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Title: Chinese Immigrants and Local Labor Markets in the U.S.: A State-Level Analysis

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Chinese Immigrants and Local Labor Markets in the U.S.:

A State-Level Analysis

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Abstract:

This paper examines how the inflows of Chinese immigrants into the U.S. affect the local labor markets outcomes of U.S. natives at the state level between 1990 and 2017. Over the past five decades, the population of Chinese immigrants in the United States has grown significantly, which raises the question how they impact the labor market in the U.S. I apply regression analysis on the state-level panel data and use fixed-effects model to address the omitted variable bias. The empirical results indicate that the inflows of immigrants from China have no significant impact on the employment rate and the average income in the U.S. local labor markets.

Key words: immigration, labor market, employment, income

I. Introduction

1.1 Research Background

It is widely concerned among the public as well as scholars whether immigrants have adverse effects on the US economy, especially the labor market outcomes of U.S. natives (Blau and Mackie, 2016). Some argue that firms introduced cheap immigrant workers to replace native workers via temporary work program such as H-1B, which leads to the unemployment of natives (Matloff, 2013; Hira, 2018). Theoretically, immigrants may also drive down the wage level in the labor market by putting more pressure on the supply side.

Chinese immigration to the U.S. has a long history that can be dated back to the 1850s Gold Rush in California. At the time when Chinese first migrated to the U.S., they were accused of "stealing" jobs from native workers and suppressing the wage level, especially in the gold mining business. Discrimination and exclusion followed and the immigration from China to the U.S. withered for more than half of a century. The number of Chinese immigrants to the U.S. started to rise again since the 1960s after the abolishment of the Chinese Exclusion Act. The skyrocketing population of Chinese immigrants again raises the question: how do Chinese immigrants affect the U.S. economy?

In this paper, I examine whether the inflows of immigrants from China influence the local labor market outcomes of US natives, including the employment rate and the average income. I exploit the variation of the inflows of Chinese immigrant into different states to identify the impact of Chinese immigrants on local labor market conditions. Using the state-level panel data from 1990 to 2017 compiled from several sources, I apply the fixed-effects model to address the problem of immigrants' endogenous geographic distribution. The results suggest that Chinese immigrants have virtually no negative impact on the employment rate and the average income of native workers in the labor market.

1.2 Literature Review

A rich literature studies the impact of immigrants on the economy of the host country. Studies show that immigrants contribute to the host country in several ways. For instance, Cortes (2008) find that low-skilled immigrants reduces the price of services, such as housekeeping. Cortes and Pan (2014) further finds that the service provided by low-skilled immigrants increased high-skilled native females' labor supply. In terms of technology and productivity, Hunt and Gauthier-Loiselle (2010) show that high-skilled immigrant boosted the innovation activities measured by patents in the US and Peri (2012) find that immigration increased the total factor productivity in the US.

On the other hand, economists have not yet settled the debate on how immigrants affect native workers' labor market outcomes (Blau and Mackie, 2016; Dustmann et al., 2016). In a seminal study, Card (1990) uses the natural experiment of the Mariel Boatlift to study the labor market impact of Cuban refugees and he finds no significant impact of immigrants on the employment of natives in Miami. On the other hand, Borjas (2017) revisits this event and finds a large and negative impact. Other than these two, there are abundant studies that identify limited to null adverse impact of immigrants (Card, 2009; Card and Peri, 2016, etc.) while other studies find immigrants substantially harming natives' wages and employment (Borjas, 2003; Llull, 2017, etc.). Overall, the existing empirical findings are mixed and further studies are warranted to provide new and informative evidence.

1.3 Research Method and General Process

I utilize regression-based analysis and pay special attention to identifying causality. The key challenge to the empirical study is the endogeneity of immigration decisions of settlement. To be specific, immigrants choose their state of residence for reasons that may be correlated with the labor market outcomes. Therefore, the OLS estimation has the omitted variable bias. I take advantage of the panel data structure and use a fixed effect model to address the endogeneity issue by eliminating the time-invariant component in the error term that is correlated with the explanatory variable. By doing so, my estimation implies a causal relationship between immigration and labor market outcomes. Figure 1 is the general process flow diagram in which the data is being modeled.

