2015

Three Essays on the Economic Impact of Immigration

James Sharpe
University of Kentucky, James.sharpe@uky.edu

STUDENT AGREEMENT:

I represent that my thesis or dissertation and abstract are my original work. Proper attribution has been given to all outside sources. I understand that I am solely responsible for obtaining any needed copyright permissions. I have obtained needed written permission statement(s) from the owner(s) of each third-party copyrighted matter to be included in my work, allowing electronic distribution (if such use is not permitted by the fair use doctrine) which will be submitted to UKnowledge as Additional File.

I hereby grant to The University of Kentucky and its agents the irrevocable, non-exclusive, and royalty-free license to archive and make accessible my work in whole or in part in all forms of media, now or hereafter known. I agree that the document mentioned above may be made available immediately for worldwide access unless an embargo applies.

I retain all other ownership rights to the copyright of my work. I also retain the right to use in future works (such as articles or books) all or part of my work. I understand that I am free to register the copyright to my work.

REVIEW, APPROVAL AND ACCEPTANCE

The document mentioned above has been reviewed and accepted by the student's advisor, on behalf of the advisory committee, and by the Director of Graduate Studies (DGS), on behalf of the program; we verify that this is the final, approved version of the student's thesis including all changes required by the advisory committee. The undersigned agree to abide by the statements above.

James Sharpe, Student

Dr. Christopher R. Bollinger, Major Professor

Dr. Jenny A. Minier, Director of Graduate Studies

THREE ESSAYS ON THE ECONOMIC IMPACT OF IMMIGRATION

DISSERTATION

A dissertation submitted in partial fulfillment of the
Requirements for the degree of Doctor of Philosophy in the
College of Business and Economics
at the University of Kentucky

By
James M. Sharpe
Lexington, KY

Director: Dr. Christopher R. Bollinger, Gatton Endowed Professor of Economics
and
Director of the Center for Business and Economics Research

Lexington, KY

2015

ABSTRACT OF DISSERTATION

THREE ESSAYS ON THE ECONOMIC IMPACT OF IMMIGRATION

With the significant rise in immigration to the U.S. over the last few decades, fully understanding the economic impact of immigration is paramount for policy makers. As such, this dissertation consists of three empirical essays contributing to the literature on the impact of immigration. In my first essay, I re-examine the impact of immigration on housing rents and completely controlling for endogenous location choices of immigrants. I model rents as a function of both contemporaneous and initial economic and housing market conditions. I show that existing estimates of the impact of immigration on rents are biased and the source of the bias is the instrumental variable strategy common in much of the immigration literature. In my second essay, I present a new approach to estimating the effect of immigration on native wages. Noting the imperfect substitutability of immigrants and natives within education groups, I posit an empirical framework where labor markets are stratified by occupations. Using occupation-specific skill to define homogeneous skill groups, I estimate the partial equilibrium (within skill group) effect of immigration. The results suggest that when one defines labor market cohorts that directly compete in the labor market, the effect of immigration on native wages is roughly twice as large as previous estimates in the literature. In my third essay, I return to the housing market and examine the effects of immigration *within* metropolitan areas. Specifically, I investigate the relationship between immigrant inflows, native outflows, and rents. Taking advantage of the unique settlement patterns of immigrants, I show that the effect of immigration on rents is lower in both high-immigrant neighborhoods and portions of the rent distribution where immigrants cluster. Contrary to the existing belief in the literature, the results suggest that the preferences of *natives*, not immigrants, bid up rents in response to an immigrant inflow.

KEYWORDS: Immigration, Impact of Immigration, Housing Rents, Substitutability, Occupation-Specific Skill, Quantile Regression.

THREE ESSAYS ON THE ECONOMIC IMPACT OF IMMIGRATION

By

James M. Sharpe

Dr. Christopher R. Bollinger
Director of Dissertation

Dr. Jenny A. Minier
Director of Graduate Studies

July 16, 2015
Date

To my loving wife, Anna, and son, Wyatt.

ACKNOWLEDGEMENTS

Though an individual work, this dissertation benefited from the direction and insight from several people. First, I would like to thank my dissertation advisor and employer at the Center for Business and Education Research, Dr. Chris Bollinger, for his guidance and support through this entire process. In addition to the instructive comments and moral support, I would like to thank Chris for believing in me from the beginning by admitting me and providing funding throughout my tenure. I would also like to thank my committee members and outside reader, respectively: Dr. Bill Hoyt, Dr. John Garen, Dr. Michael Samers, and Dr. Monika Causholli. Each individual provided invaluable comments and critiques that vastly improved the finished product.

In addition to the support I received from my advisor and committee, I received equally important support from my loving family. My wife, Anna, was invaluable throughout this process. Without your love, support, and proofreading prowess, I would not be where I am today. My son, Wyatt, not only provided much needed comic relief but gave me the extra push needed to complete this dissertation in a timely manner. My parents, Steve and Deena, instilled in me the work ethic and devotion needed to complete a Ph.D. My siblings, Brandon and Kaci, provided much needed support and perspective when times were tough. Each one of you contributed to this dissertation in different ways, but all of you were invaluable to me.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

1. Introduction

The topic of immigration is of crucial importance for both academics and policymakers. The foreign-born population share in the U.S. has risen steadily since 1970 and the current share stands at roughly 15% of the total population (levels not seen since the early 19th century). Furthermore, the most recent projections from the PEW research center suggest immigrant shares of the population are expected to reach 18.8% by 2060.[1] In fact, immigrants entering the U.S. and their descendants will account for 82% of total U.S. population growth. This projection is staggering compared to recent decades. From 1960-2005, immigrants and their descendants only accounted for 51% of overall population growth. As a result of this increased growth due to immigration, projected immigration will also have important implications for the overall demographic landscape of the U.S. Due to the projected immigration discussed above, the non-Hispanic white population share will fall from 67% to 47% while the Hispanic population share will more than double from 14% to 29%.[2] As such, the high current level of immigration and the projected rise in immigrant population shares makes understanding the effects of immigration all the more important to policymakers.

This dissertation works to reexamine and challenge commonly used methodologies in estimating the effects of immigration on the U.S. economy. In this dissertation, I examine the impact of immigration on two important markets: the rental housing market (chapters 2 and 4) and the labor market (chapter 3). The effects of immigration on both housing prices and the wages of native workers have motivated much of the discourse regarding immigration reform.

Why should we care about the impact of immigration on rents? From an equity standpoint, any immigrant-induced rent increase would be concentrated on the poorest Americans. The most recent data from the American Community Survey suggests that nearly half of all renter households are "house poor", as defined by the Federal government. That is,

[1] http://www.pewresearch.org/fact-tank/2015/03/09/u-s-immigrant-population-projected-to-rise-even-as-share-falls-among-hispanics-asians/
[2] http://www.pewhispanic.org/2008/02/11/us-population-projections-2005-2050/

these households spend more than 30% of their income on housing. Furthermore, nearly a quarter of all renter households spend more than 50% of their income on rents. While this may seem to have merit, from a social welfare point-of-view, whether immigrants raise prices should not matter. I would argue that there are two sides to every market and while rising prices may cause some tenants to lose welfare upon an immigrant inflow, the owners of these properties surely gain from these increases in prices. Put bluntly, there are no losses of efficiency when prices increase.

As such, the policy relevance of this topic may not be immediately clear. The problem is that policymakers do not seem to consider total social welfare when discussing immigration reform. Policymakers in the U.S. and abroad have used scholarly evidence that immigrant inflows cause higher housing prices to argue against immigration. In a speech to discuss the economic costs of immigration, Theresa May, the Home Secretary in the U.K., said[3]: "One area in which we can be certain mass immigration has an effect is housing...More than one third of all new housing demand in Britain his caused by immigration. And there is evidence that without the demand caused by mass immigration, house prices could be 10% lower over a 20 year period." Similar statistics and research have been used by the Labour Leader in New Zealand[4] and many other national news outlets in the U.S. to argue against immigration. On the other side of the aisle, many proponents of immigration reform have argued the economic benefit of immigration via the housing market. With homeownership rates and housing values in decline, immigrant inflows can "bring back" the housing market through demand shocks. This point-of-view is shared by many U.S. politicians like former New York Mayor Michael Bloomberg and former Governor of Utah and presidential nominee Jon Huntsman, among many others.[5] As both proponents and opponents of immigration reform use the same general result to argue both sides

[3] http://www.telegraph.co.uk/news/uknews/immigration/9739590/Curbing-mass-immigration-could-bring-down-house-prices-Theresa-May-says.html

[4] http://www.3news.co.nz/politics/david-cunliffe-blames-migrants-for-housing-crisis-2014052617#axzz3gjvE9eno

[5] Several news outlets have published pieces to this affect. Miriam Jordan (2013) published "Immigrants Buoy the Housing Market" in the *Wall Street Journal*, Jason Gold (2013) published "Killing Immigration Reform Hurts the Housing Recovery" in the *U.S. News and World Report,* among many others.

of immigration policy, identifying the true effect of immigration on housing is important for the national dialogue on immigration reform.

Chapters 2 and 4 of this dissertation examine the impact of immigration on the rental housing market. The general consensus in the literature is that immigration significantly increases housing rents: an inflow of international immigrants equal to 1% of the total population increases average rents within a metropolitan area by 1% (Saiz, 2007; Ottaviano and Peri, 2012). This result is the motivation for both chapters 2 and 4.

In chapter 2, I address the magnitude of this result. Specifically, I argue that this estimate is implausibly large as it does not fit with our knowledge of the urban housing market. The estimated effect of *immigration* on rent growth is significantly larger than most estimates of the effect of *total* population growth on rents. In fact, the existing literature examines the impact of an immigrant inflow equal to 1% of the total population, which is an increase in total population of 1%. Why would population growth attributed solely to immigration have a different impact on rents than an equal sized population flow of immigrants and natives? Furthermore, Saiz (2007) analyzes the short-run impact of immigration. How can immigration have a larger effect on rents than overall population growth when other houses are assumed to be immobile? These two questions motivate the research in Chapter 2 and the results show that the true effect of immigration on rents is much smaller than the estimates in the existing literature and quantitatively similar to the estimates of overall population growth on rents.

