Instrumenting for Immigration Using Push Factors of Origin Countries

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Abstract

Identifying the impact of immigration on local labor markets has faced significant challenges because of the evident moving to opportunity bias, where immigrants' locational choices are influenced by local labor demand shocks. I introduce a novel instrument for immigration, which is the predicted number of immigrants from the push factors of origin countries. Using a mixed effects model that incorporates both fixed and random effects, the actual number of immigrants in each city of United States is regressed on the push factors of the origin countries. Then, the predicted number of total immigrants in each city is obtained by the fitted values of the regression, which is used as an instrument for immigration. I show that the instrument strongly predicts current immigrant population and is less correlated with local labor demand shocks compared to the widely used shift-share instruments.

1 Introduction

There have been numerous attempts to identify the impact of immigrants on local labor markets, largely focusing on finding the causal effects on employment and wages of natives. The main identification problem that has challenged the previous studies is endogeneity of immigrant location choices; immigrants are more likely to settle down in cities with strong labor markets. This is often called "moving to opportunity bias," where both natives and immigrants are moving to cities with positive labor demand shocks. The most popular way of solving this problem is using the previous immigration settlement pattern as an instrument for immigration (Bartel, 1989). However, since immigrants have tendency to cluster in cities that offer best employment opportunity, it is possible that this instrument cannot completely resolve the endogeneity problem if there exists serially correlated labor demand shocks.

In this paper, I identify the effect of recent immigrants (who entered the United States within 10 years) on local labor market using the novel instrumental variable, which is the number of immigrants predicted by the supply/push factors of the countries that immigrants are from. The push factors are conditions in the origin countries which induce out-migration of immigrants, such as per capita GDP and mortality rate. Utilizing the mixed effect models, the actual number of recent immigrants in the United States are regressed on the push factors of the origin countries. Then, the predicted number of total immigrants for each city is obtained by the fitted values of the regression. There is a strong first stage relationship between the number of actual immigrants and the number of predicted immigrants. It is also shown that the number of predicted immigrants is uncorrelated with Bartik shock (Bartik, 1991; Notowidigdo, 2010), indicating that the instrumental variable is unlikely to be correlated with any local labor demand shocks.

The main regression results using the predicted number of immigrants as instruments show that there is a positive relationship between the number of recent immigrants and employment of natives. Correcting the endogeneity problem, I find that a 10% increase in the number of recent immigrants leads to a 4% increase in the number of employed natives on average. The effect on past immigrants who stayed in the United States more than 10 years is also found to be positive and even larger; a 10 % increase in the number of recent immigrants lead to a 6% increase in the number of employed past immigrants on average. The effects of immigration on wage income of natives and past immigrants are also estimated to be positive. Decomposing the positive immigration impact, the effect of high skilled recent immigrants is stronger than that of the low skilled. From the regression results, I conclude that recent immigrants are actually generating labor demand, creating jobs and increasing wages.

There are large volume of studies concerning the impact of immigrants on the labor market, which shows the continuous interest on the subject. Still, there is no definite answer to this question that most studies agree on. A meta analysis by Longhi et al. (2005) shows that the estimated effect of immigrants on wages of natives varies significantly across studies and even within the same study. More recent survey by Kerr and Kerr (2011) finds that though many papers find only minor displacement effects after very large immigration flows, some studies find larger effects, concentrated on certain parts of native population. As stated before, the fundamental challenge stems from the fact that immigrants' decisions to reside in certain cities are correlated with local shocks that also affect natives' residential choice. Therefore, the key to solving this problem is getting the exogenous variation of the number of immigrants to isolate the supply effect that is independent to local labor demand shocks. Several solutions have been proposed to overcome this endogeneity problem of immigration variable, and they can be categorized into the following (Peri, 2015).

First, it is possible to look at natural experiments such as exogenous refugee influx from the historical events. For instance, the pioneering study by Card (1990) analyzes the impact of Miami Boatlift, the influx of Cuban refugee to Miami in 1980. Also, there are some studies about the impact of the refugee flows in the countries other than the United States (Angrist and Kugler, 2003; Friedberg, 2001). Although these types of natural experiments have an advantage of being more exogenous compared to usual voluntary immigration, it should not be neglected that locational choice of those refugees after they enter into the United States may not be exogenous. That is, it is possible that they eventually choose to live in cities that offer better labor market opportunities. Moreover, focusing on certain historical events raises a question of external validity; whether the effect of certain refugees can be generalizable is questionable.

Another popular way to resolve this problem is using supply/push components of immigration as an instrumental variable that are independent to local labor demand shocks. The widely used instrument in this area is using previous share of ethnic groups in each city to predict the recent immigration inflow (Card, 2001). This instrumental variable is easier to formulate, where the only required data is the lagged number of immigrants in each city without any information on individual immigrants. Notice that this instrument is based on the assumption that the previous settlement patterns of immigrants are not correlated with current local demand shocks that affect immigrants' location choice. Yet, this instrument may also be subject to endogeneity problem if there exist serially correlated demand shocks. This problem will be discussed in more detail in section 4, where it is shown that this shift-share instrument is actually correlated with the Bartik measure.

Also, there are papers using the natural push factors of regions that immigrants migrated from. For instance, Munshi (2003) uses the rainfall data in the regions that Mexican immigrants are from as an instrument for the size of Mexican network in the United States. Similarly, Kleemans and Magruder (2015) finds out the impact of internal migration using precipitation of the origin regions that immigrants migrated from. Utilizing such regional weather variation is a convincing way to get exogenous variation of immigration size, but it is often difficult to get individual information on the regions that they migrated from and specific characteristics of the region that can be used as push factors.

Finally, Boustan (2010) identifies the urban impact of black migration from the rural South to industrialized cities in the North, instrumenting for changes in black population using the predicted number of immigrants from the push factors of the rural South. These push factors are adverse local economic conditions that cause Blacks to move to the North. I closely follow this "push factors" idea in this paper, where the instrument for the number of recent immigrants to the United States are obtained using the push factors of origin countries that immigrants are from. Yet, Boustan allocates the total predicted migrants to each city according to the established settlement patterns similar to Card (2001), whereas I allocate them without using the previous settlement patterns.

In particular, I predict the number of recent immigrants for each city from the push factors of the source countries under the critical assumption that the effects of push factors on immigration are heterogeneous across the cities. This heterogeneity assumption is reflected in the "random effects" components of the mixed effects model explained in Section 3, where the coefficients of the push factors are different across the cities. For example, the effects of mortality rate of the source countries on the number of immigrants varies with Los Angeles and Chicago. Then, I get the predicted number of immigrants for each city from the fitted value, utilizing the estimated coefficients for each city. In this way, I formulate the instrument *without* using the lagged settlement patterns of immigrants, which distinguishes this paper from the other previous studies such as Card (2001) and Boustan (2010).

The details on the difference in the formulation of the various instruments and the consequences are to be discussed in Section 4. First, it is checked whether the instruments are correlated with Bartik measure (Notowidigdo, 2010), which is widely used to identify demand shocks that are independent to any local supply shocks. If the instruments are generated only from the supply/push factors, then there should be no relationship between the instruments and the Bartik measure. I show that the instrument from this paper does not exhibit such correlation, but the Card and Boustan instrumental variables are well predicted by the Bartik measure. In addition, the falsification tests indicate that the instrument from this paper prior to the analyzed period cannot be predicted by the current labor market outcomes, unlike the previous instruments. Moreover, I run an over-identification test using the instrument from this paper and the previous instruments to test the exogeneity conditions. The results suggest that the instrumental variable from this paper is less correlated with local labor demand shocks, validating one of the main exclusion restrictions of the instrument.

2 Data and Descriptive Statistics

I use the decennial U.S. census data from the Integrated Public Use Microdata Series (IPUMS). The five percent national random samples of the 1980, 1990 and 2000 with the 5-year combined 2006-2010 American Community Survey (ACS) are utilized. The aggregated ACS data will depict the average characteristics of 2006-2010, and it will be referred to as 2010 data throughout the analysis. There are several reasons that I look at the data from 1980. First, it is possible to investigate the relatively recent trend of immigration flows. Second, the Immigration and Nationality Amendments of 1965 removed national origin quotas, which significantly changed the immigration pattern. Since the main independent variable of my analysis is recent immigrants who entered the United States in past 10 years, it is logical to use the data from 1980, when all the recent immigrants came to the United States after the removal of national origin quotas.

The microdata are collapsed into metropolitan statistical area (MSA) since the focus of the analysis of this paper is the impact of immigrants on local labor markets. Metropolitan statistical area is a region with a high population density core and corresponding areas with close economic ties. The definition of metropolitan area uses the 1999 delineations, consistent throughout the census years. The regression analysis is based on the top 83 MSAs which had largest new immigration flows during 1980-2010. Changing the number of cities included in the analysis does not significantly change the main regression results.

In the analysis, the population is divided into natives and immigrants, where immigrants are defined as foreign born. Immigration population is again divided into two categories: recent immigrants who stayed in the United States less than 10 years and past immigrants who entered the United States more than 10 years ago. Also, the education level of workers are divided into three groups: "low educated" who are high school dropouts, "mid educated" who has high school degrees, and "high educated" who has at least some college experiences. I only include observations with age between 25 and 64.

The data for the push factors of 47 largest source countries that cause immigrants to migrate are obtained from the World Bank global development data. Population, per capita real GDP (in 2011 dollars), infant mortality rate (per 1,000 births), and school enrollment rate (enrollment ratio for secondary schools) annual data from 1970 to 2010 are utilized. I use past 10 year average as a measure for each decennial year in order to be consistent with the definition of recent immigrants (who entered the US in past 10 years). For example, per capita GDP in 1980 is the 10-year-average per capita GDP from 1970 to 1979. For political freedom, the data is obtained from Freedom House, non-governmental organization which annually measures the political rights and civil liberties of countries in the world. It is in 0-10 scale, where 0 means completely free and 10 means not free at all.

The descriptive statics of the data is shown in Table 1. It should be noted that the proportion of low educated (high school dropouts) is much higher for immigrants compared to the natives. Although the average education level is getting better across time

Year	1980	1990	2000	2010
		Panel A: Natives		
Population	67,246,700	77,590,625	91,417,755	96,430,385
High Education	0.39	0.56	0.54	0.59
Mid Education	0.38	0.33	0.38	0.35
Low Education	0.23	0.12	0.08	0.07
		Panel B: Recent Immigrants (0-10yr)		
Population	2,657,760	4,838,146	7,229,764	6,732,683
High Education	0.38	0.42	0.42	0.47
Mid Education	0.21	0.25	0.29	0.28
Low Education	0.41	0.33	0.29	0.26
		Panel C: Past Immigrants (10yr+)		
Population	5,134,460	8,111,435	14,217,213	20,951,058
High Education	0.32	0.44	0.41	0.45
Mid Education	0.29	0.26	0.30	0.30
Low Education	0.39	0.30	0.29	0.25

Notes: Statistics are presented for 83 MSAs during 1980-2010 with the largest average immigration flows. The sample includes natives, recent immigrants (foreign born who stayed in the United States less than 10 years) and past immigrants (foreign born who stayed in the United States more than 10 years) whose ages are between 25 and 64. The table shows the population and the percentage of being in certain education groups. The population number and the percentage are estimated using the survey weights from the census data. "Low Education," "Mid Education," and "High Education" refer to high school dropouts, high school graduates and college graduates, respectively.

