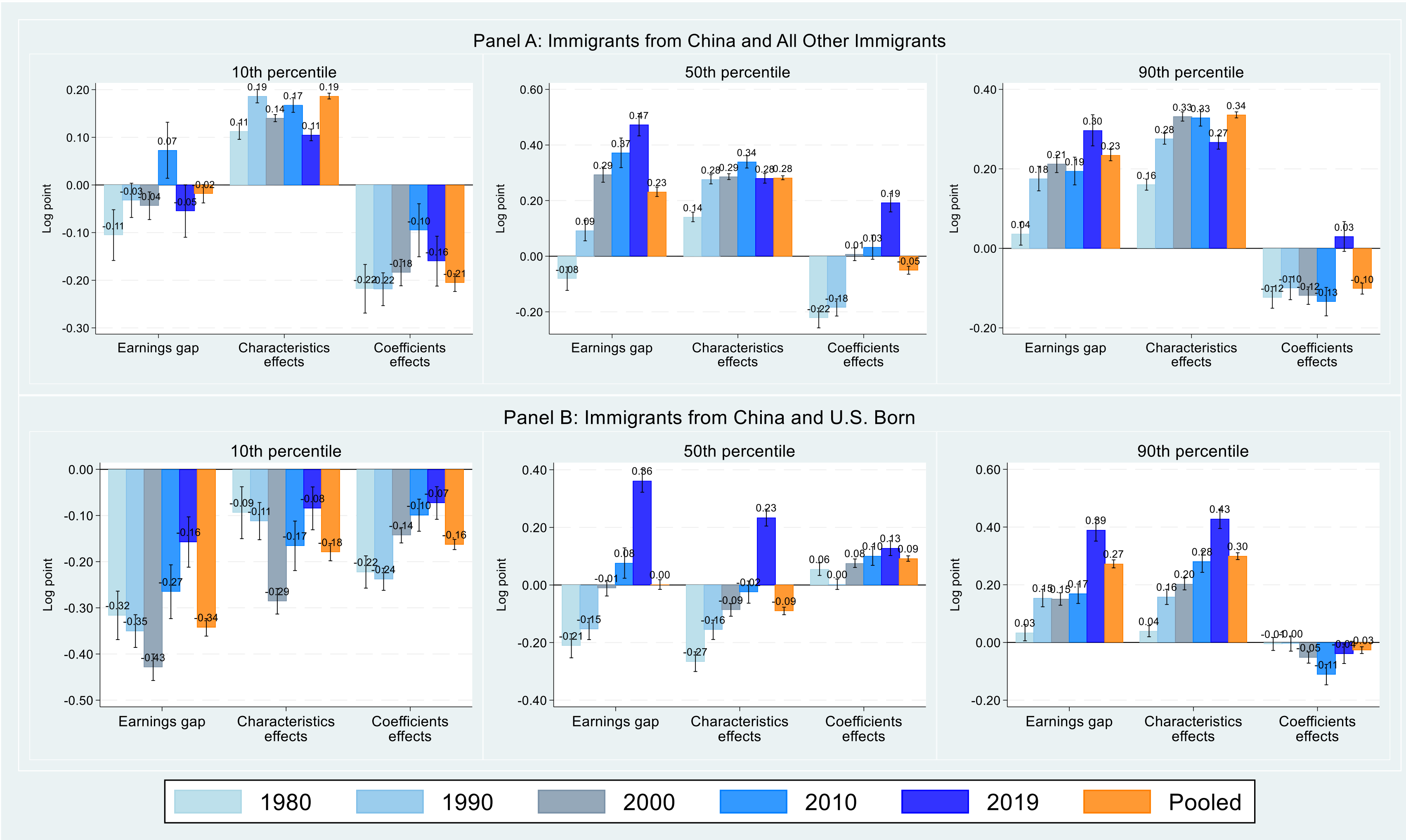
Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure B2. Detailed Oaxaca-Blinder decompositions: earnings gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

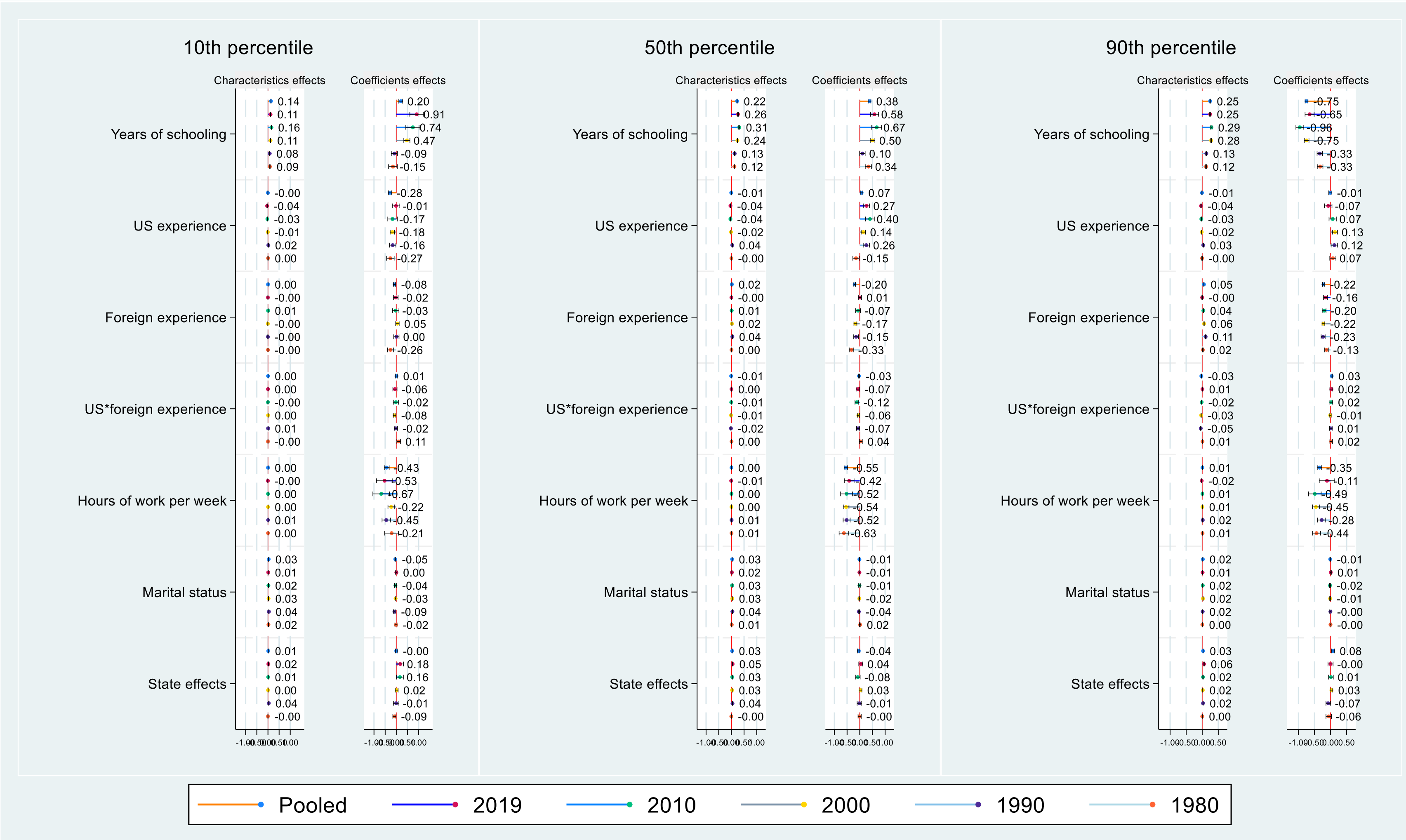
Figure B3. Quantile decompositions: earnings gaps between immigrants from China and selected groups