In chapter 4, I challenge the use of metropolitan areas as a single housing market in the previous literature. It is commonly argued that metropolitan areas are segmented into different submarkets and the implicit price of housing unit characteristics and neighborhood amenities differ across these submarkets. If submarkets exist because immigrants and natives have different locational preferences, then we would anticipate a differential impact of immigration on rents within a metropolitan area. There are two competing dynamics in play. Immigrants tend to cluster within metropolitan areas forming ethnic enclaves. These ethnic enclaves provide cultural amenities, access to employment, and ease the assimilation process. If the desire to live among immigrants is strong enough, then this increased willingness to pay for housing in a given location will bid up rents in these areas. However, when native households are mobile, white flight out of high-immigrant neighborhoods may diffuse the effects on rent. In this chapter, I analyze these two dynamics and assess the impact of immigration within metropolitan areas. My results support the white flight hypothesis and suggest that it is the increased willingness to pay of natives to live near other natives that drives the average effects found in the existing literature.

Chapter 3 diverges from the housing market and focuses on the impact of immigration in the labor market. Though I assess a different market, the underlying focus is still on the methodology used in the existing literature. When assessing the impact of immigration on native wages, researchers first group immigrants and with "demographically comparable" natives and assess the impact of relative labor supply on relative wages within skill groups (for example, see Borjas, 2003 or Ottaviano and Peri, 2012). The fundamental question in this literature then is who competes with whom in the labor market. In almost all cases, researchers stratify the labor market based on educational attainment and work experience. In this chapter, I argue that immigrants and natives with the same level of education and work experience do not necessarily compete in the labor market -- immigrants and natives are imperfect substitutes within education-experience groups. Instead, I suggest stratifying labor markets by occupation groups defined by occupation-specific skills, which will be more homogeneous with respect to skill. In doing so, the results suggest that the existing literature understates the impact of immigration on native wages. If we assess the impact of an immigrant supply shock on the wages of natives with whom immigrants directly compete for jobs, the estimated impact is twice as large.

2. Re-Evaluating the Impact of Immigration on the U.S. Rental Housing Market

2.1 Introduction

The union of the immigration and urban literatures is an emerging area of research. Work in this area was pioneered by Saiz (2003), who analyzes the impact of the 1980 Mariel Boatlift on the Miami housing market, and formalized by Saiz (2007). Using a difference-in-difference approach and the natural experiment that occurred in Miami, Saiz (2003) finds that rental prices in Miami increased by 8 – 11% more than comparable housing markets during this time; thus, Saiz (2003) concludes that immigrants cause a short-run increase in rental prices. Following the work of Saiz (2003), the literature on the impact of immigration on housing has evolved and two themes have emerged as a general consensus. First, subsequent research turned to a national setting for the analysis: Saiz (2007) and Ottaviano and Peri (2012) analyze the US housing market, Gonzalez and Ortega (2013) in Spain, Accetturo et al. (2012) in Italy, Degen and Fischer (2009) in Switzerland, and van der Vlist et al. (2011) in Israel. Second, regardless of the country of analysis, researchers typically find a significant, positive short-run impact on housing rents and housing values. Results from studies on the US are consistent: Saiz (2007) finds an inflow of new legal immigrants equal to 1% of the total population causes an increase of around 1% for both rents and housing values and Ottaviano and Peri (2012) find an increase in housing prices between 1.1 – 1.6%. In other countries, the estimates tend to be even larger: Gonzalez and Ortega (2012) find an increase in housing values of 3.4% in Spain and Degen and Fischer (2009) find an increase in housing values of 2.7% in Switzerland.

The general result found in the literature is not debatable; a one-time increase in population should have *some* positive impact on short-run housing prices, *ceteris paribus.* However, the estimates above seem implausibly large. There are sizeable discrepancies between the estimates in the studies above and previous estimates of immigration impacts in other markets and the impact of overall population growth in the urban literature. In the labor market, sizeable impacts of immigration on labor market outcomes are rare. In fact, Saiz (2007) suggests that "from the labor literature, a 1% increase in the relative share of a skill group depresses the relative wages of that group by 0.03%". However, if one accepts that an increase in the immigrant population equal to 1% of the total population of a city leads to a 1% increase in rents, then, according to Saiz (2007), this increase in rent amounts to 0.28% of the initial income of the typical rent-occupied household. The modest effects in the labor literature are not unique. Existing research assessing the fiscal effects of immigration (Borjas and Trejo, 1991; Gustman and Steinmeier, 2000; among others) and the effect of immigration on overall prices (Cortes, 2008) all find modest effects of immigration. Thus, the housing market is the only market for which large impacts are found.

Further discrepancies arise when one compares the estimates to results in the existing urban literature. As stated above, Saiz (2007) estimates the impact of an immigrant inflow equal to 1% of the total population, which is a 1% increase in population. Unless we believe immigrants have a differential impact on housing prices than native population growth, then the impact of an inflow of immigrants equal to 1% of the population on rents should be equivalent to the impact of overall population growth. Estimates of total population growth or employment growth are often included as controls in the typical housing price determination equation (Poterba, 1991; Abraham and Hendershott, 1996; Malpezzi et al., 1998; among others). The evidence of the impact of population growth on housing prices is mixed. Poterba (1991) uses age-adjusted population growth and finds negative and statistically insignificant impacts on housing prices. Similarly, Malpezzi et al. (1998) find wrong-signed and insignificant impacts of overall population growth on both housing values and rent. Abraham and Hendershott (1996) do find a positive and statistically significant impact of employment growth on housing, but the magnitude is much smaller (around 0.3% increase in housing for a 1% increase in employment), which is significantly larger than the elasticity of 1 estimated by Saiz (2007).

Thus, in order for the results in the existing literature to be taken as causal, one must believe that 1) housing markets respond differently than any other market to immigrant-induced changes in demand *and* 2) immigrant-inflows have a differential impact on housing prices than overall population growth. While it is fair to assume that the housing market adjusts more slowly than say, the labor market, there is no clear theoretical perspective that suggests immigrants should have a differential impact on housing dynamics than overall population growth.

As such, it is difficult to ascertain causality from the model specification used in much of the literature. Specifically, the model omits variables that are correlated with both immigrant location decisions and rent growth, causing estimates to be biased upwards. To see this, note that a commonly cited fact in the immigration literature is that immigrants tend to cluster in specific cities in the US (Bartel, 1989). These high-immigration cities tend to be the largest U.S. cities with thriving economies. If overall economic activity and productivity is higher in high-immigration cities, then we would expect wages and housing prices to be grow more quickly in these cities, irrespective of immigration. Saiz (2007) acknowledges the potential harm of this omitted relationship: "Omitted variables that are differentially present in cities with high immigration inflows, and that might account for the growth in rents in these cities (such as economic shocks), are a potential threat to my interpretation of the result.[6]

To this end, I account for this relationship and make three contributions to the existing literature. First, the use of a more recent dataset will supply evidence to whether the findings of past research were simply a one-time occurrence. Second, I improve upon the existing model specification and posit a more robust empirical model that includes initial city-specific

[6] Borjas (2003) further anticipates this fact: "If immigrants endogenously cluster in cities with thriving economies, there would be a spurious positive correlation between immigration and wages." Thus, it is likely this fact holds true with housing prices as well.

characteristics and a more robust treatment of housing supply. These initial conditions, described in detail later, control for initial city characteristics that impact the future evolution of rents, namely factors that predispose cities to increased future growth. In doing so, four important results emerge. First, the use of more recent data and a model specification similar to that in Saiz (2007) yield comparable results to those found in the existing literature: an immigrant inflow equal to 1% of the total population leads to an increase in rental prices of 1.3%. Second, when using the more robust empirical model, the coefficient of interest decreases by around 80% and is not statistically different from zero. This result suggests that past estimates were biased due to the spurious correlation discussed above. Third, I provide evidence that, due to the nature of the omitted variable bias, the shift-share instrumental variable strategy employed in the much of the existing literature fails to identify a causal impact of immigration on housing prices. Specifically, I show that past immigrant location choices and future rent growth are both positively correlated with the initial economic characteristics of cities. Omission of this relationship in the model leads to biased (upward) and inconsistent estimates as the instrument is correlated with the error term. Fourth, once I control for initial city characteristics, the magnitude of the impact is similar in magnitude to the estimated impact of overall changes in housing demand. Overall, I conclude that it is incorrect to assert that immigrants and natives have a differential impact on housing prices.

Last I address a more policy relevant question of how immigrants impact the rent-to-income ratio within cities. Taking the rent-to-income ratio as a proxy for housing affordability, the use of this housing market outcome allows one to speak to the overall impact of immigrants on natives as this ratio accounts for changes in both the housing and labor market. While the results do not allow for definitive statements on the impact of immigrants on housing affordability, the results do provide further evidence that the omission of city-specific effects lead to bias in previous studies. Using several measures of income in the dependent variable, a negative correlation is consistently found. Most notably, this result holds for both low-skilled and high-skilled industries. Thus, if one believes that immigration has a small positive impact on housing prices, then this result suggests that average wages are growing more quickly, relative to rents, in high-immigration cities, regardless of the relative skill mix of the industry. As this result is not supported in the labor literature, I take this as evidence that immigrants are simply settling in cities with flourishing economies where both rents and average wages are increasing.

The rest of the paper is structured as follows. Section 2.2 outlines a conceptual framework of rental housing demand and its relationship to prior empirical specifications and the present empirical model. Section 2.3 describes the data sources used in this analysis. A full description of each variable used can be found in the Data Appendix and summary statistics are provided in Table 2.1. Section 2.4 discusses the results of the preferred specification and the bias introduced by the shift-share instrument. Section 2.5 provides the methodology and results when using rent-to-income ratios as the dependent variable. Section 2.6 concludes.