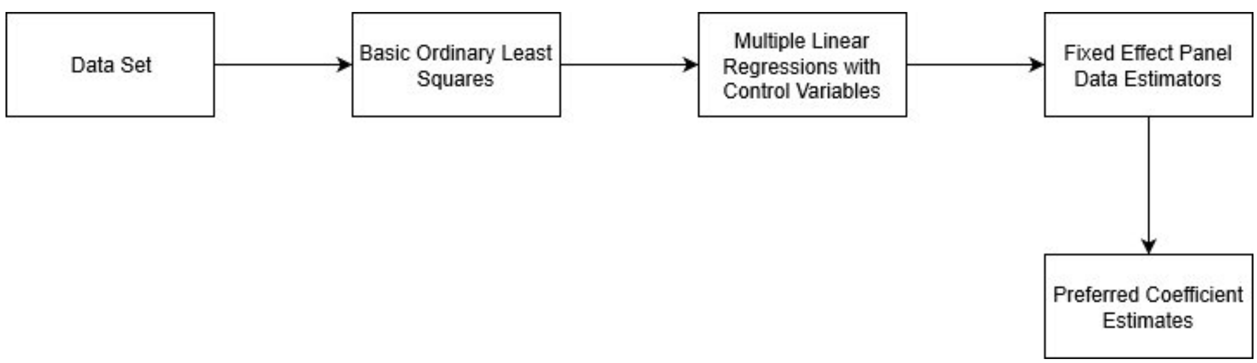

Figure 1. The general process flow diagram

II. Data and Methodology

2.1 Data Collection and Cleaning

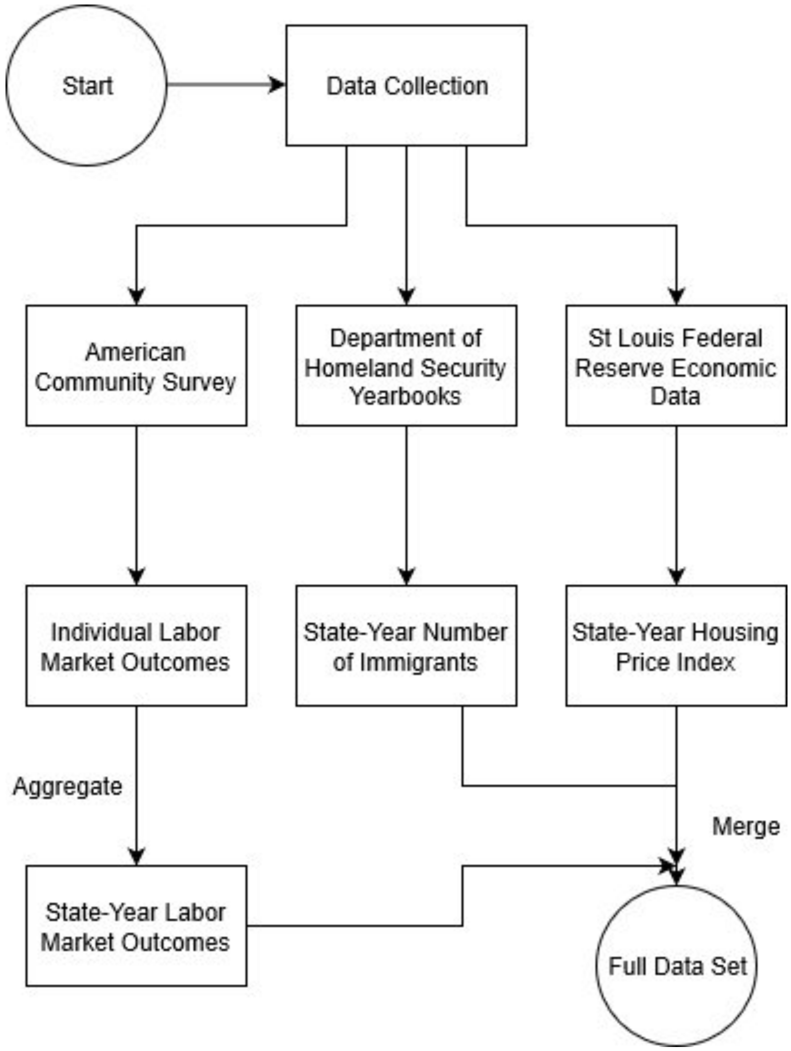

Figure 2. The process of data collection and cleaning

Figure 2 sums up my data collection and cleaning procedure. The data used in this study come from three sources. For all the years from 1990 to 2017, I obtain the annual number of Chinese immigrants to each state from the Department of Homeland Security (DHS) yearbooks, obtain the employment rate and the average income in each state from the (American Community Survey) ACS, and obtain the housing price index in each state from St. Louis Federal Reserve Economic Data (FRED).