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.

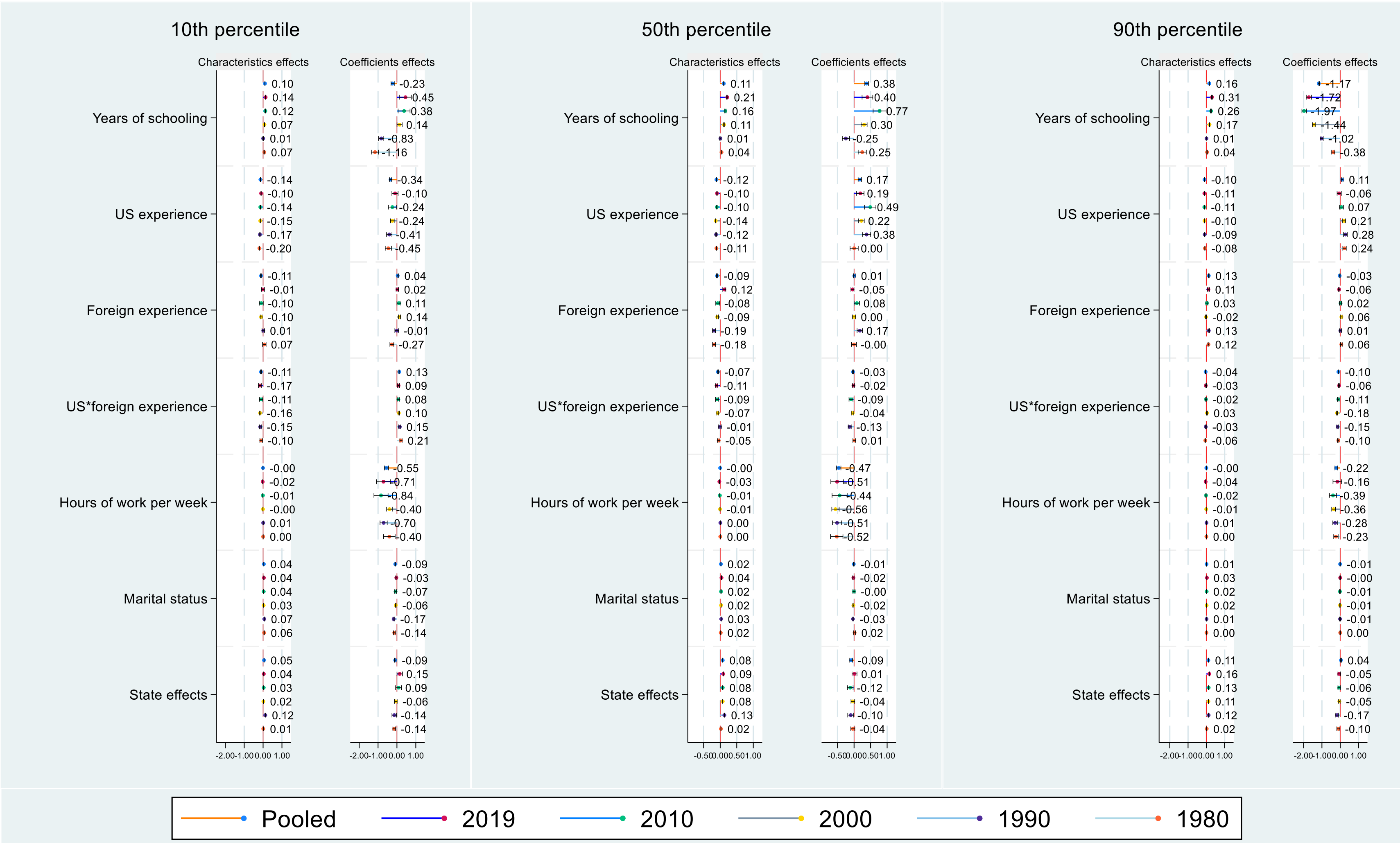
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

Figure B4. Detailed quantile decompositions: earnings gaps between immigrants from China and all other immigrants



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5. The group “All other immigrants” excludes the group “Immigrants from China” from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