2.2 Conceptual Framework

The motivation for this paper is derived from Figures 2.1 and 2.2. Figure 2.1 is a scatterplot of average rent growth and average immigrant inflows (as a percent of lagged total population) from 1999-2011 in U.S. metropolitan areas. Consistent with Saiz (2007), there is a statistically significant positive relationship between rent growth and immigrant inflows. Absent from past models, however, is a discussion regarding where immigrants are locating. Note the cities in the NE region and those in the SW region of Figure 2.1. Immigrants are locating in the largest cities in the U.S. These cities have more overall economic activity that attracts both firms and workers in the future. As shown below, these cities have a more inelastic supply of housing. Thus, one would assume that these cities, for reasons beyond changes in demographics, will have differential housing price growth.

To demonstrate this, consider a comparison of Miami, FL and Muskegon, MI in the prior period. From 1990-1998, the Miami, FL (Muskegon, MI) Core Based Statistical Area (CBSA) experienced overall population growth of 17.05% (5.32%) and real wage growth of 21.4% (14.3%).[7] Comparing high-immigration cities to low-immigration cities tells a similar story: high-immigration (low-immigration) cities experienced, on average, total population growth of 11.14% (2.17%) and real wage growth of 21.12% (13.34%).[8] Similarly, new construction in high-immigration cities is more regulated according to the Wharton Residential Land Use Regulatory Index (WRLURI). Higher values of this index suggest a less elastic supply. High-immigration cities have an average WRLURI that is about 75% of one standard deviation above the sample average, while the average WRLURI in low-immigration cities is about 75% of one standard deviation below the sample average. Thus, because of favorable economic conditions and relatively more inelastic supply, one would expect high-immigration cities to face increased growth in housing prices relative to low-immigration cities irrespective of immigration.

Saiz (2007) does attempt to control for fundamental city differences by including the initial share of the population holding at least bachelor's degree, a proxy for overall skill in a city. Glaeser and Saiz (2004) show that cities with more education (skill) experienced increased growth relative to less-skilled cities and this growth led to increases in wages and housing prices. Figure 2.2 plots this relationship from 1999-2011. Specifically, Figure 2.2 plots average rent growth from 1999-2011 against the share of the population holding at least a bachelor's degree in 1990. The data suggest that this proxy for future growth is not correlated with future rent growth. Though slightly positive, the correlation is not statistically different from zero. As this seems to be a weak indicator of future economic success[9], the model estimated by Saiz (2007) fails to

[7] Glaeser et al. (1995) suggests these as measures of city success.
[8] The 25 CBSA's that received the highest share of immigrants from 1999-2011 are classified as high-immigration cities. Low-immigration cities are the bottom 25 CBSA's.
[9] Similar graphs showing the relationship between the share holding a bachelor's and employment growth, wage growth, and population growth (available upon request) reveal the same pattern. There is no discernible relationship between economic success and this proxy for skill from 1999-2011.

control for these inherent differences between cities. The preferred empirical model herein accounts for such factors.

The empirical model follows directly from Saiz (2007). The theory underlying the empirical model is a simple framework of demand and supply of housing. Specifically, I regress rent growth on immigration inflows and a host of other explanatory variables controlling for both contemporaneous economic conditions and initial city conditions. One obvious omission from the model of Saiz (2007), however, is native population flows. In an equilibrium model of the housing market, we would expect *both* immigrant and native population flows to influence the evolution of rents. By omitting native population flows, one can think of the empirical model as a partial reduced-form model. Formally, the preferred model is written as:

$$(1)\quad \Delta \ln(r_{kt}) = \beta\left(\frac{Immigrants_{k,t-1}}{Population_{k,t-2}}\right) + \alpha X_{k,t} + \pi W_{k,t-1} + \mu \Delta Z_{k,t-1} + \delta M_{k,t^*} + \theta_{jt} + \Delta\varepsilon_{k,t}.$$

Consistent with Saiz (2007), the dependent variable is the annual change in the log of FMR in city *k* at time *t* and the main explanatory variable is the lagged annual inflow of legal immigrants admitted to city *k* at time *t-1* as a percent of the total population in period *t-2*, making β the coefficient of interest. The vector $X_{k,t}$ includes city-specific attributes, such as climate, crime, and land area, and the initial share of the population holding at least a bachelor's degree. $W_{k,t-1}$ is the lagged unemployment rate in the CBSA.

The model diverges from that of Saiz (2007), however, with the inclusion of M_{k,t^*} and a more robust treatment of housing supply. Following Glaeser et al. (1995), among others[10], M_{k,t^*} is a vector of initial CBSA-specific, time invariant variables in some year $t^* < t$. The intuition here is that past economic and housing market conditions may have a persistent long-run impact

[10] Several papers, mainly in the growth literature, use initial city conditions to explain differential growth rates among cities or metropolitan areas (Glaeser et al., 1995; Drennan et al., 1996). However, a few studies use this technique in other literatures; namely, the housing market (Engberg and Greenbaum, 1999) and the labor market (Beeson and Montgomery, 1993).

on future growth. Cities who attracted migrants in the past (both native and foreign-born) will continue to do so in the future (Blanchard and Katz, 1992; Glaeser et al., 1995). As such, these cities will experience increased future overall growth in economic activity and growth in housing demand. The vector M_{k,t^*} includes rent growth from 1980-1990, the initial Fair Market Rent (FMR) level in 1990, the share of the housing stock built before 1939 in 1990, the percent of total earnings coming from farms in 1990, per capita property tax revenues in 1997, and per capita spending in retail and service establishments in 1992. Rent growth in CBSA *k* from 1980-1990 and the FMR level in 1990 are the main inclusions in the preferred model. The intuition behind these two variables is described in detail below; however, it should be noted that both of these variables essentially serve the same purpose: to control for the fact that certain cities are predisposed to increased future rent growth. As such, these two variables do not enter into the specification together. I estimate two variants of (1) where the initial rent growth and initial rent levels enter separately.

Rent growth from 1980-1990 controls for the possibility that immigrants are locating in "superstar" cities. Gyourko, Mayer, and Sinai (2013) show that housing price appreciation in some cities is persistent and superstar cities that experience increased past price growth will face higher future appreciation. The authors show that high housing price growth in superstar cities occurs even if the inherent value of a location, the elasticity of housing supply, and the willingness to pay to live in each location is held constant. The initial FMR level in 1990 is a proxy for overall economic vibrancy in a city. Cities with higher rents in 1990 were those with thriving economies experiencing positive economic shocks. When rents are higher, the values of local amenities must be higher in order to compensate for this increase in housing expenditures (Roback, 1982). As such, these cities are attractive to in-migrants, both native and foreign-born. Furthermore, population tends to flow to area with higher housing prices and higher rents and these population flows are persistent over several decades (Rappaport, 2004). Thus, cities with high rents in period t^* will face higher future growth in housing demand (relative to those cities with lower housing prices) in period $t > t^*$. If immigrants are inherently attracted to these same cities yet the model ignores this relationship, then one might falsely attribute accelerated future rent growth to immigrant inflows.

Per capita property tax revenue is expected to have a positive impact on future housing prices. Note that this is property tax revenues, not property tax rates. Thus, this variable is not meant to control for property taxes in the user cost of owning a home; rather, this measure is a proxy for the initial amenity level of a CBSA relative to others. Higher per capita property tax revenue suggests increased spending on public goods, namely education and police/protection. In cities with higher property tax revenue, we expect higher amenity values of public goods and these amenity values should be capitalized into rents. The impact of the share of the housing stock built prior to 1939 is, *a priori*, ambiguous. On one hand, an older housing stock may depress growth in housing prices. Brueckner (1982) suggests that an inverse relationship exists between the age of the housing stock and future population growth. If so, a lack of population growth will slow housing demand and, *ceteris paribus*, slow the growth of rents in the city. On the other hand, an older housing stock could have a positive impact on future housing prices if there is an incentive to revitalize the city (i.e. gentrification). The percent of total earnings coming from farms in 1990 is included as a proxy for the opportunity cost of converting agricultural land to residential land and is expected to have a positive impact on future housing price growth. Per capita consumer spending serves as a proxy for the overall economic activity in a city and should be positively correlated with future housing price growth.

The last addition to the preferred model is a more rigorous treatment of housing supply. I include controls for the stringency of land use regulations and the cost of construction. In Saiz (2007), land area of the CBSA is the lone control for housing supply. However, it has been consistently shown that a strong positive relationship exists between housing prices and the stringency of land use regulations (Pollakowski and Wachter, 1990; Malpezzi et al., 1996; Ihlanfeldt, 2007; Gyourko et al., 2008; among others). A city with more stringent land use regulations (i.e. zoning laws, local government interventions, etc.) will face higher future housing prices. To control for the degree of land use regulations, the vector $X_{k,t}$ now includes the Wharton Residential Land Use Regulatory Index (WRLURI) (Gyourko, et al., 2008). The use of the WRLURI as a control for housing supply has advantages and disadvantages. The WRLURI is superior to the use of land area in that it encompasses a wide range and a large number of land use regulations. Pollakowski and Wachter (1990) suggest that analyzing the effect of land use regulations individually (i.e. land area), as opposed to collectively (i.e. WRLURI), will understate the impact of these controls on housing prices. The disadvantage, however, is that the WRLURI is time-invariant. Therefore, it must be assumed that land use regulations within a city are constant throughout the sample period. Similarly, to proxy for cost of new construction I include the one period lag of the change in average construction wages.