Table 1: Summary Statistics for 83 Metropolitan Areas

for both natives and immigrants, immigrants still have large proportions of low educated workers, consisting one fifth of the population in 2010. The descriptive statistics for country level data are shown in Table 2. For all the push factors, there is considerable variation between countries and across time periods, which will be helpful in predicting immigration flow from the push factors.

3 Generating Instrumental Variable

I estimate the following mixed effects model:

$$log(RI^i_{c,t}) = \underbrace{\alpha + \alpha_c + \mathbf{P}_{c,t} \cdot \mathbf{B} + \gamma_t}_{FixedEffects} + \underbrace{\alpha^i + \mathbf{P}_{c,t} \cdot \mathbf{B}^i + \gamma^i_t}_{RandomEffects} + \epsilon^i_{c,t} \quad (1)$$

Year	1980	1990	2000	2010
Per Capita GDP	5,064.39 (8,549.82)	6,034.26 (10,190.42)	6,909.83 (11,911.36)	8,296.63 (13,314.36)
Infant Mortality Rate	71.75 (42.26)	53.76 (33.65)	42.92 (25.63)	29.72 (19.51)
Enrollment Rate	47.93 (22.81)	48.94 (23.39)	59.80 (22.68)	70.52 (18.70)
Political Freedom	4.36 (2.24)	4.00 (2.14)	4.36 (2.32)	3.96 (2.48)
Number of Countries	47	47	46	46

Notes: Statistics are presented for 47 countries during 1980-2010 with the largest average immigration flows to the United States. I use the past 10 year average as a measure for each decennial year). For example, per capita GDP in 1980 is the 10-year-average per capita GDP from 1970 to 1979. Per capita GDP is in 2011 dollars. Infant mortality rate is in per 1000 births. School enrollment rate shows the enrollment ratio for secondary schools. Political freedom is a scale from 0 to 10, where 0 means free and 10 means not free.

Table 2: Summary Statistics for 47 Origin Countries

where superscript i is for city; subscripts c and t are for country and census year, respectively. $RI^i_{c,t}$ is the number of recent immigrants in city i from country c who came to the United States between t and $t-10$. $\mathbf{P}_{c,t}$ is a vector of push factors, which cause immigrants to migrate from their country c. α_c is country fixed effects; γ_t is decennial year fixed effects. α^i is constant terms that are heterogeneous across cities.

Notice that γ^i_t is city-year specific shock that can be considered to be as parts of labor demand shocks which affect the number of all recent immigrants within a city in certain census year. In section 4, I show that this γ^i_t term is actually correlated with the demand shocks, so it will be omitted in the process of getting the fitted value. Estimating equation 1 without γ^i_t does not significantly change the predicted value since it will be absorbed in the error term, but controlling for γ^i_t will further reduce the concern on the predicted number of immigrants being correlated with local labor demand shocks.

As one can tell from its name, the mixed effects model consists of both fixed effects components and random effects components, where the group variable for the random effects is city i. The coefficients are same across the cities for the fixed effects components (with superscript i), whereas the coefficients are heterogeneous across the cities for the random effects components (with superscript i). That is, the city specific effects of the push factors are random, while all the other effects (country fixed effects, time fixed effects and aggregate effects of the push factors) are fixed.

The coefficients of the random effects $\mathbf{u} = (\alpha_i', \mathbf{B}^{i\prime}, \gamma_t^i)$ follow $\mathbf{u} \sim N(0, \mathbf{G})$, where $\mathbf{G}$ is the variance-covariance matrix of the random effects. Since the random effects coefficients are mean zero, they can be interpreted as deviations from the fixed effects. Note that $\mathbf{G}$ contains the information of variance of the random effects coefficients, as well as the covariance between the coefficients. For simplicity, I assume that the covariance between the coefficients is 0 throughout the paper, and this assumption is relaxed in section 6.2 as robustness checks. The above mixed effects models are estimated using the maximum likelihood estimation with EM algorithms under the assumption that $\epsilon_{c,t}^i \sim N(0, \sigma^2 I)$.

The key assumption of the above mixed effects model is that the effects of push factors of origin countries are in fact heterogeneous across the cities. For example, the effects of mortality rate on the number of recent immigrants are different for Chicago, New York and San Francisco. Also, these heterogeneous effects are only from the fixed city characteristics that are independent to the local labor demand shocks. For instance, the diverse effects of mortality may come from the different environment surrounding the cities, such as weather conditions. This assumption is reflected in the random effects components, $\mathbf{B}^i$, where there are separate coefficients of push factors for each city i.

After estimating equation 1, I obtain the predicted number of total recent immigrants from country c to city i, using the fitted value with γ_t^i excluded. Again, I exclude γ_t^i when getting the fitted value since it is likely to be correlated with local labor demand shocks. Also, I add $\frac{1}{2}\hat{\sigma}^2 I$ since RI follows the log-normal distribution under the assumption of homoskedasticity of errors, $\epsilon_{c,t}^i \sim N(0, \sigma^2 I)$. In Theory Appendix 1, I show that heteroskedasticity of errors where $\epsilon \sim N(0, \sigma^2 R)$ does not significantly alter the instrumental variable nor the main analysis.

$$\hat{RI}^i_{c,t} = exp(\underbrace{\hat{\alpha} + \hat{\alpha}_c + \mathbf{P}_{c,t} \cdot \hat{\mathbf{B}} + \hat{\gamma}_t}_{FixedEffects} + \underbrace{\hat{\alpha}^i + \mathbf{P}_{c,t} \cdot \hat{\mathbf{B}}^{\mathbf{i}} + \frac{1}{2}\hat{\sigma}^2 I}_{RandomEffects}) \tag{2}$$

Best linear unbiased predictors of random effects, $\hat{\mathbf{u}} = (\hat{\alpha}^{\prime}_i, \hat{\mathbf{B}}^{i\prime}, \hat{\gamma}^i_t)$ are chosen to minimize the variance of the prediction error under the condition that the predictors are unbiased. That is, $E(\hat{\mathbf{u}} - \mathbf{u}) = 0$, and $Var(\mathbf{v} - \mathbf{u}) - Var(\hat{\mathbf{u}} - \mathbf{u})$ is positive semi-definite for any other unbiased predictor $\mathbf{v}$. Notice that best linear unbiased predictors (BLUPs) are similar to best linear unbiased estimators (BLUEs) except that the variance component $\mathbf{G}$ is taken account when getting the BLUPs. More formally, the best linear unbiased predictors of random effects $\mathbf{u}$ are obtained as

$$\hat{\mathbf{u}} = \hat{\mathbf{G}}\mathbf{Z}\hat{\mathbf{V}}^{-1}(\mathbf{y} - \mathbf{X}\hat{\beta})$$

where $\mathbf{X}$ is the fixed effects parameters; $\mathbf{Z}$ is the random effects parameters; $\mathbf{y}$ is the dependent variable, $log(RI^i_{c,t})$; $\hat{\beta}$ is the best linear unbiased estimator of β; $\hat{\mathbf{G}}$ is the estimated variance component $\mathbf{G}$; $\mathbf{V} = \mathbf{Z}\mathbf{G}\mathbf{Z}^{'} + \mathbf{R}$. For more details about the BLUP and its derivation, refer to Theory Appendix 2.

Then, the predicted number of total recent immigrants in city i is calculated by summing up all the immigrants from different countries c in city i

$$\hat{RI}^i_t = \sum_c \hat{RI}^i_{c,t} \tag{3}$$

Finally, I use the predicted number of total immigrants $log(\hat{RI}_{i,t})$ as an instrument for the actual number of recent immigrants $log(RI^i_t)$.

The estimation results for equation 1 are presented in Table 3. Panel A shows the

Dependent Variable: Number of Recent Immigrants	(1)	(2)	(3)	(4)
Panel A: Fixed Effect Parameter				
Log(Per Capita GDP)	1.179***	1.433***	1.481***	1.618***
	(0.147)	(0.161)	(0.159)	(0.171)
Log(Per Capita GDP)2	-0.065***	-0.081***	-0.085***	-0.095***
	(0.009)	(0.010)	(0.010)	(0.011)
Log(Mortality)	0.246***	0.376***	0.390***	0.410***
	(0.052)	(0.061)	(0.061)	(0.060)
Log(Education)		0.149**	0.173***	0.222***
		(0.064)	(0.064)	(0.065)
Political Freedom			-0.054***	-0.051***
			(0.013)	(0.013)
Log(Population)				-0.210**
				(0.095)
Panel B: Random Effect Parameter				
SD[Constant]	1.066	0.916	0.904	0.000
	(0.110)	(0.122)	(0.126)	(0.000)
SD[Log(Per Capita GDP)]	0.000***	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
SD[Log(Per Capita GDP)2]	0.004***	0.004***	0.004***	0.004
	(0.001)	(0.001)	(0.001)	(0.000)
SD[Log(Mortality)]	0.133***	0.134***	0.136***	0.143
	(0.019)	(0.018)	(0.019)	(0.000)
SD[Log(Education)]		0.129***	0.132***	0.143
		(0.035)	(0.034)	(0.000)
SD[Political Freedom]			0.044***	0.045
			(0.008)	(0.000)
SD[Log(Population)]				0.067
				(0.000)
SD[City-Year Schocks]	0.130***	0.128***	0.134***	0.135
	(0.018)	(0.019)	(0.019)	(0.000)
Country Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82
	First Stage			
F Statistics	21.7	19.1	19.2	17.6

Notes: The table summarizes the estimation results on the mixed effects model in equation 1. The group variable is MSA (i). Country fixed effects and year fixed effects are included. The dependent variable is the number of recent immigrants in each city. The key explanatory variables are the push factors of the source countries. Panel A shows the estimated fixed effects coefficients, where the coefficients are same across all the cities. Robust standard errors are clustered by MSA and reported in parantheses. Panel B shows the estimated variance components of the random effects parmeters, which are the elements of variance-covariance matrix **G**. That is, it reports the standard deviations of the random effects coefficients, and I assume that the off-diagnoal elements of **G** are zero. The estimated standard errors of the variance components are reported in parantheses. The instruments are generated from the push factors in column 1-4, utilizing the method that is discussed in Section 3. The first stage F-statistics are obtained regressing the actual number of immigrants on these instruments with city fixed effects and year fixed effects. Refer to Figure 1 for the graphical representation of the first stage relationship.