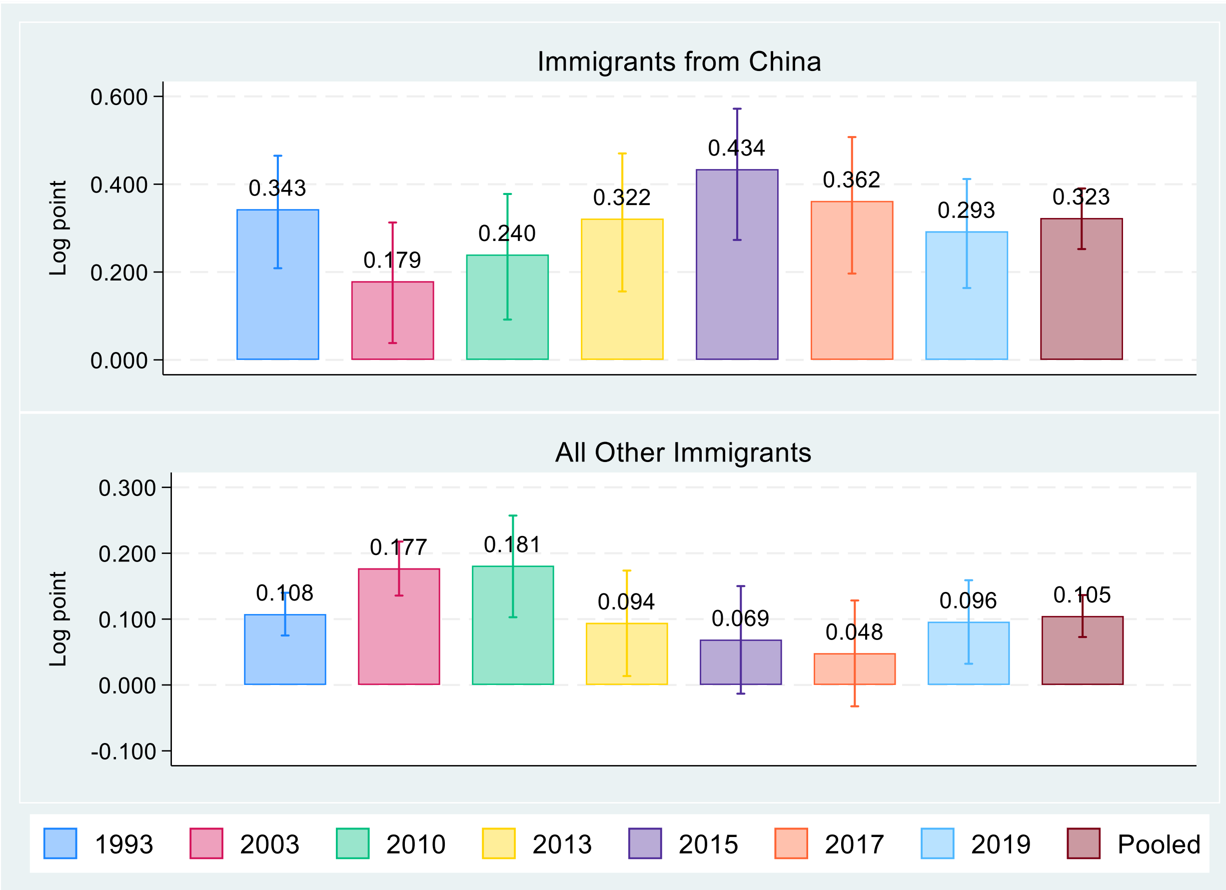
Figure B5. Detailed quantile decompositions: earnings gaps between immigrants from China and U.S.-born workers



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of selected groups. Range bars are 95% confidence intervals. All estimations use robust standard errors. The numbers of observations are identical to those in Tables 4 and 5.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS.

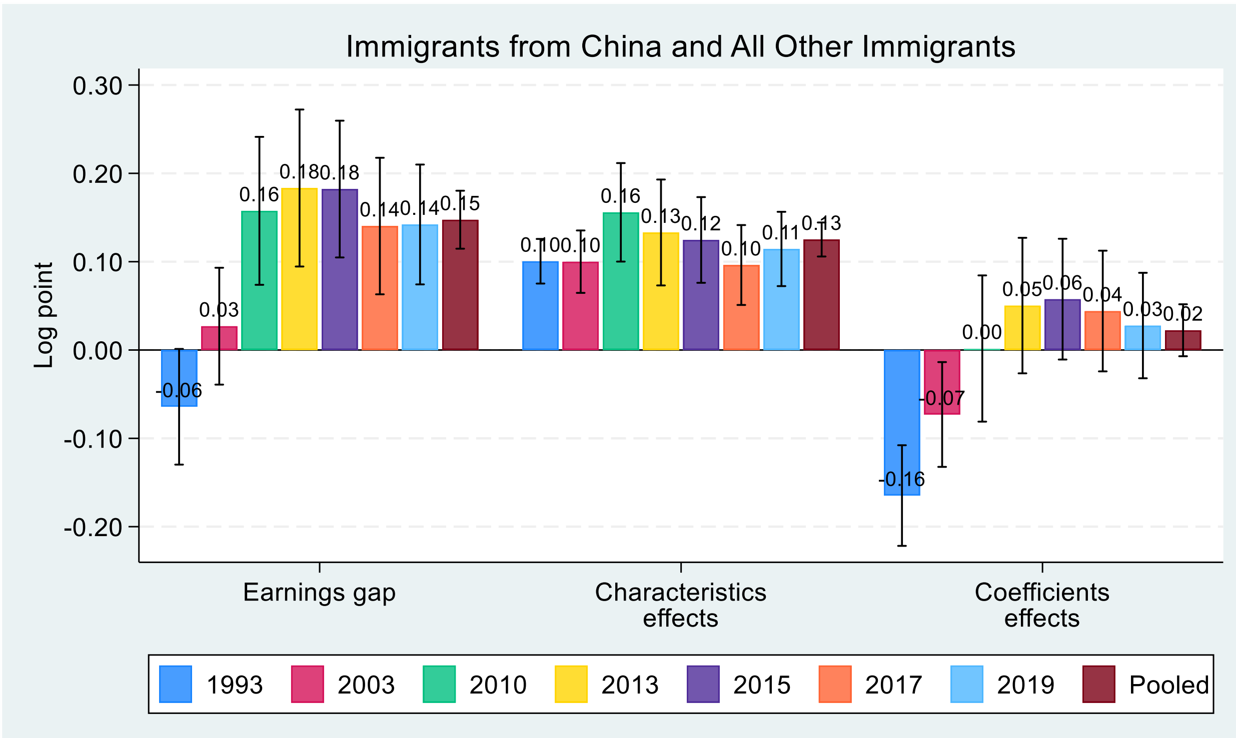
C. Results from Including Hours Worked Per Week as an Independent Variable in NSCG Data