Equation (1) is estimated using both OLS and 2SLS using the same shift-share instrumental variable strategy used in the existing literature.[11] Aside from the additional controls, two differences exist between the model in (1) and that of Saiz (2007). First, 1995 is used as the base year of the instrument, while Saiz (2007) uses 1983. I chose 1995 because it is a central date for which data on initial conditions are available.[12] As discussed below, these initial conditions also serve as controls for the location choices of the immigrants in the base year. Second, I include region fixed effects interacted year fixed effects (θ_{jt}) to control for regional differences in rent appreciation. Thus, β is estimated from changes in the number of newly arriving immigrants within a CBSA over time, compared to other CBSA's in the region.

[11] This instrument, described in detail later, is the shift-share instrument similar to that first introduced by Altonji and Card (1991). The instrumental variable strategy uses predicted immigrant inflows, derived from historical settlement patterns of immigrants, as an instrument for actual immigrant inflows.
[12] Ultimately, the choice of 1995 as the base year was an arbitrary one as all results hold when different base years are used. Results using alternate base years for the instrument are available upon request.

2.3 Data

The data used in this paper are a panel of 325 Core Based Statistical Areas (CBSA's) over the period 1999-2011.[13] I use the 2013 Core Based Statistical Area (CBSA) definitions based on population estimates from the 2010 U.S. Census. The advantage of using current CBSA definitions is that metropolitan areas are no longer defined using partial counties. Thus, county-level data is easily aggregated to the CBSA-level.

Following Saiz (2007), data on immigrant inflows comes from the "Immigrants Admitted to the United States" data series of the Department of Homeland Security (DHS).[14] Following the discussion of Saiz (2007), these data should be considered a "noisy indicator" of recent immigrant inflows for three reasons. First, I am unable to identify the actual timing of arrival to the U.S. There may be lags from the time a person is granted admission and actually arrives in the U.S. While the timing of arrival may be off for some, the data suggest the error is minimal. In 1995 (the year chosen for the base year of the instrument described below), 76% of all immigrants were admitted and arrived in the same year and more than 99% of the immigrants arrived within 1 year of admission.[15] Second, immigrant inflows are calculated using data on the zip code of *intended* residence. If an immigrant settles in a different location than stated in the data, then I overstate the immigrant inflow to certain CBSA's, while understate the inflow in the actual CBSA of residence. Third, as noted above, I do not observe illegal immigrant inflows to the U.S.

---

[13] There are 377 CBSA's defined in the 2013 definitions (less CBSA's in AK and HI); however, I only have complete data for 325 of these CBSA's. This will not impact the analysis as it compares to Saiz (2007) because most (if not all) of the 52 omitted CBSA's were not included in Saiz's sample.

[14] During the sample period analyzed in Saiz (2007), this data series was under the control of the Immigration and Naturalization Service (INS). While these data (1999 – 2012) are now managed by the Department of Homeland Security, the structure of the data is the same. While these data are from the same source as used in Saiz (2007), one difference should be noted. Due to increased security measures, the DHS does not provide the micro-data files of these data. These data are publicly available on the DHL website, but MSA definitions are not constant across years. Thus, the custom data I received were aggregated using the most current CBSA definitions (2013).

[15] I am unable to make use of these admission data because I do not have access to the micro-data for the years 1999-2011.

Though data issues exist, these data have the advantage of being the only available source of annual immigrant inflows to the US. The concern over illegal immigrant flows is most relevant to this study and one that must be addressed. One concern is that illegal immigrants may cluster differently than legal immigrants. This could occur if illegal immigrants are more heavily concentrated in border cities due to higher transportation costs. While accurate counts of the illegal immigrant population at the CBSA level do not exist, the state-level estimates are consistent with the legal immigrant population. Passel et al (2004) estimate that roughly two-thirds of all illegal immigrants live in just 6 states: California, Florida, Illinois, New York, New Jersey, and Texas. These 6 states are also the main hubs for legal immigration. From the data, 66% of all legal immigrants settled in these 6 states from 1999-2011. While illegal immigrant populations may cluster in the same state as legal immigrants, it is possible that illegal immigrants cluster in different parts of a CBSA or the willingness to pay to live near other immigrants may be stronger for illegal immigrants as the benefits from ethnic enclaves are larger. Again, I do not have data at finer geographic levels and cannot account for this in the current model. One may to alleviate this concern is to use decennial Census data that presumably counts *all* immigrants, both legal and undocumented. I re-estimate all models herein using decennial US Census data and the results, reported in Table A2.4 of the Appendix, suggest that the impact of undocumented immigrants is minimal as the results are quantitatively similar to those found in the main text.

The main source for rental price data is the Fair Market Rent (FMR) series from the Department of Housing and Urban Development (HUD). The FMR in a particular area corresponds to the market value of a vacant two-bedroom unit. HUD reports FMR's at the county-level for each county in the U.S. For most counties in the sample, the FMR is the price of this unit at the 40^{th} percentile of the rent distribution; however, starting in 2005, the FMR for a small sample of counties are reported as the 50 percentile of the rent distribution. Thus, I normalize the rental housing price measure throughout the sample, by adjusting 50^{th} percentile estimates to 40th percentile estimates. To do this, I use 40th percentile FMR data for years prior to 2005 to predict the 40th percentile estimate in 2005 $\left(\widehat{FMR}_{2005}\right)$ and take the ratio of the true and predicted values in 2005, $\left(\frac{\widehat{FMR}_{40\%,2005}}{FMR_{40\%,2005}}\right)$. Next, I use the 50th percentile FMR data for the subsequent years to predict the 50th percentile rent estimate in 2004 $\left(\widehat{FMR}_{2004}\right)$ and take the ratio of the true and predicted values in 2004, $\left(\frac{\widehat{FMR}_{50\%,2004}}{FMR_{50\%,2004}}\right)$. Last, I construct an adjustment factor equal to the average of the previous ratios to deflate 50% FMR estimates to reflect 40% FMR estimates.[16]

Income and wage data are derived from several sources. Per capita personal income and average wages per job are from the BEA Regional Information Systems (REIS). Other definitions of income are used in the rent-to-income analysis. Average wages of all industries and average wages of all good-producing industries are derived from the Quarterly Census of Employment and Wages (QCEW). All income measures are converted into real 2010 dollars using the CPI-U. Other explanatory variables come from a variety of sources and follow directly from Saiz (2007). Civilian labor force and unemployment figures are from the Bureau of Labor Statistics (BLS). Climate data are from the United States Department of Agriculture Economic Research Service Natural Amenities Scale Database. Violent Crime and murder data are (mostly) from the FBI Uniform Crime Reports (UCR).[17] Initial MSA-specific conditions come from the 1994 County and City Data Book and the 1990 Economic Census. Full definitions of these variables used can be found in the Data Appendix, while summary statistics are reported in Table 2.1.

---

[16] In 1995, HUD began to report FMR as a 40% estimate. Thus, Saiz (2007) had to adjust FMR to reflect 45% rent estimates for the years 1996-1998. The difference, however, is that both 40th and 45th percentile estimates were reported in 1995 and the ratio of these two estimates were used to adjust 45th percentile FMRs to 40th percentile FMRs. While this may seem like a crude treatment of the data, the results are not sensitive to this adjustment. Results using unadjusted FMR as the dependent variable are available upon request.

[17] Some states did not consistently report crimes to the FBI. For these states (i.e. FL, IL, KS, MN, etc.), individual state Uniform Crime Reports were used.

2.4 Results

The discussion in section 2.2 suggests that past results may have suffered from specification error as they omitted fundamental factors that impact rent growth, independent of immigration. The impact of these omitted factors is seen in the results in Tables 2.2 and 2.3. Table 2.2 presents OLS and 2SLS estimates of the model posited by Saiz (2007). These estimates, which serve as a replication of Saiz (2007), are reported in columns (1) and (2), respectively. The *replication* results in columns (1) and (2) serve as an appropriate and comparable baseline even with different CBSA definitions and more recent data, which include the Great Recession. These results are very similar to those found in the literature.[18] The point estimate in column (2) suggests that an immigrant inflow equal to 1% of the total population will cause rents to increase by 1.43%.

I then estimate several variants of the preferred specification and report the estimates in Table 2.3. I first estimate (1) with the controls discussed above, but omitting region effects. Column (1) includes the initial FMR in 1990 while Column (2) includes rent growth from 1980-1990. The reason for estimating the model with and without region fixed effects is the concern that region fixed effects may "soak up" too much of the variation in the independent variable of interest. Using this instrumental variable strategy, identification of β comes from cross-sectional variation, not variation *within* a CBSA. Last, I estimate the full preferred model implied by (1) which includes the additional controls and region fixed effects. Again, column (3) uses initial FMR in 1990 and column (4) uses rent growth from 1980-1990.

As is shown in Table 2.3, the coefficient of interest, though imprecisely estimated, consistently decreases as I control for omitted factors. When initial city conditions are included, the difference in the coefficients from the baseline estimates is roughly the same. Furthermore, the consistency across all four specifications suggests that the estimates are not sensitive to the

[18] Saiz (2007) reports a point estimate on the immigration impact variable of 1.028 (0.995) for OLS (2SLS) estimation

inclusion of region fixed effects, which alleviates any concern that the reduction in the estimated impact of immigration is due to a lack of identification. When initial city conditions are included, the impact of immigration falls by around 80% and this effect is similar when using either the proxy for superstar city status or the proxy for initial economic vibrancy. While the point estimates in columns (1) – (4) are not statistically significant, they are statistically different from the replication estimates in column (2) at the 5% level.