Table 3: Relationship between Push Factors and the Number of Immigrants

results on the fixed effects parameters, which can be interpreted as standard least squares parameters. The coefficients of per capita GDP is positive whereas the coefficients of the squared per capita GDP is negative, which shows that there is inverse U-shaped relationship between per capita GDP and the number of immigrants. That is, for potential migrants in low income origin countries, they have poverty constraint which hinder them from immigrating to the United States. However, once per capita GDP reaches the certain threshold, which is calculated to be around $9,000 from the coefficients, the number of immigrants decreases as income increases. This is consistent with the standard neoclassical view of immigrants, where utility maximizing immigrants will migrate to regions with higher wages. (Bauer and Zimmermann, 1998)

I also find that there is positive effect of infant mortality rate on immigration. A 10% increase in mortality rate in the origin countries causes a 3% increase in the number of recent immigrants to the United States. This exhibits that malignant health conditions in the origin countries will induce individuals to migrate to places with better health conditions. Moreover, a 10% increase in enrollment rate of secondary schools leads to a 2% increase in the number of recent immigrants. This is also concordant to the human capital approach to immigration, which treats migration as an investment decision (Sjaastad, 1962). That is, individuals migrate from their country of origin if expected discounted returns are larger in the destination countries. Therefore, higher education level in origin countries will increase the probability of migration since highly educated individuals can expect more returns from migration with higher ability to process information.

Furthermore, it is exhibited that countries with more political freedom have a tendency to send more migrants. This may have come from the fact that politically oppressive regimes tend to limit the freedom of residence, which reduces the number of migrants going out of their countries. The effect of population of the source countries on the number of immigrants, contrary to the usual belief, seems to be negative. However, the significance of the coefficient is lower than the other coefficients, with larger standard errors.

Panel B of Table 3 shows the results on the random effects parameters, which display the standard deviations of random effect coefficients. Notice that the individual coefficients of random effects parameters are not directly estimated; instead the variance components of the random effects coefficients, **G**, are displayed in Table 3. The best linear unbiased predictors for the individual random effects coefficients are obtained using this variance-covariance matrix. It is exhibited that the standard deviation of GDP coefficients are low, while the standard deviation of mortality and education coefficients are relatively higher.

Best linear unbiased predictors of random effects parameters for major cities are presented in Table 4 as an illustrative purpose. The top six cities are major immigration gateways with high immigrant population, while the bottom three cities are known for the low proportions of immigrants. Recall that the random effects coefficients can be interpreted as deviations from the fixed effects parameters, shown in the bottom part of the table. Thus, the total effects of certain push factor on the number of recent immigrants can be calculated by adding the fixed effects coefficient to the city-specific random effects coefficients. Table 4 shows that cities with higher immigrants population have larger constants, which shows that these cities are immigration welcoming cities. In addition, cities like Los Angeles, San Francisco and San Diego are more sensitive to mortality rate in the origin countries compared to cities like New York and St. Louis. Figure 2 in Appendix illustrates that the best linear unbiased predictors from the mixed effect estimation are not just a mere statistical artifact; the BLUPs of education have a strong relationship with the education scores of metro areas in 2016 that is published by Economic Policy Institute.

It is possible to argue that the differentiated random effects coefficients are not actually representing how these cities are heterogeneously responding to the same push

Random Effects Coefficients (β^i)	β^i_{Cons}	β^i_{GDP}	β^i_{GDP2}	β^i_{Mort}	β^i_{Edu}
LosAngeles	2.118	0.000	0.000	0.194	0.097
NewYork	1.953	0.000	0.006	-0.058	0.257
SanFrancisco	1.377	0.000	-0.000	0.128	0.098
Chicago	1.349	0.000	0.004	0.077	0.098
SanDiego	0.892	0.000	0.004	0.091	-0.026
StLouis	0.311	-0.000	-0.001	-0.027	-0.000
Pttsburgh	-0.232	0.000	0.003	-0.012	-0.018
Indianapolis	-0.376	-0.000	-0.000	-0.122	0.041
Fixed Effects Coefficients (β)	-4.62	1.44	-0.08	0.38	0.17

Notes: The table shows the random effects and the fixed effects coefficients of major cities in the United States, estimated from the mixed effects model in equation 1. Los Angeles, New York, San Francisc and Chicago are large cities with high shares of immigrants. St. Louis, Pittsburgh and Indianapolis are large cities with lower shares of immigrants. Row 1-8 show the random effects coefficients that are heterogeneous across the cities. The bottom row shows the fixed effects coefficients that are same across all the cities. The total effects of certain push factors can be calculated by adding the random effects coefficients and the fixed effects coefficietns. For example, the effect of mortality rate on the number of recent immigrants in Los Angeles is 0.38 (fixed effect coefficient) + 0.194 (random effect coefficient) = 0.574 (total effect)

Table 4: Best Linear Unbiased Predictors for Random Effects Parameters

factors; in fact, it may be just a mere representation of the composition of immigrants' nationality within a city. For example, the reason that the coefficient of mortality rate is larger in Los Angeles is that there happens to be many immigrants who are from countries with high mortality rate. To address this issue, I try to additionally include country effects in the random effects parameters. That is, I include α^i_c in the random effects parameters, so the random effects components of estimating equation become $\alpha^i + \alpha^i_c + \mathbf{P}_{c,t} \cdot \mathbf{B}^i + \gamma^i_t$ instead of $\alpha^i + \mathbf{P}_{c,t} \cdot \mathbf{B}^i + \gamma^i_t$. Although I do not report the results, it is estimated that the volatility of the random effects coefficients $\mathbf{B}^i$ do not disappear even after controlling for the country effects. This may suggest that the effects of push factors on immigration are actually different across the cities.

I use the column 1 specification from Table 3, including per capita GDP and mortality rate as the relevant push factors, to generate a preferred instrumental variable. Notice that the column 1 specification gives the most F-statistics among four different specifications, exceeding the conventional rule of thumb F-statistics of 10. The column 3 specification is going to be also utilized to generate an additional instrument,

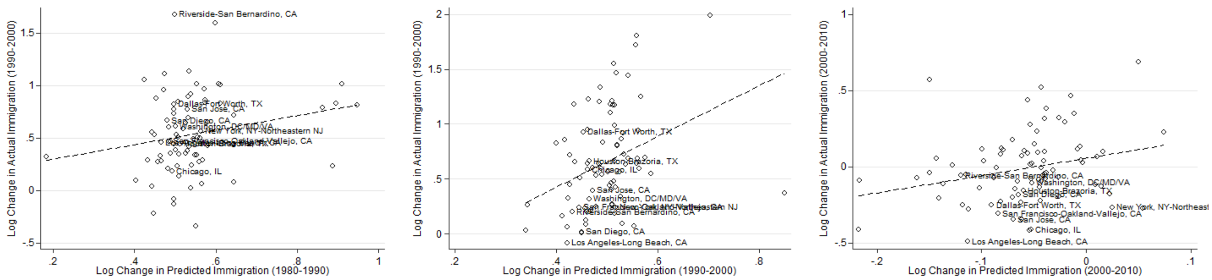

Figure 1: First Stage Relationship between the Actual Immigration and Predicted Immigration

which will be used to test over-identifying restrictions in the following section. Figure 1 shows the first-stage relationship for every decade between the predicted number of immigrants generated from the column 1 specification and the actual number of immigrants. For all decades, there is a strong relationship between the actual immigration and the predicted immigration.

4 Comparison with Other Instruments

4.1 Previous Instruments

In this section, I briefly discuss the construction of the popular instrument using immigration enclaves, pioneered by Bartel (1989) and developed by Card (2001). I also introduce the instrumental variable formed by Boustan (2010). Their analysis are based on different data sets and time frame, so here the formulation is slightly modified in the context of this paper without changing the main idea of their instruments.

Card (2001) finds out that new immigrants have tendency to be concentrated in certain cities, which are often called ethnic enclaves. Also, new immigrants are inclined to settle in cities with enclaves established by earlier immigrants. Therefore, it is possible to use the previous settlement patterns of past immigrants to predict the number of immigrants from the exogenous supply factor in each city. More specifically, the actual inflow of immigrants are allocated according to the fraction of earlier immigrants from the source countries who live in each city. Formally, we can get the supply-push component of recent immigration inflows in city i, SP^i, in the following way:

$$SP^i = \sum_c \tau^i_{c,t-10} RI_{c,t} \tag{4}$$

where $RI_{c,t}$ is the actual number of recent immigrants from country c during census year t and $t-10$; $\tau^i_{c,t-10}$ is the fraction of total US immigrants from country c who are living in city i in year $t-10$.

Moreover, Boustan (2010) introduces a similar approach, but she allocates the *predicted* inflow of immigrants estimated from a set of local push factors. The total number of predicted inflow of migrants are obtained using the fitted value of following regression:

$$log(RI_{c,t}) = \alpha + \alpha_c + \gamma_t + \mathbf{P}_{c,t} \cdot \mathbf{B} + \epsilon_{c,t} \tag{5}$$

where $RI_{c,t}$ is the total number of US recent immigrants from country c during census year t and $t-10$; α_c is the country flexed effects; γ_t is the year fixed effects and $\mathbf{P}^i{}_{c,t}$ is the push factors of country c. Then, the predicted number of total immigrants from country c is $R\hat{I}_{c,t} = exp(\alpha + \mathbf{P}_{c,t} \cdot \hat{\mathbf{B}})$, using the fitted value of the regression equation. It is noteworthy that estimating equation 5 is similar to estimating equation 1 without including the random effects components which are heterogeneous across cities.

Then, the next natural question is how to allocate this total number of immigrants to each city. Boustan follows the same approach as Card, where the allocation is determined by the fraction of earlier immigrants from the source countries who live in each city. Formerly,

$$SP^i = \sum_c \tau^i_{c,t-10} \hat{R}I_{c,t} \tag{6}$$

The main difference between the instruments by Card, Boustan and this paper can be summarized in the following way. Card allocates the *actual* inflow of immigrants according to the previous settlement patterns of immigrants. On the other hand, Boustan allocates the *predicted* inflow of immigrants according to the previous settlement pattern. Finally, this paper allocates the *predicted* inflow of immigrants *without* using the previous settlement patterns of the immigrants.