I aggregate the number of immigrants from China in each state and year from the DHS yearbooks from 1990 to 2017. The table below shows the structure of the cleaned DHS data:

State	Year	#Immigrants
Alabama	2000	234,000
Alabama	2001	253,000
Alaska	2000	132,000
Alaska	2001	143,000
Arkansas	2000	324,000
Arkansas	2001	350,000

Table 1. The illustration of the DHS data

The ACS is a repeated cross-sectional data at the individual level as table 2 shows. I collapse their employment status and income by their state of residence and year to a state-level panel data containing each state's employment rate and average income level from 1990 to 2017. The state-level panel data is shown in table 3.

Individual ID	State	Year	Employed	Income
1	Alabama	2000	1	35,000
2	Alabama	2000	0	57,000
3	Alaska	2000	1	25,000
4	Arkansas	2000	0	70,000

Table 2. The illustration of the ACS individual-level data

State	Year	Employed	Income
Alabama	2000	0.5	46,000
Alaska	2000	0.2	30,000
Arkansas	2000	0.3	80,000

Table 3. The illustration of the ACS state-level data

I then match the ACS data on labor market conditions, FRED data on the housing price, and DHS data on immigrant inflows by state and year to generate the final panel data for regression analysis.

2.2 Empirical Model

The simple cross-sectional OLS model to examine the impact of immigrants on labor market outcomes can be expressed as the following equation:

$$Y_i = \beta_0 + \beta_1 immig_i + X_i \gamma + \varepsilon_i \qquad (1)$$

In this model, Y_i is the unemployment rate or the average income in state i. $immig_i$ is the population of immigrants in state i. X_i include the state characteristics that affect the labor market outcomes. ε_i is the error term that include other factors that are not controlled but can also affect the labor market outcomes in state i. Under the zero conditional mean assumption that $E(\varepsilon_i | immig_i) = 0$, the OLS estimate of β_1 is a unbiased measure of the impact of immigrants on the local labor market outcomes.

However, immigrants usually tend to settle in states with better economic prosperity (for instance, California), i.e. they endogenously enter labor markets with higher employment opportunities and higher wages. If $immig_i$ is positively correlated with the error term ε_i, the zero conditional mean assumption is violated and the cross-sectional OLS regression yields a upward bias in the estimate of β_1.

To address this endogeneity issue, I apply the following fixed-effects model to the state-level panel data.

$$Y_{it} = \beta_0 + \beta_1 immig_{it} + X_{it}\gamma + \phi_i + \theta_t + \omega_{it} \qquad (2)$$

In this model, the dependent variable Y_{it} is the labor market outcomes (employment rate and average income) in state i at year t. $immig_{it}$ is the inflow of Chinese immigrants into state i at year t., X_{it} is the vector of time-varying characteristics of state i in time t, including the state population and the housing price index. ϕ_i is the state fixed effect to account for state i's time-invariant characteristics. θ_t is the year fixed effect to account for any systematic differences across various survey years. ω_{it} is the idiosyncratic error term.

If the omitted variables in equation (1) correlated with $immig_{it}$ are assumed to be time-invariant, I can capture them with the state fixed effect ϕ_i and exclude them from the error term in the fixed-effects model. As long as $immig_{it}$ is uncorrelated with the idiosyncratic error term ω_{it} that varies over time, the fixed-effect estimation can produce consistent estimates and make a convincing causal inference. After controlling for state population and the housing price index, I consider this a reasonable assumption in this model.

III. Results

In this section, I present the regression results estimated from the model above.