The performance of the other controls is mixed. The two proxies for supply conditions have little impact on rent growth. Both the regulation index and changes in construction wages have neither statistical nor economic significance. Consistent with Saiz (2007), changes in per capita income seem to have no impact on rent growth and the share of the population with a bachelor's degree has a significant negative impact on rent growth. The latter fact is at odds with the literature analyzing differential city growth and skill levels. The purpose of including this variable is to control for fundamental differences between cities that will lead to increased future overall growth and growth of wages and housing prices. The point estimate of the property tax revenue variable indicates a zero impact, which is unsurprising. In equilibrium, property tax revenue should not have an impact on prices because it also represents expenditures. While the marginal utility with respect to property taxes will be negative (decrease demand), the marginal utility of the expenditures that stem from property tax revenue will be positive. So, on net, the impact should be zero. This negative correlation points to the specification error in Saiz (2007). The proxies for superstar cities and overall economic vibrancy perform as expected. Cities with larger past rent growth and those with higher initial levels of rent experienced increased future price appreciation.

Again, though not statistically different from zero, the point estimates are more in line with what we would expect given the discussion above. The result found by Saiz (2007) is consistent with the standard perfectly competitive, closed city model, where migration-induced rent growth occurs due to the model assumption that, in the short-run, there is no out-migration. In the short-run, this assumption is not overly restrictive, especially in the rental housing market. In the short-run, renter households may be "tied" to their current dwelling due to moving and search costs, contracts/leases, etc. However, if one considers the role of vacancy rates in rental housing demand, then one would not expect the one-for-one impact found in the existing literature. Rental prices do not clear instantaneously. In fact, changes in demand are first reflected in vacancies, then prices (Blank and Winnick, 1953; Smith, 1974; Eubank and Sirmans, 1979; Rosen and Smith, 1983).

A simple back-of-the-envelope calculation, similar to the one presented in Saiz (2007), shows that the present results are more in line with what is seen in the labor literature. Assuming the impact of immigration on rents is around 0.25%, as is implied in Table 2.3, then the impact of an immigrant inflow equal to 1% of the total population amounts to a reduction in initial income of 0.0735% for the typical renting household.[19] However, a more straightforward interpretation suggests that, as in the labor market, the impact of immigration is negligible. Immigrants are not *causing* a substantial increase in rental prices; rather, immigrants are locating in growing superstar cities where rents are predisposed to housing price growth.

2.4.1 Consistency of the Shift-Share Instrument

The results in Table 2.3 suggest that current period rent growth is positively correlated with initial economic conditions in the city. Once we account for these characteristics, the impact of immigration on rent decreases significantly and is no long statistically different from zero. One possible explanation for the above is that the shift-share instrument introduces bias. The instrument is defined as:

[19] In 2010, the population-weighted average share of foreign-born population in the US was 14.5%. In order to increase the each cities foreign-born population by 1%, the total population in each city would have to increase by 1.18%. Thus, an immigrant inflow of 1.18% yields an increase in rental prices of 0.295%. Assuming the typical renting household spends 25% of its income on shelter, increase in rent amounts to a 0.0735% decrease in income.

(2) $\widehat{Immigrants}_{k,t} = \theta_{k,t^*} * I_{US,t}$.

The first term on the right-hand side is the share of newly arriving immigrants that migrated to city *k* in some base year t^*. The second term is the total number of immigrants admitted to the US in year *t*. The intuition behind this instrument is that while current location decisions are endogenous to current economic and housing market conditions in the city, settlement decisions of *previous* immigrant waves (θ_{k,t^*}) are uncorrelated with *current* economic conditions. This follows from the standard result that the only significant determinant of immigrant location decisions is the existing share of foreign born in a city. In fact, it has been shown that other factors, such as labor market conditions, do not have a discernible effect on location decisions of immigrants (Bartel, 1989). Thus, one can use imputed immigrant inflows, based on historical migration patterns, to instrument for current period immigrant inflows.

Concern would arise, however, if either θ_{k,t^*} or $I_{US,t}$ are, in fact, correlated with initial economic conditions that are positively correlated with future rent growth. If either is the case, then past estimates relying on the shift-share instrument are biased and inconsistent. To test the exogeneity of the first term, I estimate the determinants of this initial immigrant share via the following model:

(3) $\theta_{k,t^*} = \beta M_{k,t^*} + \varepsilon_{k,t}$.

The dependent variable is the share of total immigrants that entered CBSA *k* at base year t^*. The vector M_{k,t^*} includes the initial CBSA-level variables used above. I estimate (3) using several different base years as a robustness check and report the results in Table 2.4. Panel A includes initial rent levels in 1990 as a control, while Panel B includes initial rent growth.

The results in Table 2.4 confirm the bias introduced by the shift-share instrument. Initial FMR level and past rent growth are both *positively* correlated with immigrant shares, regardless of the choice in base year. Newly-arriving immigrants in t^* were attracted to large, vibrant superstar cities with high rent levels that were predisposed to increased future rent growth. As past both of these variables were shown to have an independent positive impact on future rent growth in Table 2.3, this result suggests instrument is, in fact, correlated with the error term. The omission of this relationship explains the large estimates in previous models.

Similarly, the exogeneity of annual inflow of immigrants to the US as a whole ($I_{US,t}$) is taken as exogenous. However, if one considers immigrant inflows over the past 10 years, it is clear that immigrant inflows are somewhat cyclical. To see this, Figure 2.3 plots inflows of legally admitted immigrants to the U.S as a percentage of lagged total population from 2003-2012.[20] The data suggest that immigrants do respond to overall economic conditions in the U.S. Legal immigration steadily increased through 2006; however, after the start of the Great Recession in 2008, immigration stagnated and has actually decreased in recent years. This trend is not unique to legal immigrants. Passel et al. (2013) show that, during the Great Recession, the growth of the illegal immigrant population also slowed considerably.

These national trends, however, are only important insomuch as the immigrants who do immigrate to the U.S. display similar preferences when choosing their final destination within the U.S. To see this, Figure 2.4 plots weighted average immigrant inflows as a percent of total population for a) the 10 states most adversely affected by the Great Recession, b) the 10 states that were least affected by the Great Recession and c) all other states from 2006-2011.[21] From Figure 2.4, we see that immigrant inflows slowed in states that were most affected by the recession and this decline was much more pronounced than in the other two groups. Perhaps more importantly, California and Nevada are two states included in the group that were most harmed by the recession. As both also have high shares of foreign-born populations (in 2000,

[20] Specifically, each data point is the annual immigrant inflow at time t divided by the total population in t-1.
[21] I use the 10 states with the highest Economic Security Index (ESI) (Hacker et al., 2012). The ESI is defined as "an integrated measure of insecurity that captures the prevalence of large economic losses among households".

California was ranked first and Nevada fifth), the data contradict the theory that the lone determinant of immigrant locations is the existing share of foreign-born populations.

The above analysis suggests that the widely-used shift-share instrumental variable strategy introduces bias unless one controls for initial city characteristics. Immigrants in the base year were choosing cities that provided them the best economic opportunities, but these same cities were predisposed to higher future rent growth. If we believe that the lone determinant of immigrant location choices is the share of existing population that is foreign-born, then new immigrants settle in these same cities in search of the cultural amenities. Without explicitly controlling for this relationship, we would falsely attribute this increased rent growth to immigration. However, the results in Figure 2.4 suggest immigrants' preferences may be influenced by overall economic climate. As such, a more likely explanation is that all immigrants, both past and present, choose final destinations that afford them the best economic opportunities.

2.4.2 Robustness Checks

2.4.2.1 Alternate Proxies for Economic Vibrancy

The results in Table 2.3 suggest that past results were driven by specification error. Once one controls for initial city characteristics that are correlated with future rent growth and immigrant location choices, the impact of immigration on rents is significantly lower. To lend credence to this result, several robustness checks are performed. First, as the controls for initial city conditions are the primary additions to the model, it must be the case that the results from Tables 2.3 and 2.4 hold when using alternate proxies. Superstar cities can be thought of, generally, as large cities that possess certain characteristics that lead to future growth and prosperity. Thus, the alternate proxies used are variables that describe the initial level of economic vibrancy of the city. Specifically, I re-estimate (1) using the following proxies in place of initial rent level and initial rent growth: FMR growth from 1983-90, initial median gross rent in 1990, the average commute in 1990, and the price-to-rent ratio in 1990. The first three proxies follow directly from the discussion in section 2.2. The price-to-rent ratio is included as it has been shown to be positively correlated with future capital gains (Capozza and Seguin, 1996) and future rent growth (Clark, 1995; Gallin, 2008). The intuition is that when the price-to-rent ratio is high in year *t-k*, owner-occupied housing is overvalued. As such, rents increase in future periods as the market works to correct itself.

The 2SLS results, presented in Table 2.5, reaffirm the results in Table 2.3, with the exception of column (1). The difference between column (1) and columns (2) – (4) is that our proxy for initial economic conditions in (1) is not correlated with future rent growth. While this is a somewhat disconcerting, it does allow for comparison that validates the discussion regarding the shift-share instrument above. Table A2.1 of the Appendix provides results similar to those in Table 2.4. Specifically, I estimate equation (3) using these alternate proxies. The results suggest that immigrant shares in the base year are positively correlated with the proxies in columns (2) – (4), but not past FMR growth in column (1). Because immigrant shares are not correlated with the initial condition in (1), the estimate remains artificially high. As FMR growth from 1983-90 is an imperfect proxy for economic vibrancy, the instrument remains correlated with the error term.

2.4.2.2 Overall Housing Demand Growth and Rents

A second test for robustness analyzes the impact of overall housing demand on rent growth. As total population growth to a city is likely endogenous (and there is no clear cut instrumental variable strategy), I use an oft-used proxy; the Bartik-style predicted labor demand shocks to a city (Bartik, 1991). The predicted employment growth rate is derived from the industrial mix of a CBSA and *national* employment growth.[22] In using national employment trends, I predict employment growth in each CBSA that would have occurred had the industrial

[22] A full discussion of the calculation of this variable can be found in the data appendix.

mix remained constant. The idea is that while actual employment growth is likely correlated with local conditions, a national shock to employment levels is likely exogenous with regards to these unobserved city conditions. Though typically used in the labor literature, this measure of predicted employment growth has been used in the housing literature as a proxy for changes in housing demand (Quigley and Raphael, 2005; Saks, 2008). The intuition is that when a city experiences a positive labor demand shock, migrants enter the city in search of employment; which, in turn, increases housing demand.