Therefore, the previous instrumental variables by Card and Boustan rely on the assumption that the previous settlement patterns of immigrants are not correlated with current local labor demand shocks. Nevertheless, it is possible that labor demand shocks are serially correlated. Also, it is entirely possible that current settlement patterns of immigrants are also correlated with local labor demand shocks. For example, one of the main reasons that Indians are concentrated in the Bay area in the first place is that it experienced positive local labor demand shocks for tech labor. If that is the case, there is a possibility that the predicted inflow of immigrants generated by Card and Boustan are also correlated with the local labor demand shocks, threatening the validity of the instruments. On the contrary, the predicted immigration flow constructed from this paper does not use the previous settlement patterns, so it is expected that the instrument is somewhat less correlated with the local labor demand shocks compared to the previous instruments.

4.2 Relationship between Bartik Measure and Instruments

In order to check the above prediction that the instrument from this paper suffers less endogeneity problem, I analyze whether the predicted immigration flow is independent to local labor demand shocks. This can be done by looking at the relationship between the instruments and Bartik measure (Notowidigdo, 2010) which is widely used to identify the demand shocks that are independent to local supply shocks. Consider the following regression:

$$Instruments_{i,t} = \alpha_i + \beta \cdot Bartik_{i,t} + \gamma_t + \epsilon_{i,t} \tag{7}$$

where $Instruments_{i,t}$ are the log of predicted number of immigrants (three instruments) from the supply shocks; $Bartik_{i,t}$ is the number of employment predicted from exogenous demand shocks independent to local labor supply shocks. More specifically, $Bartik_{i,t} = n_{i,1970} \cdot (1 + BartikGrowthRate_{i,t})^t$, where $n_{i,1970}$ is the total number of people employed in city i and year 1970, and $BartikGrowthRate_{it}$ is defined as

$$BartikGrowthRate_{i,t} = \sum_{j=1}^{J} s_{i,j,t-10}(n_{-i,j,t} - n_{-i,j,t-10}). \tag{8}$$

where $s_{i,j,t}$ is the share of population employed in industry j (3-digit) in city i in year t; $n_{-i,j,t}$ is the log of national employment of industry j excluding city i, so $(n_{-i,j,t} - n_{-i,j,t-10})$ term represents the national 10-year growth rate of employment for industry j in census year t. In words, Bartik growth rate is the weighted average of national growth rate of each industry, where the weights are determined by the lagged shares of industries in a given city.

The key identifying assumption of Bartik measure is that national changes in industry shares are closely related to local labor demand, but unrelated to any changes in local labor supply. Therefore, β should be 0 in the estimating equation, if the instruments, which are generated from exogenous supply variation of immigrants, are independent to local labor demand shocks.

The relationship between the instruments and Bartik measure is summarized in Table 5. I construct the Bartik measure separately by using all industries, industries with average educational attainment is low (high school graduates), and industries with average educational attainment is high (some college or more). The coefficient of Bartik measure in column 1 shows that the correlation between the instrumental variable from this paper and Bartik measure is nearly zero, which indicates that the IV is not related to labor demand shocks. In column 2, I include city-year shocks (γ_t^i) terms when generating the instrument from the fitted value. Recall that γ_t^i is likely to be the components of local labor demand shocks since it is the shocks that affect every immigrant in city i and year t. Consistent with the above prediction, the instrument with city-year specific shocks are positively related with Bartik growth. A 10% increase in the predicted number of workers from the low skilled Bartik schoks leads to a 5% increase in the predicted number of immigrants.

On the contrary, column 3-5 exhibit that the previous instruments are actually highly correlated with Bartik. Column 4 shows that for a 1% increase in predicted number employment from demand shocks for the low skilled, we have a 1.7% increase in the predicted number of immigrants. It is often argued that having more lags for the previous settlement patterns will make the instrument less subject to endogeneity problem, but that is not the case according to column 5. I use 20 years of lag instead of 10 years to get the predicted number of immigrants, but it seems that the instrument is still strongly correlated with demand shocks. The instrument variable by Boustan appears to show similar patterns with Card Instrument, where the coefficient of Bartik measure is large and statistically significant.

In sum, there seems to be a firm relationship between the former instruments and demand shocks, which may have resulted from the fact that previous settlement patterns of immigrants are not independent to labor demand shocks. On the other hand, the instrument from this paper is less correlated with labor demand shocks, which gives justification for the exogeneity assumption.

Depndent Variables	IV	IV with γ_t^i	Card IV	Card IV with 20yr lags	Boustan IV
Bartik (All)	0.034	0.435	1.261	2.316	1.390
	(0.350)	(0.480)	(1.831)	(1.614)	(1.665)
Bartik (Low Skill)	0.189	0.486**	1.743*	1.758**	1.959**
	(0.151)	(0.211)	(0.884)	(0.851)	(0.755)
Bartik (High Skill)	-0.133	0.014	-1.269	-1.466	-1.125
	(0.398)	(0.520)	(1.276)	(1.568)	(1.213)

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the Bartik meausre from equation 8. I construct the Bartik measure separately by using all industries (row 1), industries with average educational attainment is low (row 2; high school graduates), and industries with average educational attainment is high (row 3; some college or more). The dependent variables in column 1-2 are the preferred instrument from this paper and the instrument with city-year shocks. Refer to section 3 for a detailed description of the instrument's construction. The depednent variables in column 3-5 are the previous instruments that are explained in section 4.

Table 5: Relationship Between Bartik Measure and Instruments

4.3 Falsification Test

Another way to indirectly test the exogeneity assumption of the instrumental variables is a falsification test. That is, it is possible to ask whether trends in labor market outcomes in current periods are correlated with trends in the instruments in the past periods (Peri, 2015). If the instruments are truly exogenous (for Card and Boustan instruments, lagged origin shares being random), there should be less correlation between the instruments and the outcomes. For instance, it is unlikely that the mean wage income or housing values of natives in a certain period is unlikely to be correlated with the predicted number of recent immigrants in past periods, which are constructed from the push factors independent to local labor demand conditions.

The results on falsification tests are shown in Table 6. Each cells represent separate regression, where I regress the 10-year-lagged instruments on wage income and housing prices of natives, stratified by education levels. Again, the instruments are the instrument from this paper (column 1), Card Instrument (column 2), and Boustan Instrument (column 3). In column 1, the regression results indicate that the lagged value of instrument from this paper is not strongly correlated with the current labor and housing market conditions. In contrast, the lagged values of Card IV and Boustan

Dependent Variables	IV_{t-10}	Card IV_{t-10}	Boustan IV_{t-10}
Low Edu Natives Wage Income	0.118	1.444***	1.542***
	(0.083)	(0.437)	(0.345)
Mid Edu Natives Wage Income	0.095	2.207***	2.228***
	(0.143)	(0.660)	(0.555)
High Edu Natives Wage Income	0.257	2.354***	2.376***
	(0.172)	(0.699)	(0.546)
Low Edu Natives Housing Prices	0.064	0.661***	0.719***
	(0.041)	(0.132)	(0.109)
Mid Edu Natives Housing Prices	-0.002	0.523***	0.590***
	(0.040)	(0.147)	(0.124)
High Edu Natives Housing Prices	0.045	0.649***	0.700***
	(0.051)	(0.155)	(0.138)
City Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. Each cells represent separate regressions, where the depedndent variables are the lagged value of the instrument variable from this paper (column 1), Card IV (column 2) and Boustan IV (column 3), respectively. In row 1-3, the independent variables are wage income of natives with low edcuation, mid education and high education, respectively. In row 4-6, the the independent variables are housing prices of natives with low edcuation, mid education and high education, respectively. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. For all specifications, I include fixed effects and year fixed effects.

Table 6: Falsification Tests

IV exhibit a significant relationship with current outcome variables of natives. The striking dissimilar results between the instruments again come from the fact the previous instruments exploit trends in the settlement patterns of immigrants, whereas the instrument from this paper is more independent to such regional patterns.

4.4 Over-identification Test

Since there are more instrumental variables than the endogenous variable, it is possible to run an over-identification test to check the validity of the instruments. The null hypothesis is that the instruments satisfy the exclusion restriction, where they are uncorrelated with the error terms. The plausibility of various instruments mentioned in the paper is checked in the following way. First, it is tested whether the preferred instrument and the alternative instrument from this paper satisfy the over-identifying restrictions. If I reject the null, then this means at least one of the instruments from the paper is invalid. Also, it is checked if the preferred instrumental variable from this paper and the previous instruments, Card IV and Boustan IV, are valid. If I reject the null, again this shows that at least one of the instruments, though it is not possible to identify what the problematic instruments are, is correlated with the error terms.

Notice that the assumption of the main estimating equation is the presence of clustered and heteroscedastic error terms, so Hansen's J statistics is utilized for the over-identification test. For all the specifications, our preferred instrumental variable from this paper is included in the baseline, and additional instruments are included in the order of the alternative instrument from this paper, Card instrument, and Boustan instrument. The over-identification test results using equation 9 are shown in Table 6.

In Panel A, I use the total number of employed natives as a dependent variable. The over-identification test results show that I cannot reject the null hypothesis of the instruments being valid when I only include the instruments from this paper since the Hansen J statistics are small (high p value). Card and Boustan instruments also pass the over-id test when the dependent variable is the number of low educated natives. Nevertheless, the null hypothesis of validity of these previous instruments is rejected when the dependent variable is the number of highly educated natives. The difference between the over-id results may have come from the fact that highly educated natives have much higher mobility than the low educated. That is, local shocks that affect immigration flows are more correlated with labor market outcomes of high skilled natives, compared to low skilled natives. Failing the over-id tests depicts that at least one of the excluding instruments are correlated with the error terms, which may undermine the exogeneity assumption of the previous instruments.