Figure C1. Effects of U.S.-earned highest degrees on immigrant earnings



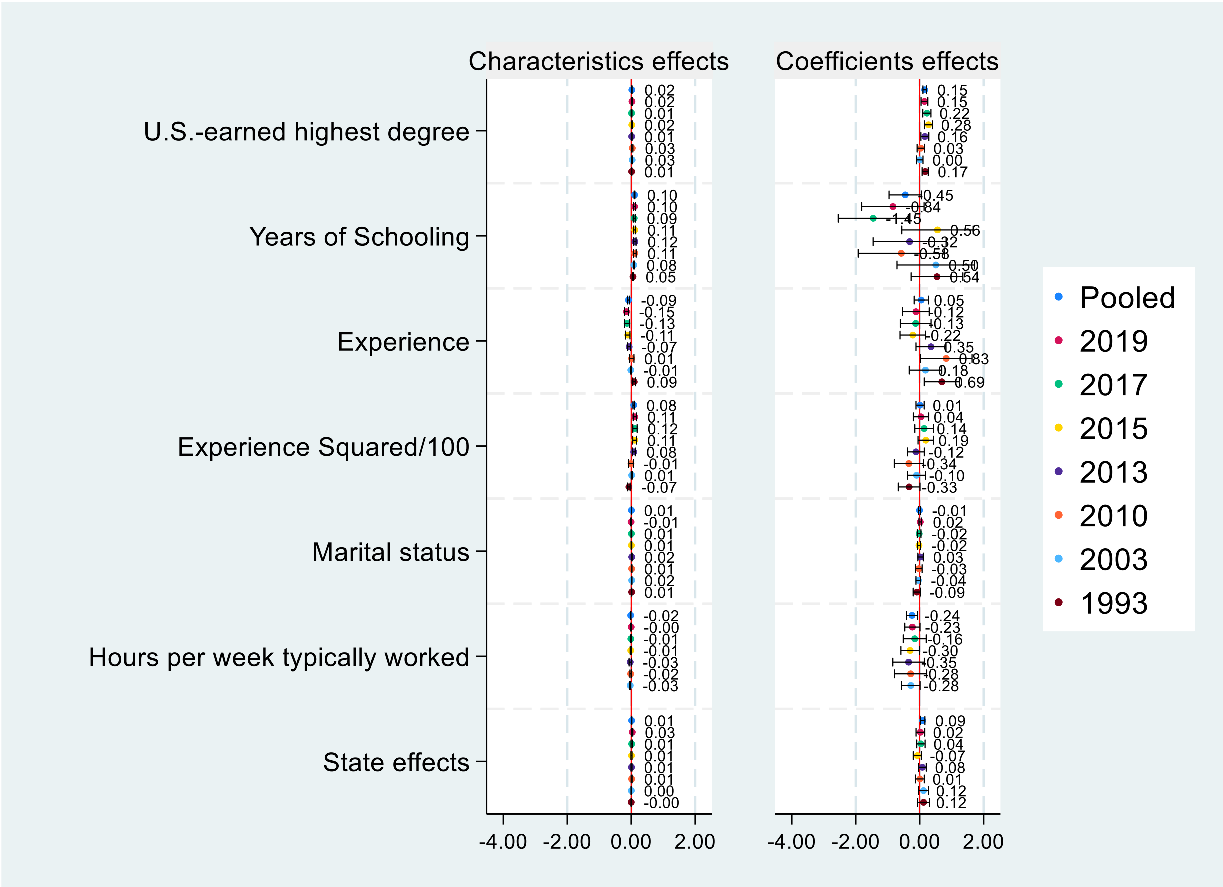
Note: Estimations of the year 1993 do not include hours per week typically worked because the year does not have the information. The numbers in the graph are estimates of the dummy variable U.S.-earned highest degree that equals one if the person earned the highest degree in the U.S. The dependent variable earnings is the log of basic annual salary on a principal job before deductions (excluding bonuses, overtime, or additional compensation). All estimations use the final survey-specific weight, robust standard errors, and additionally include years of schooling, experience, experience squared, marital status, hours per week typically worked, and state effects. Sample observations are men, salaried workers who were born in China and aged 22 to 64 during the survey year. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. Range bars are 95% confidence intervals.
Source: National Survey of College Graduates.

Figure C2. Oaxaca-Blinder decompositions: earnings gaps of college graduates between immigrants from China and all other immigrants



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of all other immigrants. Range bars are 95% confidence intervals. All estimations use robust standard errors. Estimations of the year 1993 do not include hours per week typically worked because the year does not have the information. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. Estimations of the year 1993 do not include hours per week typically worked because the year does not have the information.
Source: National Survey of College Graduates.

Figure C3. Detailed decompositions: earnings gaps of college graduates between immigrants from China and all other immigrants



Note: The earnings gap is equal to the log earnings of immigrants from China minus the log earnings of all other immigrants. Range bars are 95% confidence intervals. All estimations use robust standard errors. Estimations of the year 1993 do not include hours per week typically worked because the year does not have the information. The numbers of observations are reported in Table A3. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. Estimations of the year 1993 do not include hours per week typically worked because the year does not have the information.
Source: National Survey of College Graduates.