I first start with pooled OLS regressions without controlling for the state and year fixed effects. For the convenience of interpretation, the variable of immigrant inflow is rescaled by 1/1000 so the coefficient indicates the impact of the increase of 1000 Chinese immigrants in the state on the outcomes.

$$\widehat{empl\_rate_{it}} = 0.618 + (-4.2 \times 10^{-3}) \times immig_{it} \qquad (3)$$

$$\widehat{empl\_rate_{it}} = 0.649 + (1.17 \times 10^{-3}) \times immig_{it} + (-1.04 \times 10^{-8}) \times state\_pop_{it} \quad (4)$$

Equations 3 and 4 show the point estimates of coefficients from pooled OLS regression using the employment rate in state i at year t as the dependent variable In equation (3), I only include the inflow of Chinese immigrants on the right hand side. In equation (4), I further control for $state\_pop_{it}$, the state population in state i at year t. Equation (3) shows that an increase of 1000 Chinese immigrants is associated with the decrease of the employment rate by 0.042 percentage point. After controlling for the state population, the estimated coefficient on Chinese immigrants in equation 4 becomes positive It shows that an increase of 1000 Chinese immigrants is associated with the increase in the employment rate by 0.117 percentage point. The negative coefficient on state population suggests that states with a larger population have lower employment rates. The comparison of coefficients on immigrants indicate that the number of Chinese immigrants are positively correlated with state population, i.e. Chinese immigrants choose to reside in more populous states. However, the estimates may be contaminated by the omitted variable bias in the OLS regression and do not imply a convincing causal relationship. Especially in equation 4, the number of the Chinese immigrants is positively correlated with the employment rate, which suggests it is very likely upward biased.

The pooled OLS estimates of regressions using the average income as the dependent variables are presented below:

$$\widehat{avg\_inc_{it}} = (3.62 \times 10^{4}) + 45.1 \times immig_{it} \qquad (5)$$

$$\widehat{avg\_inc_{it}} = (3.81 \times 10^{4}) + 141.1 \times immig_{it} + (-6.21 \times 10^{-4}) \times state\_pop_{it} \qquad (6)$$

Equations 5 and 6 show that an increase of 1000 immigrants is associated with an increase of $45.1 and $141.1 in the average income. We can from the comparison of the coefficients that the state population is negatively correlated with average income but positively correlated with immigration level. The two equations as well may have the omitted variable bias and do not imply causality.

$$\widehat{empl\_rate}_{it} = 0.548 + (3.5\times10^{-4})\times immig_{it} + (-6.65\times10^{-9})\times state\_pop_{it} + (3.04\times10^{-4})\times house\_price \tag{7}$$

$$\widehat{avg\_inc}_{it} = (1.78\times10^{4}) - 25.4\times immig_{it} + (1.30\times10^{-4})\times state\_pop_{it} + 61.3\times house\_price \tag{8}$$

In equations 7 and 8 I further control for the housing price index and the results show that the coefficients on Chinese immigrants are unbiased in equation 5 and 6. For the labor market outcome of employment rate, there is a decrease of the employment rate by 0.035 percentage point corresponding to an increase of 1000 immigrants; for the average income, there is a decrease of $25.4 in average income level corresponding to an increase of 1000 immigrants.

$$\widehat{empl\_rate}_{it} = 2.06 + (-7.15\times10^{-6})\times immig_{it} + (-3.61\times10^{-9})\times state\_pop_{it} + (8.14\times10^{-2})\times house\_price + \phi_s + \theta_t \tag{9}$$

$$\widehat{avg\_inc}_{it} = (-2.1\times10^{6}) - 14.2\times immig_{it} + (-3.82\times10^{-4})\times state\_pop_{it} + 2.41\times house\_price + \phi_s + \theta_t \tag{10}$$

In equations 9 and 10, I estimate the full fixed-effects model controlling for the state population, the housing price index, state and year fixed effects. The results indicate the pooled OLS estimate using the employment rate as the dependent variable is upward biased. The fixed-effects estimation in equation 9 shows that the impact of Chinese immigrants on the employment rate is negative but very weak: a increase in the number of Chinese immigrant by 1000 will only result in a 0.000715% decrease in employment rate in local labor markets. This means that Chinese immigrants are not a significant factor that influences the local labor market outcomes, so the sayings in social media or news that immigrants especially from China are stealing jobs from American workers are ungrounded.

On the other hand, the comparison of equations 8 and 10 shows that the pooled OLS estimate of the coefficient on immigrant is slightly downward biased when using the average income as the outcome. The fixed-effects estimation shows that the average income level decreases by $14.2 corresponding to an increase in number of Chinese immigrants by 1000. The results suggest that the inflows of Chinese immigrants actually impose an insignificant downward pressure on wages.