In Panel C, the total number of employed past immigrants is used as a dependent variable for the over-identification test. Overall, Card and Boustan instruments have larger Hansen J statistics than the instrumental variable used in this paper. In particular, when it comes to low skilled past immigrants, the problem of previous instru-

	Dependent Variables: Number of Employed					
Additional IV	IV3		Card		Boustan	
Edu Level	Low	High	Low	High	Low	High
Panel A: Natives (No Bartik Control)						
Log(Number of Recent Immigrants)	0.327***	0.466***	0.293***	0.331***	0.276***	0.340***
	(0.079)	(0.053)	(0.058)	(0.055)	(0.059)	(0.045)
Overidentification Test						
Hansen J Stats	0.024	0.300	0.003	8.821	0.040	7.474
p value	0.877	0.584	0.955	0.003	0.842	0.006
Panel B: Natives (Bartik Control)						
Log(Number of Recent Immigrants)	0.268***	0.456***	0.270***	0.320***	0.254***	0.335***
	(0.093)	(0.067)	(0.058)	(0.059)	(0.057)	(0.048)
Overidentification Test						
Hansen J Stats	0.463	0.024	0.077	8.560	0.006	6.583
p value	0.496	0.876	0.782	0.003	0.937	0.010
Panel C: Past Immigrants (No Bartik Control)						
Log(Number of Recent Immigrants)	0.696***	0.658***	1.207***	0.783***	1.258***	0.812***
	(0.200)	(0.128)	(0.156)	(0.125)	(0.157)	(0.116)
Overidentification Test						
Hansen J Stats	3.277	0.323	12.022	2.358	15.756	3.570
p value	0.070	0.570	0.001	0.125	0.000	0.059
Panel D: Past Immigrants (Bartik Control)						
Log(Number of Recent Immigrants)	0.657***	0.693***	1.235***	0.796***	1.293***	0.833***
	(0.234)	(0.166)	(0.168)	(0.129)	(0.168)	(0.115)
Overidentification Test						
Hansen J Stats	5.060	1.501	10.619	1.599	13.756	2.571
p value	0.024	0.221	0.001	0.206	0.000	0.109
Panel D: Past Immigrants (Bartik Control)						

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. The depedent variable is the number of employed natives (Panel A and C) or past immigrants (Panel B and D), stratified by education levels. I additionally control for the Bartik measure in Panel C and Panel D. Refer to section 4.2 for the detailed information on how to construct the Bartik measure. ”Low Edu,” and ”High Edu” refer to high school dropouts/high school graduates and college graduates, respectively. Column 1-2, column 3-4 and column 5-6 report 2SLS estimates of β and overidentification results for equation 9, where the two instruments are the preferred instrument from this paper and another additional instrument. The additional instruments are the instrument from column 1 specififcation of Table 3, Card IV and Boustan IV, respectively. In the bottom row, it reports Hansen J statistics and the corresponding p value for the overidentification test. The null hypothesis for the over-identification test is that the instruments satisfy the exclusion restriction, where they are uncorrelated with the error terms.

Table 7: Over-identification Test

ments failing the over-id test is more severe; adding Card or Boustan instrument leads to Hansen J statistics greater than 10 ($p < 0.001$). It is noteworthy that the previous instruments use lagged ethnic settlement patterns, which are expected to be highly correlated with labor market outcomes of past immigrants. Thus, the previous instruments violating the exclusion restriction becomes more problematic when analyzing the impact of recent immigrants on outcomes of past immigrants.

In sum, the previous instruments seem to perform well when we focus on low educated natives, but it is likely that they violate the exclusion restriction when analyzing the impact on highly educated natives or past immigrants. One of the possible solution suggested by Basso and Peri (2015) is adding Bartik shocks as controls, which is expected to capture local labor demand shocks components. Hence, I additionally control for *Bartik* in panel B (the total number of employed natives as a dependent variable) and panel D (the total number of employed past immigrants as a dependent variable). Overall, this has an impact of reducing the Hansen J Statistics (or increasing p value) of the previous instruments, but they still fail to reject the over-identification tests. This is consistent with Basso and Peri (2015), where it is shown that adding Bartik as control does not significantly change the coefficients. The possible causes are two-fold. First, the Bartik shocks do not capture all of local labor demand shocks, where some components of labor demand shocks still remaining in the error term. Second, even if the Bartik fully captures local labor demand shocks, settlement patterns of earlier immigrants and recent immigrants are highly correlated, causing the exogenous restriction to be violated.

Dependent Variables	OLS			IV		
:Employment	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
			Panel A: Natives			
Log(Number of Recent Imm)	0.265***	0.267***	0.273***	0.306***	0.398***	0.474***
	(0.045)	(0.038)	(0.033)	(0.113)	(0.083)	(0.059)
			Panel B: Past Immigrants			
Log(Number of Recent Imm)	1.073***	0.583***	0.438***	0.636**	0.520***	0.643***
	(0.103)	(0.070)	(0.061)	(0.269)	(0.198)	(0.134)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report OLS estimates of β in equation 9. Column 4-6 report 2SLS estimates of β in equation 9, where the instrumental variable is the the predicted number of immigrants. Section 3 contains a detailed description of the instrument's construction.

Table 8: Immigration and Change in Employment

5 The Impact of Recent Immigrants on Local Labor Markets

5.1 General Effects of Recent Immigrants

Using the instrumental variable generated from Section 3, I estimate the following model to find out the impact of recent immigrants on local labor market:

$$y_t^i = \alpha^i + \gamma_t + \beta \cdot log(RI_t^i) + \epsilon_{it} \tag{9}$$

where y_t^i are the labor market outcome variables which are total number and wage income of natives and past immigrant workers, respectively; α^i is city fixed effects and γ^t is the time fixed effects. Since the city fixed effects are included, within variation of city over time is identified in β. The main explanatory variable $log(RI_t^i)$ is instrumented using the predicted number of immigrants $log(\hat{RI_t^i})$ obtained from the push factors of the source countries.

The main estimation results on employment are summarized in Table 8. Panel A depicts the impact of immigration on the total number of employed natives, which are categorized into low educated, mid educated and highly educated groups. The OLS regression results in column 1-3 show that there is a positive correlation between the number of recent immigrants and the number of natives. Column 4-6 show the 2SLS estimation results using the predicted number of immigrants as an instrumental variable. From the IV results, I find that the effects of immigration on natives employment are in fact positive; a 10% increase in the number of recent immigrants is associated with a 4% increase in the number of employed natives on average.

Panel B shows the impact of recent immigrants on employment of past immigrants who entered the United States more than 10 years ago. For the OLS estimation results, there is even stronger positive relationship between the number of recent immigrants and the number of past immigrants compared to that of natives. Nevertheless, it should be noted that the coefficients are likely to be biased. As mentioned before, immigrants tend to cluster in certain regions, so it seems natural to have high correlation between the number of recent immigrants and past immigrants. Not only that, immigrants are usually more sensitive to positive labor demand shocks than natives, which may also have resulted in the larger OLS coefficients for the past immigrants.

In the 2SLS estimation results that are shown in column 4-6 of Panel B, the large positive relationship between recent and past immigrants are greatly attenuated. This is resulted from the fact that the instrument corrects the endogeneity bias of the OLS estimates. Still, there exist positive effects of the number of recent immigrants on employment of past immigrants; a 10% increase in the number of recent immigrants leads to a 6% increase in employment of past immigrants on average. In addition, the positive effects are fairly similar across past immigrants with different educational attainments.

Table 9 summarizes the effect of immigration on wage income, where the dependent variables are mean wage income of natives and past immigrants for Panel A and

Dependent Variables	OLS			IV		
:WageIncome	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
			Panel A: Natives			
Log(Number of Recent Imm)	0.074***	0.034***	0.029***	0.136***	0.061**	0.056**
	(0.016)	(0.012)	(0.011)	(0.036)	(0.028)	(0.025)
			Panel B: Past Immigrants			
Log(Number of Recent Imm)	0.086*	0.086***	0.011	0.050	0.117	0.091*
	(0.050)	(0.029)	(0.020)	(0.105)	(0.072)	(0.055)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the mean wage income of natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the mean wage income of past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. ”Low Edu,” ”Mid Edu,” and ”High Edu” refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report OLS estimates of β in equation 9. Column 4-6 report 2SLS estimates of β in equation 9, where the instrumental variable is the the predicted number of immigrants. Section 3 contains a detailed description of the instrument's construction.

Table 9: Immigration and Change in Wage Income

B, respectively. The IV results from column 4-6 find a positive relationship between immigration and wage income. It is shown that a 10% increase in the number of recent immigrants is associated with an average 1% increase in wage income of natives and past immigrants. Though the results are not reported here, the effects of immigration on total working hours are estimated to be small, so the above results on wage income can be directly interpreted as positive impact on hourly wages.

It is important to analyze mobility response of natives and past immigrants when estimating the impact of immigration on local labor markets. If natives and past immigrants move out in response to inflows of recent immigrants, then the wage effect of immigration on local labor markets cannot be correctly estimated. That is, it is possible that wages of natives and past immigrants increase because of this mobility response, not by the positive labor market effects of immigration. However, column 4-6 of Table 8 shows that the number of highly educated increases from influx of recent immigrants, which indicates that there is either positive effects on employment rates or net inflows of natives and past immigrants (refer to Table A2 for the effect on employment rate).

This gives suggestive evidence that outflows of natives and past immigrants are not significant; rather, it seems that recent immigrants are "crowding in" both natives and foreign born workers since $\beta > 0$. Moreover, the effect of immigrants on internal migration presented in Table A1 shows that outflow rates of natives and past immigrants are not significantly affected by influx of recent immigrants. Rather, immigration increases inflow rate of natives and past immigrants, as seen in column 4-6, which is predicted from the employment results in Table 8.

The above regression results on employment and wages can be summarized into the statement that recent immigration and labor market outcomes are generally positively related for both natives and past immigrants. Note that this is not simply a correlation relationship generated from local labor demand shocks; it is supposed to be a casual relationship between immigration and labor market outcomes that is induced by the supply shocks from the push factors. This may seem to contradict the standard economic theory that the supply shocks in labor market should be associated with lower employment and lower wages for existing natives and past immigrants. This somewhat puzzling phenomenon can be explained by the possibility that immigrants can cause "labor demand shocks" which can create jobs and increase wages.

5.2 Heterogeneous Effects of Recent Immigrants

The above analysis focuses on the general impact of immigrant influx on local labor market outcomes, where I use the total number of recent immigrants as a key explanatory variable. Yet, several previous studies suggest that the effects are heterogeneous across different skill groups of immigrants. Thus, I further stratify immigrants according to their educational attainment: low skill group (high school dropouts and high school graduates) and high skilled group (some college or more). Then, I construct separate push factor instruments for low and high skilled groups, as documented in

Section 3. This is based on the additional assumption that low and high skilled groups respond differently to the push factors of the source countries, which leads to heterogeneous city slopes. For example, it is possible that low-skilled immigrants care more about mortality than high-skilled immigrants when making decision about choosing the best city to live, leading to different fixed and random effects coefficients from equation 9.

I estimate equation 9 separately for low skilled and high skilled immigrants using the separate instruments for each, where the results are exhibited in Table 10. Again, the outcome variables are employment of natives and past immigrants, stratified by three education levels (low education, mid education and high education). Column 1-3 show the OLS results, while column 4-6 display the IV results. Overall, there exists positive correlation between high/low skilled immigrants and employment of natives and past immigrants. Nonetheless, high skilled immigrants have stronger employment effect compared to the low-skilled; the IV estimates in column 4-6 display a 10 % increase in low skilled recent immigrants leads to a 2-3% increase in the total number of employed natives and past immigrants, while a 10 % increase in high skilled immigrants generate a larger 5-6% increase in employment.