D. *Results Using Mean Occupational Earnings as the Dependent Variable*

Table D1. Determinants of occupational earnings of immigrants from China and selected groups: OLS estimates

Dependent variable: log of mean occupational annual earnings	Year	Immigrants from China		All other immigrants		U.S. born	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of schooling	Pooled	.054***	.001	.024***	.000	.065***	.000
	2019	.062***	.003	.053***	.000	.072***	.000
	2010	.062***	.003	.057***	.000	.079***	.000
	2000	.053***	.002	.047***	.000	.065***	.000
	1990	.048***	.002	.045***	.000	.061***	.000
	1980	.042***	.002	.036***	.000	.042***	.000
U.S. work experience	Pooled	-.000	.001	.007***	.000	.007***	.000
	2019	-.004	.003	.002***	.001	.003***	.000
	2010	-.005	.003	.003***	.001	.003***	.000
	2000	-.003	.002	.003***	.000	.001***	.000
	1990	.015***	.003	.009***	.000	.003***	.000
	1980	-.004	.003	.008***	.000	.005***	.000
U.S. work experience squared /100	Pooled	.000	.003	-.011***	.000	-.011***	.000
	2019	.005	.008	-.006***	.001	-.005***	.000
	2010	.009	.009	-.004***	.001	-.005***	.000
	2000	.004	.005	-.002***	.001	-.000	.000
	1990	-.026***	.007	-.013***	.001	-.000	.000
	1980	.012	.009	-.013***	.001	-.004***	.000
Non-U.S. work experience	Pooled	-.008***	.001	.008***	.000		
	2019	.001	.004	.004***	.001		
	2010	-.010**	.004	.005***	.001		
	2000	-.006***	.002	.006***	.000		
	1990	.000	.003	.009***	.000		
	1980	-.015***	.003	.009***	.000		
Non-U.S. work experience squared /100	Pooled	.025***	.003	-.006***	.000		
	2019	-.011	.011	-.007***	.002		
	2010	.020**	.010	-.009***	.002		
	2000	.017***	.005	-.009***	.001		
	1990	.018***	.006	-.012***	.001		
	1980	.040***	.006	-.012***	.001		
U.S. and non-U.S. work experience interaction	Pooled	-.000	.000	-.000***	.000		
	2019	.000	.000	-.000***	.000		
	2010	-.000	.000	-.000*	.000		
	2000	-.000	.000	-.000***	.000		
	1990	-.000***	.000	-.000***	.000		

	1980	.000	.000	-.000	.000		
Hours worked per week	Pooled	-.002***	.000	.002***	.000	.001***	.000
	2019	-.002**	.001	.001***	.000	.000**	.000
	2010	-.002*	.001	.003***	.000	.001***	.000
	2000	-.001*	.000	.002***	.000	.001***	.000
	1990	-.002***	.001	.001***	.000	.000***	.000
	1980	-.002**	.001	.000***	.000	-.001***	.000
Married, spouse present	Pooled	.041***	.007	.039***	.001	.040***	.000
	2019	.034*	.018	.048***	.003	.052***	.001
	2010	.004	.022	.047***	.003	.041***	.001
	2000	.037***	.011	.030***	.001	.027***	.000
	1990	.031**	.016	.040***	.002	.026***	.000
	1980	.075***	.017	.025***	.002	.022***	.000
English well	Pooled	-.103***	.006	-.184***	.001		
	2019	-.075***	.015	-.173***	.003		
	2010	-.117***	.018	-.181***	.004		
	2000	-.078***	.010	-.132***	.002		
	1990	-.119***	.016	-.106***	.002		
	1980	-.149***	.016	-.073***	.002		
English not well	Pooled	-.352***	.010	-.283***	.001		
	2019	-.386***	.029	-.205***	.004		
	2010	-.393***	.035	-.233***	.004		
	2000	-.334***	.016	-.166***	.002		
	1990	-.321***	.020	-.137***	.002		
	1980	-.324***	.023	-.091***	.003		
English not at all	Pooled	-.367***	.014	-.317***	.002		
	2019	-.390***	.047	-.191***	.006		
	2010	-.473***	.043	-.210***	.006		
	2000	-.325***	.022	-.147***	.002		
	1990	-.336***	.026	-.137***	.004		
	1980	-.314***	.033	-.077***	.004		
Constant	Pooled	5.338***	.025	5.585***	.003	5.723***	.001
	2019	5.474***	.090	5.256***	.015	4.931***	.006
	2010	5.488***	.098	4.944***	.015	4.762***	.006
	2000	5.371***	.060	5.090***	.006	5.027***	.002
	1990	5.153***	.073	5.081***	.008	5.033***	.002
	1980	5.426***	.055	5.258***	.006	5.308***	.001
Observations	Pooled	22,220		758,460		6,548,850	
	2019	3,774		82,299		433,395	
	2010	2,697		74,857		391,415	
	2000	8,136		303,696		2,017,059	
	1990	4,400		183,280		1,914,349	
	1980	3,213		114,328		1,792,632	
Adjusted R^2	Pooled	.519		.303		.113	
	2019	.495		.371		.275	

	2010	.565	.408	.303
	2000	.514	.371	.302
	1990	.462	.358	.286
	1980	.513	.337	.252

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Observations are men between 18 and 64 years of age who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The dependent variable is the geometric mean of annual earnings (the mean of the log earnings) in the occupation for about 500 occupations. The earnings have been adjusted for inflation and are expressed in 2010 dollars. The numbers of observations are identical to those in Tables 4 and 5. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. The reference category of English language proficiency is "English only" and "English very well". All regressions include state fixed effects and the pooled estimations additional control for year fixed effects.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