To address this question I estimate the following model:

$$(4) \quad \Delta \ln(r_{kt}) = \beta \hat{E}_{kt-1} + \alpha X_{kt} + \pi W_{kt-1} + \mu \Delta Z_{k,t-1} + \delta M_{kt^*} + \tau_t + \theta_j + \theta_j * \tau_t + \Delta \varepsilon_{kt}.$$

The lone difference of (4) relative to the preferred specification (1) is that the independent variable of interest is the predicted employment growth in period *t-1* ($\hat{E}_{kt-1}$). This model is estimated using OLS as this measure of population growth is a *plausibly* exogenous source of population inflows into a city. The results are reported in Table 2.6. Column (1) provides estimates without initial city conditions, while columns (2) and (3) use the additional variables from the preferred model. The results provide further evidence that previous estimates of the impact of immigration were biased upward. A 1% increase in housing demand leads to an increase in rents around 0.4 – 0.5%, or about 63% less than the estimates implied by column (2) of Table 2.2. The inclusion of initial city conditions, though significant determinants of rental price growth, do not impact the point estimate of interest. This provides support for this measure of housing demand growth as it seems to be uncorrelated with local market conditions.[23] Similarly, the estimates provide further evidence to the bias of previous estimates. It seems unreasonable that immigrant inflows alone would have an impact on rents that is more than twice as large as overall growth in housing demand. Lastly, the coefficient of interest in all

[23] Table A2.2 of the appendix provides results similar to those in Table 2.4 when using predicted employment growth. Indeed, the results show that this measure of labor demand growth is uncorrelated with the initial conditions in the full model.

specifications in Table 2.6 is similar in magnitude to those found in columns (3) and (4) of Table 2.3. Though direct comparison is difficult as the results in Table 2.3 are not statistically significant, the results provide further evidence that previous estimates were significantly biased.

2.5 The Affordability of Rental Housing

The above analysis has shown that the actual impact of immigration on housing rents is significantly less than past research suggests. However, the housing market is simply one avenue through which immigrants may impact the well-being of the native population. While immigration-induced housing price growth is certainly a concern of policymakers, it may not tell the entire story. Of greater concern, perhaps, is if immigrant inflows cause housing prices to increase faster *relative* to income; in which case, this increase in rents leads to a higher incidence of "housing-induced poverty" (Thalmann, 1999; Kutty, 2005). Furthermore, by using the rent-to-income ratio as a measure of housing affordability, one improves upon earlier specifications as rents are now normalized across cities controlling for city differences in purchasing power.

I contribute to the immigration literature by formally addressing this issue. To my knowledge, Greulich et al. (2004) is the only existing study to address the impact of immigration on the affordability of housing. However, the present model diverges from the model of Greulich et al., (2004) in two key ways. First, Greulich et al. (2004) does not account for the endogeneity of immigrant location choices. Second, I use a larger more representative sample and a more extensive set of controls for economic conditions in the city.

Using the same data as in previous sections, I posit the following model to assess the impact of immigration on housing affordability:

$$(5)\quad \Delta \ln\left(\frac{r_{k,t}}{I_{k,t}}\right) = \beta\left(\frac{Immigrants_{k,t-1}}{Population_{k,t-2}}\right) + \alpha X_{k,t} + \pi W_{k,t-1} + \mu \Delta Z_{k,t-1} + \delta M_{k,t^*} + \tau_t + \theta_j + \theta_j * \tau_t + \Delta\varepsilon_{k,t}.$$

Here, the dependent variable is the annual change in log of the rent-to-income ratio. The numerator is the FMR in city *k* and the denominator is a measure of average monthly wages in city *k*. The explanatory variables are the same, making β the coefficient of interest. In keeping the same explanatory variables, I implicitly assume any additional factors impacting average wages are captured by year-by-region fixed effects. As before, the model is estimated by 2SLS using the shift-share instrument.

Before I proceed to the results, I first discuss the expected sign of β. Given the results and discussion in the previous sections, we should expect immigration to have a slight positive impact on rents. As such, the impact on average wages will determine the sign of β. A simple demand and supply model of the labor market suggests a clear cut answer – a positive shock to labor supply should depress average wage, *ceteris paribus*. Here, one would expect an immigrant inflow to have a positive impact on the rent-to-income ratio. Though straightforward theoretically, the empirical evidence is mixed. The majority of studies using the "area approach" – where one uses a CBSA (or MSA in the previous literature) to define a local labor market – find that an immigrant inflow is associated with *increases* in average wages (Card, 2001; Card, 2007; Ottaviano and Peri, 2008). The explanation for this seemingly counterintuitive result is that immigrants and natives are complements in production. Thus, an immigrant-induced labor supply shock will have a net positive effect on average wages. If so, the sign of β is ambiguous, depending on the relative impact on rents and wages.

I estimate three variants of (5) using different measures of income in the dependent variable. The results from the preferred specification, including region effects and CBSA-specific variables, are reported in Table 2.7. For the sake of brevity, I report baseline estimates (those estimated without initial CBSA controls) in the final row of Table 2.7. First, I use the measure of average wages per job provided by the BEA as the income measure. The use of the CBSA-specific average FMR and average wages will allow for inferences about the typical resident in the city. In column (1), we see a similar pattern as was shown in Tables 2.2 and 2.3. The estimates from the baseline model suggest that immigrants cause housing to become more expensive relative to income; however, once one adds the controls of the preferred model, the results suggest that immigrant inflows are negatively correlated with housing affordability. This negative correlation suggests that housing is becoming less expensive, relative to income, in high-immigration cities.

Though negative, the estimate is not statistically significant. Thus, a more straightforward interpretation of these results is that immigrant inflows have a zero effect on the rent-to-income ratio. One feasible explanation for this result is that the model suffers from specification error. In particular, contrary to the assumption above, region-by-year fixed effects and initial city characteristics are not sufficient in controlling for factors that differentially affect wages but not rents. This assumption was necessary as data limitations prevent me from controlling for annual CBSA demographics and the instrumental variable strategy prevents the use of CBSA-fixed effects.

While I acknowledge that specification error could contribute to the results in Table 2.7, I argue that the effect is likely minimal and does not impact the *qualitative* interpretation. On the demand side of the labor market, region-by-year fixed effects pick up regional shifts in labor over time. One plausible explanation for the increase in average wages is changes in labor demand. If firms move to cities with high immigrant populations increasing overall demand or there are changes in the industrial mix of a CBSA (i.e. low-wage jobs are replaced with high-wage jobs), then average wages would increase, *ceteris paribus*. While this would certainly explain an increase in average wages, region-by-year fixed effects should control for this as I use 8 narrow BEA-defined regions. To mitigate the concern over specification error driving the differences in wage growth, I have also estimated the above model using 1) state-level fixed effects to control for more local trends in labor demand and 2) the Bartik-style imputed employment growth, discussed above, as a control for labor supply shifts. In both cases, the results, reported in Table A2.4 in the Appendix, are quantitatively similar to those in Table 2.7. Furthermore, the initial city characteristics pick up any inherent differences in wage growth across CBSA's. Lastly, I suggest that specification error is not driving the results as they are consistent with the labor literature using the area approach to estimate the impact of immigration on average native wages. As I implicitly adopt the area approach here by defining a CBSA as the housing market, a positive impact on average wages is expected. As such, I interpret the results in Table 2.7 as evidence that immigrant inflows are positively correlated with both rents and wages and the net effect is zero.

To check the robustness of the estimate in column (1), I re-estimate (5) using alternate sources of average wages. Column (2) uses average wages of all individuals derived from the Quarterly Census of Employment and Wages (QCEW). Using these alternate data confirms the results in column (1): once one controls for initial city characteristics, the positive statistically significant impact of immigration on rent-to-income ratios disappears.

While columns (1) and (2) analyzed the wages for the average worker, one might expect that immigration would have differential impacts based on the skill level of workers. From the immigration literature, it is expected that, because immigrants are typically less skilled than the average native, a large proportion of immigrants will enter low-skill occupations and average wages in these industries will fall. If so, we would expect a more pronounced positive impact on the rent-to-income ratio when using average wages in these industries, *ceteris paribus*. Thus, column (3) uses the average wages of goods-producing industries reported in the QCEW as the measure of income in the rent-to-income ratio[24]. The results, however, do not support the theory above. Comparing the immigration impact in columns (2) and (3), we see that immigration is *more negatively* correlated with the rent-to-income ratio when we consider the average lower-

[24] Goods-producing industries include construction, manufacturing, and natural resources and mining (BLS).

skilled worker. In other words, immigrants are locating in cities where average low-skilled wages are rising faster than average total wages in high-immigration cities. As such, I take this as further evidence that immigrants are locating in cities that provide them the best economic opportunities, which happen to be large urban "superstar" cities where both wages (regardless of skill level) and housing prices are increasing.[25]

2.6 Conclusion

While one would expect a one-time population shift to increase housing prices, specification error in previous models makes causal inference difficult. Rents growth is larger in high-immigrant cities, but this relationship is not causal; rather, I show that previous estimates of the impact of immigration on housing prices are biased upward. The upward bias is due to a lack of controls for city-specific characteristics that 1) attract immigrants and 2) predispose these cities for higher rent growth. This result further compels one to question the validity of the shift-share instrumental variable when these city-specific factors are omitted. Recall, the main identifying assumption of the shift-share instrument was that immigrant inflows in the base year are not driven by omitted variables that are correlated with future rent growth. However, the positive correlation between the initial economic conditions and immigrant location choices in the base year suggests that past immigrants were also attracted to large, growing cities. Omitting these city characteristics leads the shift-share instrument to be correlated with the error term and the impact of immigration to be inconsistently estimated.