Notice that if one only focuses on the OLS results, the large estimated coefficients misleadingly suggest that the past immigrants, especially the low educated, are (positively) affected the most by influx of recent immigrants. Nevertheless, the coefficients get reduced significantly in the IV estimation, compared to those of the OLS estimates. From column 1 and column 4, for example, the coefficient of the low skilled recent immigrants and high skilled recent immigrants are 0.8 and 1.0, respectively, whereas the IV estimates are 0.3 and 0.6, respectively. After accounting for the endogeneity, the IV estimates indicate that the positive employment effects are not significantly different across natives and past immigrants. Also, the positive effects are fairly evenly distributed across workers with different levels of educational attainment.

The heterogeneous effects of recent immigrants on wage income of natives and past immigrants are presented in Table 11. The IV estimation results in column 4-6 indicate that there is no evidence of negative immigration impact on wage income, which is analogous to the positive employment effect stated in Table 10. In addition, the larger IV estimates show that high skilled recent immigrants induce stronger wage impact on natives and past immigrants, compared to the low skilled. In particular, it is noteworthy that the effect of the low skilled immigrants on past immigrants are not statistically different from 0, while a 10% increase in the number of high skilled recent immigrants lead to a 1-2% increase in wage income of past immigrants.

To summarize the heterogeneous effects of recent immigrants, the causal effects of recent immigrants on employment and wage income of natives/past immigrants are in fact positive. However, their positive effects are not homogeneous; the high-skilled immigrants bring larger demand for labor in local labor markets compared to their low-skilled counterparts. Moreover, the positive effects are fairly evenly distributed across natives and past immigrants with different education levels.

5.3 Possible Mechanisms

After identifying the positive effects of low/high skilled immigrants on labor market outcomes of natives and past immigrants, the next natural question is about the mechanisms behind the positive effects. Because this paper mostly focuses on correctly estimating general effects of immigration, it is beyond the scope of this paper to analyze every possible mechanism. Still, it is worth reviewing the possible factors, under the standard assumption that "the slope of labor demand is negative." In particular, it is possible to check which possible factors are consistent with the IV results in Table 8-11.

First, it is noteworthy that immigrants are consumers who create demand for goods

Dependent Variables	OLS			IV		
:Employment	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
			Panel A: Natives			
Log(Low Skill Recent Imm)	0.175***	0.169***	0.168***	0.151*	0.263***	0.284***
	(0.035)	(0.031)	(0.028)	(0.086)	(0.080)	(0.067)
Log(High Skill Recent Imm)	0.357***	0.351***	0.355***	0.489***	0.482***	0.467***
	(0.051)	(0.039)	(0.028)	(0.093)	(0.065)	(0.056)
			Panel B: Past Immigrants			
Log(Low Skill Recent Imm)	0.846***	0.422***	0.286***	0.307	0.262**	0.211*
	(0.072)	(0.055)	(0.048)	(0.202)	(0.133)	(0.120)
Log(High Skill Recent Imm)	1.022***	0.702***	0.596***	0.635***	0.590***	0.585***
	(0.148)	(0.083)	(0.059)	(0.219)	(0.165)	(0.101)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. Each cells represent separate regressions with different dependent variables and independent variables. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. ”Low Edu,” ”Mid Edu,” and ”High Edu” refer to high school dropouts, high school graduates and college graduates, respectively. For each panels, the main explnatory variables are the log of the number of low skilled recent immigrants (high school dropouts or high school graduates), or high skilled recent immigrants (some college or more). Column 1-3 report OLS estimates of β in equation 9. Column 4-6 report 2SLS estimates of β in equation 9, where the instrumental variable is the the predicted number of immigrants, generated separtely for the low skilled and high skilled recent immigrants. Section 3 contains a detailed description of the instrument's construction.

Table 10: Heterogeneous Effects of Immigrants on Employment

Dependent Variables	OLS			IV		
:WageIncome	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
			Panel A: Natives			
Log(Low Skill Recent Imm)	0.045***	0.016*	0.014	0.069**	-0.008	-0.022
	(0.012)	(0.009)	(0.009)	(0.032)	(0.023)	(0.023)
Log(High Skill Recent Imm)	0.101***	0.061***	0.055***	0.099***	0.051	0.049***
	(0.014)	(0.011)	(0.012)	(0.028)	(0.037)	(0.017)
			Panel B: Past Immigrants			
Log(Low Skill Recent Imm)	0.056	0.056**	0.002	-0.219	0.074	-0.034
	(0.037)	(0.022)	(0.015)	(0.215)	(0.056)	(0.061)
Log(High Skill Recent Imm)	0.093*	0.098***	0.055**	0.137*	0.223***	0.136***
	(0.053)	(0.035)	(0.024)	(0.081)	(0.065)	(0.052)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. Each cells represent separate regressions with different dependent variables and independent variables. For Panel A, the depedent variable is the wage income of natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the wage income of past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. ”Low Edu,” ”Mid Edu,” and ”High Edu” refer to high school dropouts, high school graduates and college graduates, respectively. For each panels, the main explnatory variables are the log of the number of low skilled recent immigrants (high school dropouts or high school graduates), or high skilled recent immigrants (some college or more). Column 1-3 report OLS estimates of β in equation 9. Column 4-6 report 2SLS estimates of β in equation 9, where the instrumental variable is the the predicted number of immigrants, generated separtely for the low skilled and high skilled recent immigrants. Section 3 contains a detailed description of the instrument's construction.

Table 11: Heterogeneous Effects of Immigrants on Wage Income

and services in local labor markets. New immigrants spend their money on food, housing, transportation and other good and services in the city they live. Then, it is quite plausible to predict that demand for labor (both natives or past immigrants) also increases from influx of those recent immigrants. It is even possible that the demand for labor may rise even before the rise in labor supply because they engage in active consumption activity even before obtaining jobs (Simon, 1989; Van Den Berg and Bodvarsson, 2013). This story is consistent with the results here since immigrants have positive impact on labor market outcomes of both natives and past immigrants. Also, larger impact of high skilled immigrants may demonstrate that they have more spending power, leading to greater demand effect.

Second, it is possible that immigrants are significantly different from natives, which induce complementarity between the two types of labor (Ottaviano and Peri, 2012; Peri and Sparber, 2009). If this mechanism exists, it is likely that the positive effects are stronger for natives than past immigrants, since recent immigrants and past immigrants are easily substitutable. This mechanism is not exactly identified in the previous estimation results, however, where the positive effects are pretty similar for natives and past immigrants. Moreover, it is possible that there also exists complemantirity between low skilled and high skilled labor; influx of low skilled immigrants will have positive effects on high skilled natives and past immigrants, and influx of high skilled will immigrants will bring about positive effects on low skilled natives and past immigrants. Nonetheless, this mechanism is not clear by just looking at the estimation results since the positive effects are fairly evenly distributed across different education groups.

Finally, productivity of natives and past immigrants can increase by highly educated recent immigrants, through innovation and spillovers. If that is the case, I should see stronger effects of high-skilled immigrants compared to the low-skilled counterparts. The results on heterogeneous impacts of immigration, highlighted in Table 10-11, are consistent with this explanation, where the coefficients of high-skilled immigrants are larger than those of the low-skilled. According to, Kerr and Lincoln (2010) highly educated immigrants with H-1B visas increase science and engineering employment and patening, which are closely related to higher productivity and innovation. Also, Peri et al. (2015) find that increases in STEM (science, technology, engineering, and mathematics) workers are associated with significant wage gains for both non-college and college educated natives.

There are other mechanisms behind the positive effects of immigration on wages and productivity, highlighted by several studies on this topic. For instance, Olney (2013) argues that firms respond to low-skilled immigration by expanding their production activities within a city. That is, firms tries to utilize the ample supply of immigration workers by increasing the number of establishments. Also, immigrants have much higher business formation rate per month compared to natives. According to

2007 survey of business owners, the business formation rate per month among immigrants is 0.62 percent, compared to 0.28 percent for natives (Fairlie, 2012). These different effects of immigration, but not limited to the ones that are mentioned here, may have contributed to creating labor demand, "crowding in" new workers instead of "crowding out."

6 Robustness Checks

6.1 Limited Information Maximum Likelihood Estimation

To check the robustness of the IV regression results, it is possible to utilize the limited information maximum likelihood (LIML) estimation strategy to compare the results with those of the two stage least least squares estimators. It is known that the LIML estimators are less biased than those of 2SLS in case where there are weak instruments. I use the two instruments from column 1 and column 3 of Table 3 since the results of 2SLS and LIML are different when the number of instruments are more than one. I use the number of natives and past immigrants workers as a dependent variable, and the results are similar when using wage income (not reported). Table 12 shows the standard 2SLS results (column 1-3) and the LIML results (column 4-6). Notice that the LIML results in column 4-6 are quantitatively similar to the 2SLS results in column 1-3 with similar coefficients, which shows that the main 2SLS results are robust.

6.2 Relaxing the Independence Assumptions of Random Effects

The main assumption of the random effects parameters in Section 3 is that the coefficients are independent from each other, where the covariance terms are equal to zero. That is, the off-diagonal elements of variance covariance matrix **G** are assumed to be zero. For example, it is assumed that the random effects coefficients of mortality and

Dependent Variables :Employment	2SLS Low Edu	2SLS Mid Edu	2SLS High Edu	LIML Low Edu	LIML Mid Edu	LIML High Edu
			Panel A: Natives			
Log(Number of Recent Imm)	0.295***	0.396***	0.466***	0.296***	0.396***	0.470***
	(0.109)	(0.076)	(0.053)	(0.110)	(0.076)	(0.055)
			Panel B: Past Immigrants			
Log(Number of Recent Imm)	0.725***	0.569***	0.658***	0.632*	0.566**	0.663***
	(0.269)	(0.192)	(0.128)	(0.342)	(0.221)	(0.131)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. ”Low Edu,” ”Mid Edu,” and ”High Edu” refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report 2SLS estimates of β in equation 9. Column 4-6 report Limited Information Maximum Likelihood estimates of β in equation 9. The two excluded instrumentes are generated from the push factors that are shown in column 1 and column 3 of Table 3. Section 3 contains a detailed description of the instrument's construction.

Table 12: Immigration and Change in Employment (Comparing 2SLS with LIML)

per capita GDP are not correlated. Nonetheless, it is possible that there exists some correlation between the random effects parameters, which may alter the values of instrumental variable significantly. To deal with this issue, I relax the independence assumptions of random effects, allowing all covariances to be distinct when estimating the first stage equation 1.

The comparison between the 2SLS results using different assumptions on random effects parameters are summarized in Table 13. Column 1-3 shows the estimates based on independent covariance (which is the assumption that is used throughout the whole paper), whereas column 4-6 displays the estimates relying on dependent covariance. The positive effects on employment of natives and past immigrants get somewhat smaller under the assumption of dependent covariance compared to that of independent covariance. Still, the estimates under the independent and dependent covariance assumptions are not statistically indistinguishable; we generally see positive impact of recent immigration on employment of natives and past immigrants for both of the heterogeneous assumptions on the variance covariance matrix.