Table D2. Estimates of Ordered Probit Models of Occupational Attainment

Dependent variable: log of mean occupational annual earnings	Year	Immigrants from China		All other immigrants		U.S. born	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of schooling	Pooled	.155***	.003	.067***	.000	.155***	.000
	2019	.164***	.009	.142***	.001	.249***	.001
	2010	.179***	.011	.143***	.001	.274***	.001
	2000	.153***	.005	.132***	.001	.272***	.000
	1990	.145***	.007	.134***	.001	.259***	.000
	1980	.142***	.008	.143***	.001	.224***	.000
U.S. work experience	Pooled	.002	.004	.022***	.001	.026***	.000
	2019	-.009	.008	.008***	.002	.010***	.001
	2010	-.017	.011	.011***	.002	.010***	.001
	2000	-.003	.007	.009***	.001	.005***	.000
	1990	.038***	.009	.027***	.001	.010***	.000
	1980	-.011	.011	.029***	.002	.023***	.000
U.S. work experience squared /100	Pooled	-.003	.009	-.035***	.001	-.042***	.000
	2019	.012	.020	-.017***	.003	-.015***	.001
	2010	.032	.026	-.018***	.004	-.016***	.001
	2000	.007	.017	-.009***	.002	-.000	.001
	1990	-.068**	.021	-.043***	.003	.002**	.001
	1980	.044	.032	-.047***	.004	-.019***	.001
Non-U.S. work experience	Pooled	-.018***	.004	.023***	.001		
	2019	.008	.010	.012***	.002		
	2010	-.023*	.012	.012***	.002		
	2000	-.016**	.006	.017***	.001		
	1990	-.002	.009	.026***	.001		
	1980	-.043***	.010	.031***	.001		
Non-U.S. work experience squared /100	Pooled	.067***	.010	-.017***	.001		
	2019	-.031	.030	-.018**	.006		
	2010	.053	.031	-.021***	.006		
	2000	.061***	.016	-.027***	.003		
	1990	.057**	.020	-.036***	.003		
	1980	.129***	.023	-.044***	.004		
U.S. and non-U.S. work experience interaction	Pooled	-.000	.000	-.001***	.000		
	2019	.000	.000	-.000*	.000		
	2010	.000	.000	-.000	.000		
	2000	-.000	.000	-.000***	.000		
	1990	-.001**	.000	-.001***	.000		
	1980	-.000	.000	-.001***	.000		
Hours worked per week	Pooled	-.005***	.001	.003***	.000	.004***	.000
	2019	-.001	.003	.003***	.000	.001**	.000
	2010	-.004	.003	.006***	.001	.005***	.000
	2000	-.004*	.002	.003***	.000	.003***	.000

	1990	-.007***	.002	.001***	.000	.001***	.000
	1980	-.009**	.003	-.001*	.000	-.003***	.000
Married, spouse present	Pooled	.126***	.021	.123***	.003	.149***	.001
	2019	.091	.051	.147***	.009	.166***	.004
	2010	.005	.064	.136***	.009	.128***	.004
	2000	.134***	.034	.105***	.004	.104***	.002
	1990	.111*	.050	.129***	.006	.106***	.002
	1980	.230***	.058	.094***	.008	.080***	.002
English well	Pooled	-.332***	.019	-.503***	.003		
	2019	-.263***	.046	-.450***	.010		
	2010	-.401***	.057	-.441***	.010		
	2000	-.286***	.032	-.364***	.005		
	1990	-.355***	.045	-.314***	.007		
	1980	-.441***	.052	-.295***	.008		
English not well	Pooled	-.884***	.027	-.798***	.004		
	2019	-.890***	.070	-.535***	.013		
	2010	-.882***	.088	-.600***	.012		
	2000	-.877***	.045	-.486***	.006		
	1990	-.881***	.058	-.420***	.008		
	1980	-.928***	.073	-.387***	.011		
English not at all	Pooled	-.930***	.041	-.949***	.005		
	2019	-.864***	.108	-.571***	.021		
	2010	-1.127***	.125	-.636***	.019		
	2000	-.868***	.065	-.485***	.009		
	1990	-.976***	.086	-.463***	.012		
	1980	-.952***	.126	-.368***	.016		
μ_1	Pooled	.674***	.079	-1.334***	.010	-1.213***	.003
	2019	-1.822***	.310	.033	.046	1.572***	.023
	2010	.307	.312	.284***	.045	2.006***	.023
	2000	.401*	.183	-.024	.021	1.826***	.010
	1990	1.057***	.232	.007	.026	1.623***	.009
	1980	.295	.195	-.295***	.027	.784***	.007
μ_2	Pooled	1.075***	.079	-.589***	.010	-.418***	.003
	2019	.935***	.258	.873***	.046	2.494***	.023
	2010	.801*	.311	1.090***	.045	2.931***	.022
	2000	.829***	.183	.706***	.021	2.664***	.009
	1990	1.442***	.233	.811***	.026	2.416***	.009
	1980	.617**	.194	.550***	.026	1.587***	.007
μ_3	Pooled	1.084***	.079	.207***	.010	.425***	.003
	2019	1.364***	.258	1.592***	.046	3.199***	.023
	2010	.803**	.311	1.814***	.045	3.631***	.023
	2000	.836***	.183	1.518***	.021	3.496***	.010
	1990	1.449***	.233	1.652***	.026	3.329***	.009
	1980	.638**	.194	1.530***	.027	1.698***	.007
	Pooled	1.383***	.079	.769***	.010	.472***	.003

μ_4	2019	1.587***	.259	2.106***	.046	3.710***	.024
	2010	1.030***	.312	2.347***	.045	4.173***	.023
	2000	1.145***	.183	2.130***	.021	3.532***	.010
	1990	1.793***	.233	2.256***	.026	3.387***	.009
	1980	.991***	.195	1.573***	.027	2.649***	.007
μ_5	Pooled	1.389***	.079	.798***	.010	1.028***	.003
	2019	1.604***	.259	2.123***	.046	4.372***	.024
	2010	2.042***	.317	3.043***	.045	4.904***	.024
	2000	1.149***	.183	2.807***	.021	4.167***	.010
	1990	2.534***	.236	2.294***	.026	4.023***	.010
	1980	1.686***	.200	2.264***	.027	3.337***	.007
μ_6	Pooled	2.256***	.081	1.413***	.010	1.620***	.003
	2019	2.603***	.265	2.781***	.046	4.408***	.024
	2010	2.976***	.246	3.061***	.045	4.947***	.024
	2000	2.073***	.186	2.834***	.021	4.892***	.010
	1990	2.537***	.236	2.955***	.026	4.742***	.010
	1980	1.696***	.200	2.850***	.027	4.004***	.008
Observations	Pooled	22,220		734,857		6,139,133	
	2019	3,774		82,299		433,395	
	2010	2,697		74,857		391,415	
	2000	8,136		303,696		2,017,059	
	1990	4,400		183,280		1,914,349	
	1980	3,213		114,328		1,792,632	
Pseudo R^2	Pooled	.218		.094		.033	
	2019	.206		.118		.095	
	2010	.260		.132		.103	
	2000	.213		.116		.096	
	1990	.202		.119		.095	
	1980	.232		.121		.090	

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Samples are men between 18 and 64 years of age who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The dependent variable is the geometric mean of annual earnings (the mean of the log earnings) in the occupation. The earnings have been adjusted for inflation and are expressed in 2010 dollars. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population. The reference category of English language proficiency is "English only" and "English very well". All regressions include state fixed effects and the pooled estimations additional control for year fixed effects.
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.