Once one controls for initial conditions, the impact of immigration decreases significantly and is no longer statistically significant from zero. Although point estimates are imprecisely estimated, it is clear that the true impact of immigration on rents is significantly less than the 1%

[25] This fact is confirmed using several other definitions of income measuring average wages of different demographic groups. In this analysis, which is available upon request, both low-skilled and high-skilled wage measures were used. The results suggest that a negative correlation between the rent-to-income ratio regardless of the wage measure, which is further evidence that high-immigration cities were predisposed to larger (relative) rent and wage growth.

reported in previous studies. In fact, the results of in Table 2.6 suggest that the impact of a 1% increase in overall housing demand is around 0.45%. Lastly, the analysis of the rent-to-income ratio strengthens the previous argument. Using several measures on income, it is shown that immigrant inflows are consistently negatively correlated with changes in the rent-to-income ratio. This negative correlation implies that following an immigrant inflow, average wages grow more quickly than rental housing prices. This relationship holds using average total wages and proxies for average unskilled wages. As this seems to defy the underlying theory in the labor literature, these results are not taken as causal; rather, as evidence that immigrants are choosing to locate in cities experience positive economic shocks.

As immigrants, both past and present, are attracted to large urban cities and these cities experience higher future rent growth, it seems that this is not a story of immigrants causing rents to grow faster; instead, this is merely a story about where immigrants choose to locate. Past immigrants located in cities that provided them the best economic opportunities. These cities were large, urban areas rich with cultural amenities, thriving economies, and increasing populations. As a result, housing prices were higher. Then, new immigrants follow suit. However, these new immigrants did not cause housing prices to increase faster; rather, these cities were predisposed to faster rent growth.

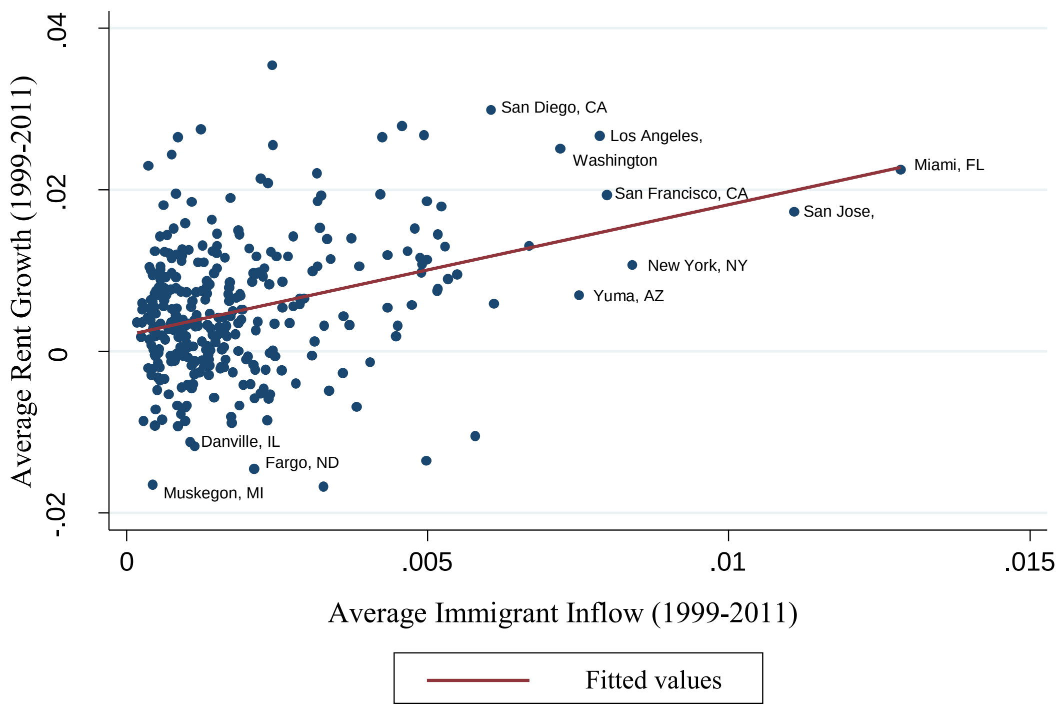
The implications of this result are far-reaching. First, these results provide evidence that the shift-share instrumental variable approach for dealing with the endogeneity of immigrant location choices may not be appropriate without controls for city-specific characteristics. While this is shown to be true in an analysis of the housing market, the results in Table 2.7 suggest the same problem may exist in labor studies. Thus, the results provide support to the national labor market approach to analyzing the impact of immigration on wages. As immigrants tend to locate in cities with faster wage growth, analyzing local labor market impacts of immigration on native outcomes, without controlling for city characteristics, will bias estimates toward zero.

In the urban literature, we should not expect immigrant inflows to have a differential impact on housing prices than any other one-time population increase. There has been extensive discussion since the beginning of the Great Recession that immigrants will help to “bring back” the housing market. While this is true in the sense that immigrants add to housing demand, there does not seem to be inherent differences between immigrants and natives. Along the same lines, the results also contribute to the migration literature. The common result in this literature is that the main (and in most cases, the only) determinant of immigrant settlement decisions is the fraction of the existing population that is foreign-born. However, it has been shown here that both past and present immigrants are attracted to cities with thriving economies with growing wages and housing prices. Thus, the migratory response to the existing share of immigrants in the population may be the joint impact of both cultural amenities and these initial city characteristics.

Ultimately, more research is needed in this area before definitive conclusions can be reached about the true impact of immigration on the housing market. One potential shortcoming of the above analysis is the use of metropolitan areas as local housing markets. It is well known that immigrants tend to cluster in certain states and metropolitan areas; however, it is also likely that immigrants cluster *within* metropolitan areas. Thus, in using the CBSA as the unit of analysis, we may be masking any effect on rents as these impacts are averaged across the entire CBSA. I address this in chapter 4 of this dissertation.

Figures and Tables

Figure 2.1: Rent Growth and Immigrant Inflows



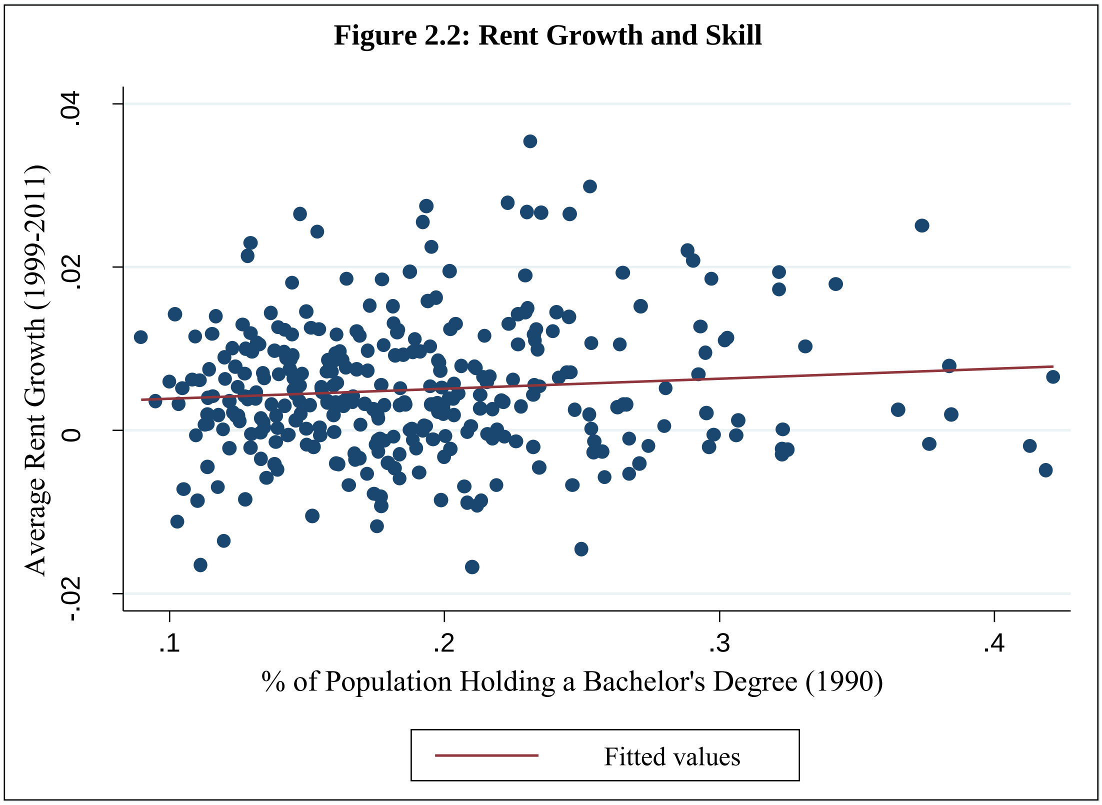
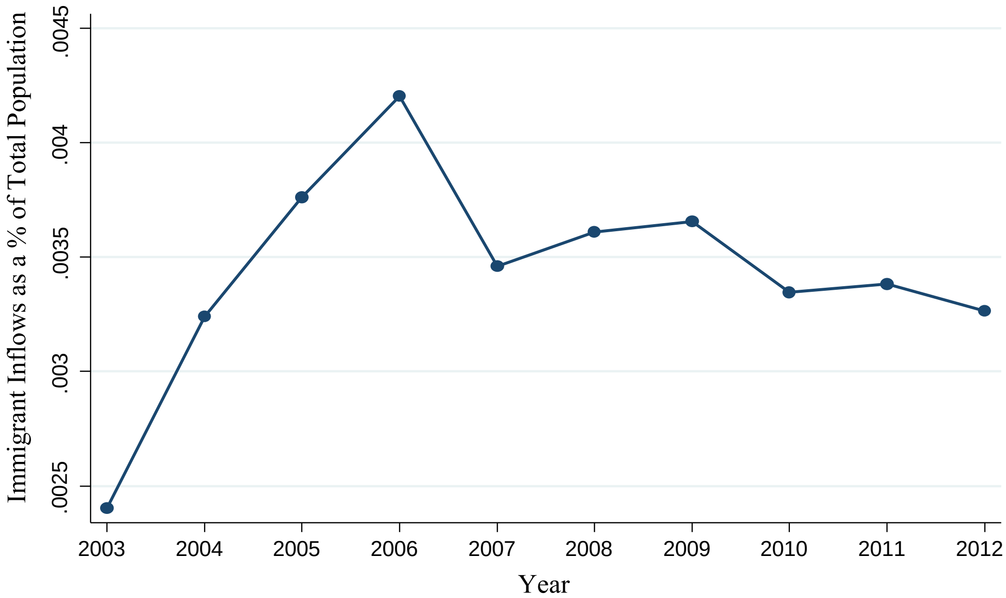