Dependent Variables	IV (Independent Covariance)			IV (Dependent Covariance)		
:Employment	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
	Panel A: Natives					
Log(Number of Recent Imm)	0.306***	0.398***	0.474***	0.228*	0.301***	0.413***
	(0.113)	(0.083)	(0.059)	(0.125)	(0.104)	(0.074)
	Panel B: Past Immigrants					
Log(Number of Recent Imm)	0.636**	0.520***	0.643***	0.595**	0.427**	0.609***
	(0.269)	(0.198)	(0.134)	(0.248)	(0.214)	(0.155)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report the 2SLS estimates under the assumption that the off-diagonal elements of the variance-covariance matrix of random effects coefficients in equation 2, , are 0. Column 4-6 report the 2SLS estimates relaxing the assumption that the off-diagonal elements of the variance-covariance matrix of random effects coefficients in equation 2, , are 0. I include per capita GDP, per capita GDP squared, mortality rate, education and political freedom as the relevant push factors, which gives the most first stage F-stat. Section 3 contains a detailed description of the instrument's construction.

Table 13: Immigration and Change in Employment (Relaxing the Independence Assumptions)

6.3 Addressing Concerns about "China Syndrome"

The key exclusion restriction for the instrumental variable from this paper is that the push factors in origin countries affect the local labor market outcomes in the United States only through the change in the number of immigrants. Nevertheless, it is possible that economic conditions in certain source countries have significant effects on local labor market through alternative mechanisms. For example, there are large trading partners of the United States, and any changes in trading conditions between those countries can have direct impact on industry structures of local labor markets.

Autor et al. (2013) analyze the effect of rising Chinese import competition on local labor markets in the United States, which is called "China Syndrome." They find that rising imports from China caused higher unemployment and reduced wages in local labor markets that rely heavily on import-competing manufacturing industries. It is likely that per capita GDP in China, which is one of the push factors used to generate the instrumental variable, is highly correlated with rapidly rising imports from China.

If that is the case, it is possible that GDP increase in China will negatively affect local labor markets through change in trade conditions between the United States and China. Then, the standard IV estimates from this paper will be invalid because of the violation of the exclusion restriction.

Hence, I generate an alternative instrumental variable without using the push factors from China. In other words, the observations of Chinese immigrants and the push factors are dropped when estimating the first stage equation. Since the instrumental variable does not contain the information about China, the concern on "China Syndrome" invalidating the exclusion restriction is significantly reduced. When estimating the second stage, I also drop Chinese immigrants when calculating the total number of recent immigrants just to be consistent with the first stage. The regression results are presented in Table 14, where column 1-3 use the standard instrumental variable from this paper including the Chinese push factors, while column 4-6 utilize the alternative instrumental variable without the Chinese data. The results are qualitatively similar regardless of the types of the instruments, which further justifies the exclusion restriction of the instrument.

6.4 Addressing Concerns about Return Migration

Another concern on the push factor instrumental variable is that there is a possibility of return migration. That is, it is possible that immigrants may be attracted to better conditions in their home countries, such as better economic or health conditions of their home countries. Yang (2006) analyzes return migration behavior of Philippine immigrants induced by exchange rate shocks. In addition, the report by Mexicans and Americans Thinking (2013) finds out that improved economic conditions in Mexico and the economic downturn of the United States due to the recession in 2008 caused many Mexican immigrants to voluntarily return to Mexico.

Dependent Variables	IV Including Chinese Push Factors			IV Excluding Chinese Push Factors		
:Employment	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
	Panel A: Natives					
Log(Number of Recent Imm)	0.304***	0.395***	0.471***	0.275**	0.368***	0.458***
	(0.112)	(0.084)	(0.062)	(0.111)	(0.082)	(0.062)
	Panel B: Past Immigrants					
Log(Number of Recent Imm)	0.631**	0.516***	0.638***	0.615**	0.481**	0.628***
	(0.258)	(0.191)	(0.132)	(0.265)	(0.190)	(0.130)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years, excluding Chinese immigrants. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report the 2SLS estimates using the preferred instrumental variable used in Table 7. Column 4-6 report the 2SLS estimates, where the instrument is constructed without using the push factors of China. Section 3 contains a detailed description of the instrument's construction.

Table 14: Immigration and Change in Employment (IV Excluding China)

Then, it is entirely possible that the 2SLS coefficients of the number of recent immigrants are still biased if the dependent variables are labor market outcomes of past immigrants. For instance, suppose that the source countries experience positive economic shocks which lowers the number of recent immigrants entering the United States. When the past immigrants in the United States are sensitive to the changes in economic conditions in their home countries and return to their countries, then the number of employment in a given cities will also decrease. In the end, we have positive relationship between the number of predicted recent immigrants and the employment of past immigrants induced by the shocks in the source countries. Thus, the 2SLS coefficients of the number of recent immigrants will be positively biased.

To address this issue, I modify the instrumental variable without using the push factors of Mexico to find the impact of non-Mexican immigrants inflow on past Mexican immigrants. It is unlikely that Mexican immigrants in the United States migrate again to countries other than Mexico, so the concern about return migration is largely reduced. Table 15 shows the impact of the number of non-Mexican recent immigrants

Dependent Variables :Employment	IV Including Mexican Push Factors Low Edu	Mid Edu	High Edu	IV Excluding Mexican Push Factors Low Edu	Mid Edu	High Edu
			Panel A: Natives			
Log(Number of Recent Imm)	0.173*	0.290**	0.439***	0.287**	0.348**	0.387***
	(0.098)	(0.118)	(0.071)	(0.144)	(0.137)	(0.051)
			Panel B: Past Mexican Immigrants			
Log(Number of Recent Imm)	0.626**	0.821***	0.544**	0.177	0.439	0.311
	(0.309)	(0.262)	(0.233)	(0.341)	(0.273)	(0.248)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	47	47	47	47	47	47

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 47 MSAs from 1980-2010, with the largest Mexican population. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years, excluding Mexican immigrants. The dependent variable is the number of employed past Mexican immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. ”Low Edu,” ”Mid Edu,” and ”High Edu” refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report the 2SLS estimates using the preferred instrumental variable used in Table 7. Column 4-6 report the 2SLS estimates, where the instrument is constructed without using the push factors of Mexico. Section 3 contains a detailed description of the instrument’s construction.

Table 15: Immigration and Change in Mexican Employment (IV Excluding Mexico)

employment of natives and past Mexican immigrants. Column 1-3 use the standard instrument from this paper with all the push factors of the source countries included in the instrument generation process, whereas column 4-6 use the modified version of the instrument without using the push factors of Mexico.

The estimation results in Panel B indicate that there is a strong positive relationship between the number of recent immigrants and the number of past Mexican immigrants. However, it is noteworthy that the size of the coefficients are different across the instrumental variables. The coefficient from the instrumental variable without using the Mexican push factors (column 1-3) is smaller than the coefficient from the instrument including the Mexican push factors (column 4-6). Recall that we may have a positive bias on the IV coefficients if there is a possibility of return migration, which may be reflected in this considerable difference in the estimates between the two instrumental variables. On the contrary, the coefficients for natives shown in Panel A are quantitatively similar across the different instruments since natives do not engage in such return migration behavior.

7 Conclusion

The lingering question about the impact of immigration on local labor market outcomes has still been largely remained unsolved mainly due to the difficulties in identification, often called "moving to opportunity bias." Does the positive correlation between labor market outcome and immigration comes from the fact that both natives and immigrants are attracted to cities with more employment opportunities? Or do immigrants actually *cause* positive labor demand shocks which creates more jobs and increases wages? To tackle this identification problem, I propose a new instrument for immigration, which is the number of immigrants predicted from the push factors of the source countries that immigrants originate from. It is shown that the instrument, generated from the exogenous supply/push factors, is more independent to local labor demand shocks compared to the previous instruments that are widely being used. The IV estimates suggest that influx of recent immigrants to a city causes increase in employment and wage levels of natives and past immigrants in that city.

Although this paper introduces a novel instrument that seems to be less correlated with local labor demand shocks, it relies on somewhat unfamiliar assumption that the effects of the push factors are random and heterogeneous across cities. The plausibility of this assumption and the consequent mixed effects regression model is thus open to various questions. For example, one may ask why some cities are more sensitive to the push factors compared to the others, and it is difficult to come up with a convincing story for such question. On the other hand, using previous instruments like the shift-share instrument by Card (2001) have an advantage of having a clear and persuasive "first stage story;" which is from the simple fact that immigrants tend to cluster in certain cities. Therefore, the credibility of the instrument from this paper will be largely dependent on carefully explaining the validity of the random effects parameters.

Moreover, even if the instrument succeeds in quantifying the relationship between immigration and local labor market outcomes, the mechanism behind the positive effects is still left unresolved. I try to propose some possibilities such as immigrants playing a role of consumers and bringing innovation, but they are not sufficient enough to explain all the phenomena. Thus, investigating this mechanism behind the positive impact of immigrants on local labor markets will be crucial in substantiating the results from this paper and also provide directions for future research.

Albeit its evident limitations, this supply/push factor immigration instrument presented in this paper can be particularly useful when it is impossible to get data on prior ethnic composition. The use of standard Card instrument is limited in such situation, so utilizing the IV from this paper can be an alternative way to solve the endogeneity problem. It is also noteworthy that the application of the push factor immigrant instrument from this paper is not particularly limited to the setting where we analyze the effects of immigrants on local labor markets. Pioneered by Borjas (2003), another big stream of immigration literature relies on utilizing national variation across skill-cells, rather than variation across geographic spaces. Although this approach is considered to be more immune to the problems of endogeneity of immigrant flows, there is still a possibility that the estimates of immigration impact is biased from various factors. Notice that the ethnic enclave instrument is not suitable in this skill-cell approach since it relies on geographic settlement patterns of ethnic groups. Instead, the supply/push factor instrument from this paper can be utilized under the assumption of heterogeneity of push factors effects across different skill-occupation cells.

Moreover, this paper sheds lights on the possible application of mixed effects model to the field of economics. Mixed models are largely exploited in biometrics literature, but it has not been widely used in economics, especially in the applied fields. The possible application of the model is not just restricted to the immigration literature, but other various applied fields in general. For example, Bartik-style shift share instrument that identifies local labor demand shocks can be modified by the analogous mixed model used in this paper; changes in local labor demand can be predicted from changes in industry structures of major trading countries, which are independent to local labor supply shocks in the United States. Not only that, there is a similar shift-share measure that uses the weighted shares of interest rate composition in the banking literature, where the model from this paper can be applicable. These are just a few examples among numerous possible ways to apply this novel methodology, which is expected to provide meaningful contributions to the existing realm of research.