E. Results from the Two-Step Heckit Model

Table E1. Heckman selection model: two-step estimates

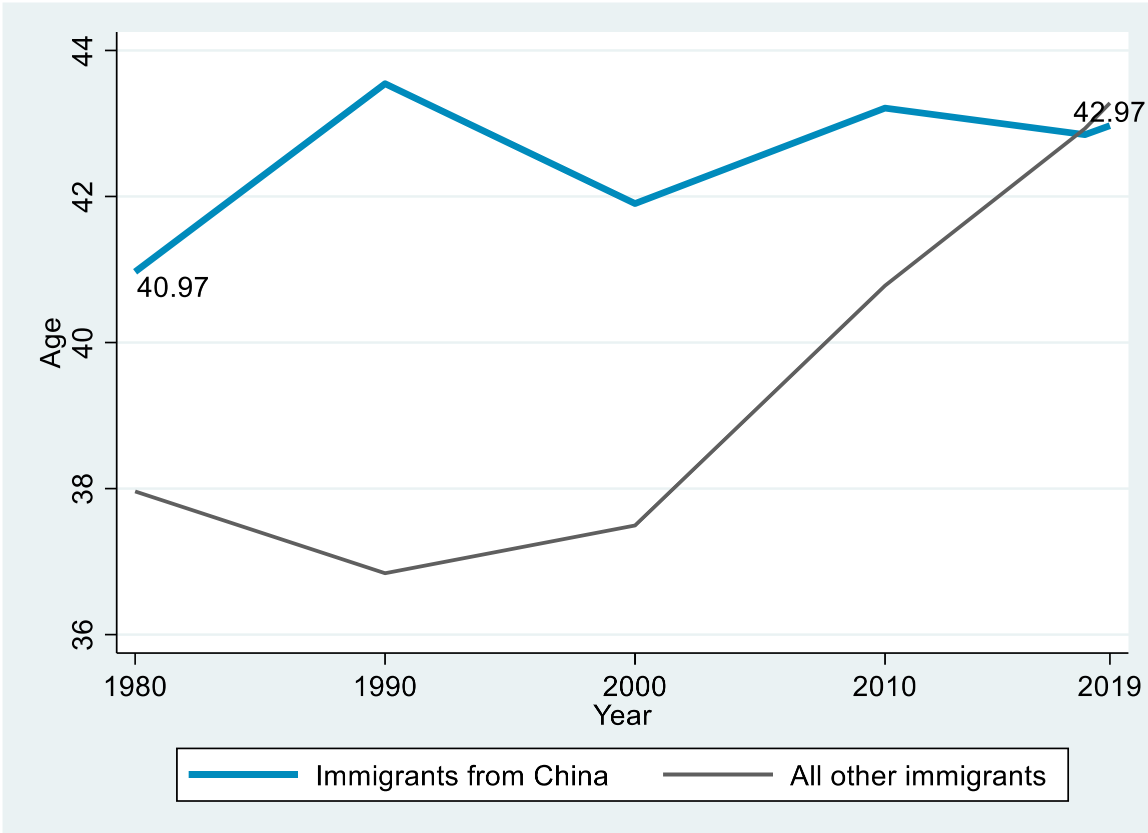
	Year	Immigrants from China				All other immigrants				U.S. born			
		Second-stage estimates		First-stage probit estimates		Second-stage estimates		First-stage probit estimates		Second-stage estimates		First-stage probit estimates	
		Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Years of schooling	Pooled	.065***	.003	-.027	.015	.064***	.014	.011***	.002	.099***	.002	.031***	.001
	2019	.084***	.004	.009	.030	.082***	.001	.009	.006	.121***	.007	.003	.017
	2010	.078***	.004	-.022	.032	.079***	.001	.020***	.005	.127***	.000	.028***	.004
	2000	.067***	.002	.016	.029	.065***	.017	-.003	.006	.106***	.009	.032***	.004
	1990	.052***	.003	.010	.023	.064***	.011	.001	.004	.103***	.000	.019***	.002
	1980	.049***	.003	.007	.012	.055***	.001	.034***	.002	.082***	.000	.087***	.001
U.S. work experience	Pooled	.054***	.006	.024	.027	.037	.028	.036***	.004	.049***	.001	.013***	.001
	2019	.049***	.005	.068	.046	.044***	.001	.034***	.009	.044***	.006	-.006	.018
	2010	.064***	.006	-.077	.053	.049***	.001	.023**	.008	.053***	.000	.046***	.003
	2000	.052***	.004	.121	.067	.041	.030	.028**	.009	.044***	.007	.017***	.003
	1990	.077***	.005	-.007	.041	.055**	.020	.021***	.006	.052***	.000	.043***	.001
	1980	.053***	.007	.075**	.024	.071***	.001	.045***	.003	.051***	.000	.042***	.000
U.S. work experience squared /100	Pooled	-.101***	.014	-.055	.065	-.054	.065	-.072***	.010	-.076***	.003	-.039***	.002
	2019	-.087***	.013	-.201	.109	-.075***	.002	-.063**	.020	-.067***	.012	-.019	.033
	2010	-.118***	.014	.090	.121	-.081***	.003	-.044*	.018	-.088***	.001	-.086***	.006
	2000	-.095***	.010	-.223	.174	-.061	.076	-.074***	.021	-.067***	.016	-.051***	.007
	1990	-.143***	.012	-.031	.098	-.085	.051	-.047**	.015	-.082***	.000	-.102***	.003
	1980	-.111***	.019	-.202**	.064	-.134***	.003	-.110***	.009	-.081***	.000	-.089***	.001
Non-U.S. work experience	Pooled	.008	.005	.000	.024	.030	.022	.005	.004				
	2019	.035***	.006	-.025	.044	.037***	.001	.020	.012				
	2010	.011	.006	-.062	.054	.031***	.001	.008	.010				
	2000	.006	.004	-.006	.054	.021	.031	.018*	.009				
	1990	.013**	.005	-.018	.039	.034	.020	-.007	.006				
	1980	-.005	.005	-.004	.019	.032***	.001	.029***	.003				