IV. Conclusion

This study empirically examines the effect of Chinese immigrants on the employment rate and the average income in the U.S. local labor markets. I use a state-level panel data from 1990 to 2017 compiled from multiple sources and use the fixed-effects model to address the endogeneity issue and to identify the causal effect. The results imply that the inflows of Chinese immigrants do not significantly affect the US native workers' employment rate and average income level at the state level. The findings shed light on the policy discussion about the impact of immigration on the U.S. economy and suggest no adverse effect of immigrants imposed on native workers' labor market outcomes.

One speculation is that Chinese immigrants tend to be more high-skilled and less homogeneous to native workers. They can specialize in tasks and cause less intense competition with natives in the labor market. A promising research question that worths further studying is how the labor market impact of Chinese immigrants may differ across workers with various skill levels.

Another limitation of the study is that our estimation relies on the assumption that the omitted variables are time-invariant. If the immigrant inflows are correlated with time-varying unobservables, our fixed-effects estimation may still be subject to biases (for instance, if the immigrant inflows are attracted by the significant growth in the tech industry in California). Although this study is a major improvement from standard OLS estimates, further studies can investigate other potential outcomes in the labor market that is affected by immigration and deal with time-variant omitted variables. One potential way to address this problem is to develop new identification strategies, such as instrumental variable.

Also, there are concerns about the loss of labor in China --- “brain drain” from the origin of immigration. Consequently, it is also necessary to study the immigration impact on the exporting countries’ local labor markets in future studies.

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VI. Acknowledgements

As described by Qi Lixin, president of Beijing Association of Private Entry and Exit Intermediaries, Chinese immigration after the reform and opening up (in the 1940s) have been through three significant stages: The first stage was from 1979 to the mid-to-late 1980s, with national public factions as the mainstay, accompanied by overseas reunion of family, and studying abroad at their own expense. The second stage was from the mid 1990s to 2003, during which most of the immigrants are employed in comparatively low-end occupations such as babysitting. The third phase began in 2007. With the accelerated development of China's economy, especially the heating up of property markets, people have accumulated considerable wealth, and investment immigrants have grown at a remarkable rate add the source of this quote. With the fast pace of increase in Chinese immigrants, the changing purpose of immigrants, and the growing tension between the US and its immigrant community, it is important to study the effect immigrants have on their destination local economies, and it was also my initial intuitive to do the research on this field.

Eva Yiran Li, a junior student from Cushing Academy in Ashburnham, Massachusetts, is the only student writing the paper. Mr. Zhu is a graduate student at the Economics Department in Yale University. He is Eva's instructor on this paper, who advised her on the pulling and cleaning of data, as well as the basics of conducting regression models.

VII. Declaration

本参赛团队声明所提交的论文是在指导下进行的研究工作和取得的研究成果。尽本团队所知，除了文中特别加以标注和致谢中所罗列的内容之外，论文中不包含其他人已经发表或撰写过的研究成果。如有不实之处，本人愿意承担一切相关责任。

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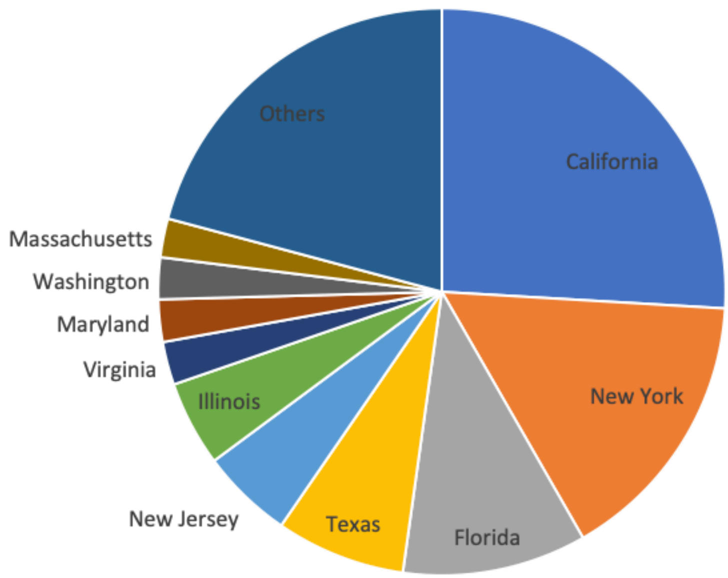
2019 年 9 月 5 日

VIII. Appendix

1997 Immigration by States



2016 Immigrations by States