Appendix

Tables and Figures

Dependent Variables	Outflow Rate			Inflow Rate		
:MigrationRate	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
		Panel A: Natives				
Log(Number of Recent Imm)	0.011	0.015	0.028	0.012	0.081*	0.155***
	(0.037)	(0.039)	(0.032)	(0.039)	(0.043)	(0.045)
		Panel B: Past Immigrants				
Log(Number of Recent Imm)	0.032	0.034	0.030	0.276***	0.202***	0.231***
	(0.053)	(0.040)	(0.047)	(0.077)	(0.051)	(0.055)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2000. Each cells represent separate regressions with different dependent variables and independent variables. For Panel A, the depedent variable is the in(out)flow rate of natives (age 25-64), stratified by education levels; for panel B, the dependent variable is in(out)flow rate of past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. For each panels, the main explnatory variables are the change in the log of the number of low skilled recent immigrants (high school dropouts or high school graduates), or high skilled recent immigrants (some college or more). Column 1-3 report 2SLS estimates where the depednet variable is outflow rate. Column 4-6 report 2SLS estimates of β in equation 9, where the dependent variable is inflow rate. In(out)flow rate is defined as the total number of native inflows (outflows) to (from) city i during year t-5 and t divided by the total number of natives population in year t.

Table A1: Immigration and Internal Migration

Dependent Variables	OLS			IV		
:EmploymentRate	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
	Panel A: Natives					
Log(Number of Recent Imm)	0.009	-0.014*	-0.001	0.041	-0.000	0.020*
	(0.013)	(0.008)	(0.003)	(0.033)	(0.022)	(0.011)
	Panel B: Past Immigrants					
Log(Number of Recent Imm)	0.076***	0.013	0.013*	0.082	0.041	0.026
	(0.024)	(0.014)	(0.008)	(0.058)	(0.034)	(0.023)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the population to employmnet ratio of natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the population to employment ratio of past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report OLS estimates of β in equation 9. Column 4-6 report 2SLS estimates of β in equation 9, where the instrumental variable is the the predicted number of immigrants. Section 3 contains a detailed description of the instrument's construction.

Table A2: Immigration and Change in Employment Rate

Dependent Variables	Homoscedasticity			Heteroscedasticity		
:Employment	Low Edu	Mid Edu	High Edu	Low Edu	Mid Edu	High Edu
	Panel A: Natives					
Log(Number of Recent Imm)	0.306***	0.398***	0.474***	0.216*	0.286***	0.396***
	(0.113)	(0.083)	(0.059)	(0.123)	(0.101)	(0.061)
	Panel B: Past Immigrants					
Log(Number of Recent Imm)	0.636**	0.520***	0.643***	0.794***	0.433**	0.597***
	(0.269)	(0.198)	(0.134)	(0.228)	(0.210)	(0.123)
City Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of MSAs	82	82	82	82	82	82

Notes: Robust standard errors are clustered by MSA and reported in parantheses. The sample includes decennial longtitudinal Census data of 82 MSAs from 1980-2010. I estimate equation 9 with city fixed effects and year fixed effects. The main explanatory variable is the number of recent immigrants who stayed in the United States less than 10 years. For Panel A, the depedent variable is the number of employed natives (age 25-64), stratified by education levels; for panel B, the dependent variable is the number of employed past immigrants who stayed in the United States more than 10 years (age 25-64), stratified by education levels. "Low Edu," "Mid Edu," and "High Edu" refer to high school dropouts, high school graduates and college graduates, respectively. Column 1-3 report 2SLS estimates of β in equation 9 under the assumption of homoskedasticity or error structure. Column 4-6 report 2SLS estimates of β in equation 9 under the assumption of heteroskedasticity or error structure, where the instrumental variable is the the predicted number of immigrants. Section 3 contains a detailed description of the instrument's construction. Theory Appendix has a detailed explanation on how to get the instruments under different assumptions of error structures.

Table A3: Immigration and Change in Employment Under Homoskedasticity and Heteroskedasticity

Figure 2: Best Linear Unbiased Predictors and Education Score in 2016 (EPI)

Theory Appendix 1

Exponentiating the log predicted value does not give the predicted unlogged value, which is often called "retransformation bias." In this paper I assume homoskedasticity of errors, though the bias is small that it does not affect the main result of the paper. Here is the way to get the predicted value of the log-linear model that is used in this paper.

Case1: Homoskedasticity of Errors

Suppose we have the following linear mixed model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\epsilon}$$

where $\mathbf{y}$ is the vector of the dependent variable; $\mathbf{X}$ is a matrix for the fixed effects $\boldsymbol{\beta}$; $\mathbf{Z}$ is a matrix for the random effects $\mathbf{u}$; $\boldsymbol{\epsilon}$ is the error term. We assume that $\mathbf{u} \sim N(0, \mathbf{G})$ and $\boldsymbol{\epsilon} \sim N(0, \sigma^2 I)$. Under these assumptions, the conditional expectation of y given u is

$$log(y)|u \sim N(X\beta + Zu, \sigma^2 I)$$

Since y follows the log-normal distribution, we have

$$E(y|u) = exp(X\beta + Zu + \frac{1}{2}\sigma^2 I)$$

Thus, the predicted value $\hat{y}|u = X\hat{\beta} + Z\hat{u} + \frac{1}{2}\hat{\sigma}^2 I$, where $\hat{\beta}$, $\hat{u}$ and $\hat{\sigma}^2$ are estimated from the maximum likelihood estimation.

Case2: Heteroskedasticity of Errors

The above method is based on the assumption that the errors are homosecadistic. However, it is possible that the errors are heteroskedastic, where $\epsilon \sim N(0, \sigma^2 R)$. Then,

$$E(y|u) = exp(X\beta + Zu + \frac{1}{2}\sigma^2 R)$$

but we do not know the exact form of R. It is possible to estimate R using the maximum likelihood estimation, but it is computationally expensive. In order to circumvent this problem, I follow a heteroskedasticity adjusted re-transformation method proposed by Baser (2007). In particular, I assume that $\sigma^2 R$ is a function of explanatory variables X and Z, where $R(X, Z)$. After estimating the above model, I obtain the squared residuals, $\hat{\epsilon}_i^2$. Then, I run regression $log(\hat{\epsilon}_i^2)$ on $x_{i1,} x_{i2} \cdots z_{i1}, z_{i2} \cdots$ and estimate the fitted value, which is denoted as $\hat{R}$. Finally, the unbiased transformation is

$$E(\hat{y}|u) = exp(X\hat{\beta} + Z\hat{u} + \frac{1}{2}exp(\hat{R}))$$

I generate a new instrument using the above transformation method and rerun the same analysis. As shown in Table A4, the IV results are not significantly different across different assumptions on the error terms. Thus, I conclude that re-transformation bias is not significant enough to alter the main results.

Nevertheless, the above method may not be a perfect solution since it relies on the assumption that the relationship between R and the explanatory variables are linear. Therefore, the ultimate solution for the above problem is using the generalized linear mixed model, where I use logarithm as a link function. However, there is a practical problem that the generalized linear mixed model often fails to converge due to the large number of observations and random effects parameters in this paper. In future research, it should be more plausible to find a way to achieve convergence of the generalized mixed model, which can completely eliminate the re-transformation bias.

Theory Appendix 2

The "fitted value" of the random effects are called Best Linear Unbiased Predictors (BLUPs.), and the details about BLUPs are added in the revised version of the paper (page 11). Suppose we have the following linear mixed model

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\mathbf{u} + \boldsymbol{\epsilon}$$

where $\mathbf{y}$ is the vector of the dependent variable; $\mathbf{X}$ is a matrix for the fixed effects $\boldsymbol{\beta}$; $\mathbf{Z}$ is a matrix for the random effects $\mathbf{u}$; $\boldsymbol{\epsilon}$ is the error term. We assume that $\mathbf{u} \sim N(0, \mathbf{G})$ and $\boldsymbol{\epsilon} \sim N(0, \boldsymbol{R})$. We estimate $\boldsymbol{\beta}$, $\mathbf{G}$ and $\mathbf{R}$ using the maximum likelihood estimation method. After the estimation, the BLUPs of the random effects, $\hat{\mathbf{u}}$, are chosen to minimize the variance of the prediction error under the condition that the predictors are unbiased. More formally, they satisfy the following conditions:

1. $E(\hat{\mathbf{u}} - \mathbf{u}) = 0$

2. $Var(\mathbf{v} - \mathbf{u}) - Var(\hat{\mathbf{u}} - \mathbf{u})$ is positive semi-definite for any other unbiased predictor $\mathbf{v}$

Here, I provide a brief sketch on how to derive the Best Linear Unbiased Predictors (BLUPs). For complete derivation, refer to Henderson (2009). We use the property that the BLUP of $\mathbf{u}$ is the BLUE of $E(\mathbf{u}|\mathbf{y})$. From the assumption of $\mathbf{u} \sim N(0, \mathbf{G})$ and $\boldsymbol{\epsilon} \sim N(0, \boldsymbol{R})$, the joint distribution of y and u is

$$\begin{bmatrix} y \\ u \end{bmatrix} \sim N\left(\begin{bmatrix} X\beta \\ 0 \end{bmatrix}, \begin{bmatrix} Z & I \\ I & 0 \end{bmatrix} \begin{bmatrix} G & 0 \\ 0 & R \end{bmatrix} \begin{bmatrix} Z' & I \\ I & 0 \end{bmatrix} \right).$$

Then, $E(\mathbf{u}|\mathbf{y})$=$\mathbf{GZ}(\mathbf{ZGZ}^{'}+\mathbf{R})^{-1}(\mathbf{y}-\mathbf{X}\hat{\beta})$, and consequently, the BLUP of $\mathbf{u}$ is

$$\hat{\mathbf{u}} = \hat{\mathbf{G}}\mathbf{Z}\hat{\mathbf{V}}^{-1}(\mathbf{y}-\mathbf{X}\hat{\beta})$$

where $\mathbf{V} = \mathbf{ZGZ}^{'} + \mathbf{R}$. Notice that the derivation relies on the normality assumption of the joint distribution.

It is possible to relax the normality assumption by exploiting generalized linear mixed model, where we are able to impose distributional assumptions on random effects and error terms, other than Gaussian. There are many ways to predict random effects in the generalized linear models; see Skrondal and Rabe-hesketh (2009) for a comprehensive review. However, there exists a practical problem that convergence is not achieved easily when we have a lot of random effects parameters to be estimated. More importantly, previous studies such as Mcculloch and Neuhaus (2011) find that the impact of random effects distribution mispecification is marginal; theoretical calculations and simulations show that maximum likelihood estimators are largely robust under various distributional assumptions.

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