Non-U.S. work experience squared /100	Pooled	-.006	.014	-.008	.055	-.044	.064	-.015	.010				
	2019	-.079***	.017	.029	.110	-.073***	.004	-.047	.030				
	2010	.010	.016	.061	.121	-.054***	.004	-.020	.026				
	2000	-.003	.009	.154	.167	-.029	.090	-.063**	.024				
	1990	-.011	.011	.026	.085	-.055	.054	.014	.016				
	1980	.017	.012	.033	.044	-.055***	.003	-.058***	.007				
U.S. and non-U.S. work experience interaction	Pooled	-.001***	.000	-.001	.001	-.001	.001	-.001***	.000				
	2019	-.001***	.000	-.001	.002	-.001***	.000	-.000	.000				
	2010	-.001***	.000	.001	.002	-.001***	.000	-.000	.000				
	2000	-.001***	.000	-.005*	.002	-.001	.001	-.001	.000				
	1990	-.001***	.000	-.000	.001	-.001	.001	-.000	.000				
	1980	-.000	.000	-.002*	.001	-.001***	.000	-.001***	.000				
Hours worked per week	Pooled	.003*	.002	-.023***	.004	.021	.012	-.012***	.001	.014***	.001	-.015***	.000
	2019	.006***	.002	.007	.014	.014***	.000	-.005*	.003	.017***	.002	-.014***	.003
	2010	.004*	.002	-.020	.014	.015***	.000	.001	.002	.016***	.000	.006***	.001
	2000	.003***	.001	-.030***	.009	.016	.011	-.014***	.002	.017***	.003	-.016***	.001
	1990	.000	.001	.014	.008	.018	.009	-.013***	.001	.009***	.000	.001***	.000
	1980	-.002	.001	-.007	.005	.007***	.000	.000	.001	.006***	.000	.001***	.000
Married, spouse present	Pooled	.166***	.031	-.007	.146	.208	.107	.011	.022	.264***	.010	.138***	.008
	2019	.189***	.030	.707**	.252	.224***	.006	.100	.052	.279***	.035	-.059	.093
	2010	.111***	.032	.357	.287	.199***	.006	.171***	.042	.247***	.002	.218***	.019
	2000	.152***	.019	.099	.299	.202	.138	.063	.050	.249***	.042	.049*	.021
	1990	.096***	.027	.403	.228	.202*	.100	.031	.033	.259***	.001	.270***	.009
	1980	.196***	.034	.243*	.118	.209***	.006	.306***	.016	.254***	.001	.453***	.004
English well	Pooled	-.228***	.030	-.070	.139	-.167	.127	-.056*	.024				
	2019	-.293***	.029	.482	.281	-.305***	.007	.199***	.060				
	2010	-.230***	.030	.116	.316	-.264***	.007	.053	.048				
	2000	-.205***	.019	-.038	.362	-.182	.163	.008	.058				
	1990	-.208***	.026	.219	.254	-.113	.116	-.071*	.036				
	1980	-.232***	.030	.006	.124	-.146***	.006	-.071***	.016				
English not well	Pooled	-.552***	.039	-.198	.159	-.288	.149	-.041	.027				
	2019	-.648***	.042	.264	.322	-.348***	.008	.119	.073				
	2010	-.569***	.044	.179	.356	-.360***	.008	.070	.054				
	2000	-.524***	.025	-.158	.353	-.294	.186	.000	.064				

	1990	-.504***	.032	.064	.281	-.222	.140	-.084*	.041				
	1980	-.467***	.040	-.197	.143	-.275***	.007	-.110***	.020				
English not at all	Pooled	-.665***	.057	.442	.343	-.360	.211	-.016	.037				
	2019	-.689***	.069	.797	.435	-.332***	.013	-.134	.112				
	2010	-.777***	.061	.298	.427	-.374***	.012	.117	.076				
	2000	-.581***	.035	.124	.485	-.346	.258	-.012	.084				
	1990	-.553***	.045	-.111	.363	-.349	.200	-.037	.059				
	1980	-.678***	.064	-.309	.213	-.357***	.011	-.170***	.027				
Number of own children under age five in household	Pooled			.085	.126			.018	.017			.027***	.007
	2019			-.337	.263			.023	.051			.131	.166
	2010			.056	.260			-.021	.036			.056**	.020
	2000			.250	.402			-.024	.039			.081**	.025
	1990			-.290	.231			.028	.026			-.047***	.008
	1980			.256*	.111			-.036***	.011			-.041***	.003
Mills (Lambda)	Pooled	-1.821	1.179			-4.340	4.311			-11.073***	1.355		
	2019	.310	.320			-.002	.167			-1.602	23.198		
	2010	-.053	.372			-.414	3.290			.070	.052		
	2000	-.246	.941			-.370	6.962			-.272	1.861		
	1990	-.482	.529			-.1.893	1.559			.035	.021		
	1980	.013	.260			-.034	.047			-.065***	.007		

Note: Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Samples are men between 18 and 64 years of age who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The group “All other immigrants” excludes the group “Immigrants from China” from the entire immigrant population. The reference category of English language proficiency is “English only” and “English very well”. All regressions include state fixed effects and the pooled estimations additional control for year fixed effects. In the first-step probit model, we include the number of own children under age five in household
Source: Based on 5% 1980, 1990, 2000 U.S. Censuses and 2010, 2019 ACS; author’s tabulations.

Figure F1. Average ages of immigrant groups by survey year



Note: Observations are men aged 18–64 who are full-time workers with positive earnings and hours of work, are not self-employed, are not part of the military, are not living in group quarters, and are not in full-time education. The group "All other immigrants" excludes the group "Immigrants from China" from the entire immigrant population.
Source: Based on 5% 1980, 1990, and 2000 U.S. Censuses and 2010, 2019 ACS; author's tabulations.