Figure 2.2: Rent Growth and Skill
Average Rent Growth (1999-2011)
.04
.02
0
-.02
.1
.2
.3
.4
% of Population Holding a Bachelor's Degree (1990)
Fitted values

Figure 2.3: National Immigrant Inflows, 2003-2012



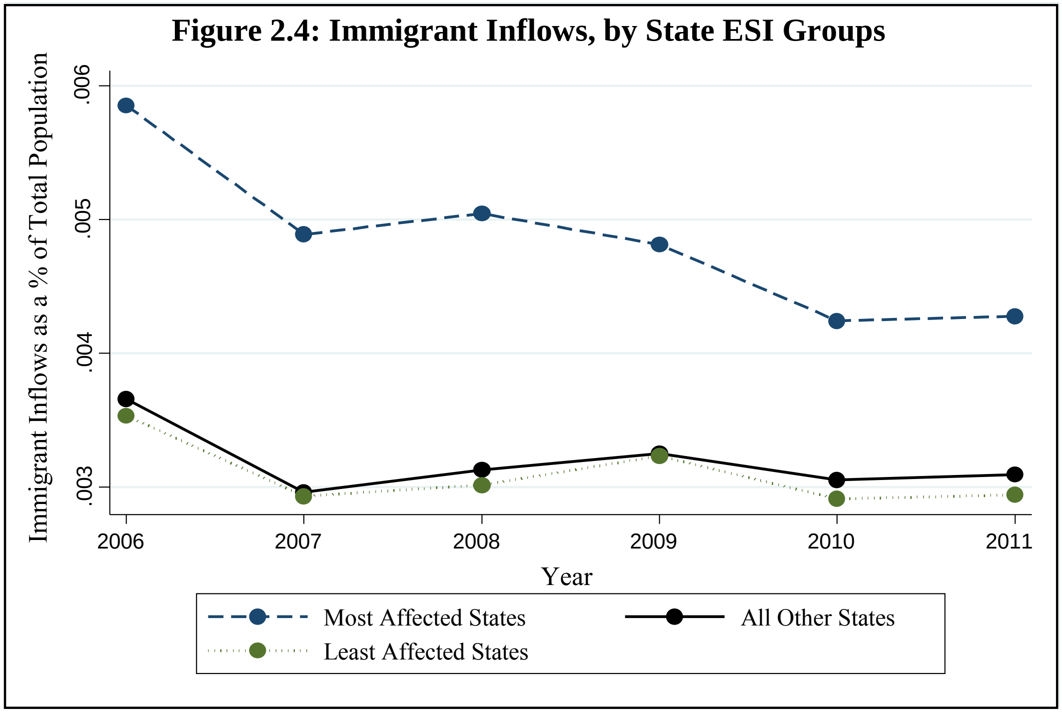


Figure 2.4: Immigrant Inflows, by State ESI Groups
Immigrant Inflows as a % of Total Population
.006
.005
.004
.003
2006
2007
2008
2009
2010
2011
Year
Most Affected States
All Other States
Least Affected States

Table 2.1: Descriptive Statistics (2010)					
Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Total Population	325	777,053.50	1,691,680	55,212	19,567,410
Real FMR (Constant 40th Percentile)	325	784.97	202.55	546.16	1656
Real FMR (Unadjusted)	325	781.90	197.50	546.16	1656
Immigrants	325	3,005.59	12,889.28	22	186,086
Immigration Impact	325	0.0021	0.0018	0.00017	0.0154
Immigrant Share (1995)	325	0.0027	0.0134	0	0.2144
% of Pop with Bachelor's (1990)	325	0.1905	0.0621	0.0896	0.4214
Murder Rate, per 1000 population	325	4.3391	3.1873	0	20.8321
Land Area	325	2700.79	2880.46	145.59	27278.47
Average January Temperature	325	35.9846	12.1993	4.4	66.8
Average July Humidity	325	56.8031	16.1934	14	80
Unemployment Rate	325	0.0946	0.0272	0.0380	0.2616
Per Capita Income	325	36,340.77	6,205.52	20,946	71,768
Real Monthly Wages, BEA	325	3398.96	571.63	2439.30	7449.18
Real Monthly Wages, QCEW	324	3232.56	634.80	2168.30	7592.69
Real Monthly Wages, Good Prod	324	4121.75	929.07	2026.33	10478.82
Rent-to-Income Ratio, BEA	325	0.2294	0.0417	0.1563	0.4666
Rent-to-Income Ratio, QCEW	324	0.2432	0.0499	0.1525	0.5089
Rent-to-Income Ratio, Good Prod	324	0.1956	0.0575	0.1066	0.5175
% Housing Stock Built Pre-39 (1990)	325	0.1639	0.1044	0.0072	0.4993
% Total Earnings from Farms (1990)	325	0.0248	0.0321	0.0005	0.2256
Rent Growth (1980-90)	325	0.0386	0.1290	-0.5517	0.3693
Log Per Capita Prop Tax Rev (1997)	325	6.6783	0.4648	5.1394	7.8753
Log Per Capita Sales (1992)	325	10.9068	0.3051	9.4086	12.0878
FMR (1990)	325	795.36	179.01	454.43	1640.88
Price-to-Rent Ratio (1990)	325	166.52	42.08	104.06	348.93
Change Real Average Constr Wages	325	-0.0070	0.0504	-0.3243	0.3412
Predicted Employment Growth	325	-0.0062	0.0033	-0.0222	0.0080
WRLURI	325	-0.2169	0.7507	-1.7647	4.3353

1. All dollar values are 2010-constant dollars, adjusted using the CPI-U.

Table 2.2: Immigration and Rents – Replication of Saiz (2007)		
	(1)	(2)
	OLS	2SLS
VARIABLES	$\Delta\ln(r_{kt})$	$\Delta\ln(r_{kt})$
Immigration Impact	1.425***	1.314***
	(0.347)	(0.428)
Unemployment Rate (t-1)	-0.126***	-0.123***
	(0.0331)	(0.0338)
Δ Per Capita Income (t-1)	0.0129	0.0125
	(0.0313)	(0.0310)
% Pop with at least Bachelor's (1990)	-0.0116	-0.0103
	(0.00866)	(0.00937)
Murder Rate (2000)	0.000176	0.000171
	(0.000179)	(0.000178)
Log Land Area (1990)	0.000463	0.000505
	(0.000577)	(0.000586)
Log Mean January Temperature	0.00795***	0.00807***
	(0.00118)	(0.00121)
Log Mean July Humidity	0.000847	0.000852
	(0.00128)	(0.00128)
Initial CBSA Variables?	No	No
Year Fixed Effects?	Yes	Yes
Observations	4,225	4,225
R-squared	0.158	0.158

1. Each column represents a unique specification. The dependent variable is the change in the FMR of CBSA *k* at time *t*. Robust standard errors clustered by CBSA are reported in parentheses.

Robust standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table 2.3: Immigration and Rents – Preferred Model				
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
VARIABLES	$\Delta \ln(r_{kt})$	$\Delta \ln(r_{kt})$	$\Delta \ln(r_{kt})$	$\Delta \ln(r_{kt})$
Immigration Impact	0.258 $^{\lambda}$	0.264 $^{\lambda}$	0.257 $^{\lambda}$	0.179 $^{\lambda}$
	(0.506)	(0.511)	(0.476)	(0.504)
Unemployment Rate (t-1)	-0.137***	-0.136***	-0.139***	-0.139***
	(0.0379)	(0.0381)	(0.0492)	(0.0510)
Δ Per Capita Income (t-1)	0.00887	0.0115	0.0318	0.0337
	(0.0305)	(0.0303)	(0.0311)	(0.0310)
Bachelor Rate (1990)	-0.0182**	-0.0163*	-0.0195**	-0.0199**
	(0.00897)	(0.00911)	(0.00959)	(0.00980)
FMR (1990)	0.0125***		0.00973***	
	(0.00316)		(0.00366)	
Rent Growth (1980-90)		0.0174***		0.0148***
		(0.00489)		(0.00565)
Per Capita Sales (1992)	0.00206	0.00315*	0.00191	0.00280
	(0.00180)	(0.00175)	(0.00181)	(0.00174)
Per Capita Prop Tax Rev (1997)	-0.00124	-0.00129	-0.00106	-0.00115
	(0.00107)	(0.00107)	(0.00114)	(0.00116)
% Housing Stock Built Pre-39 (1990)	0.0112**	0.0160***	0.00902	0.0136**
	(0.00555)	(0.00541)	(0.00667)	(0.00665)
% Total Earnings from Farms (1990)	0.0320*	0.0297*	0.0191	0.0159
	(0.0167)	(0.0161)	(0.0164)	(0.0155)
WRLURI	0.000847	0.00105*	0.000603	0.000666
	(0.000661)	(0.000625)	(0.000690)	(0.000643)
Δ Average Construction Wages (t-1)	0.0120	0.0119	0.0101	0.0102
	(0.0158)	(0.0158)	(0.0154)	(0.0154)
Include Other Variables from Saiz (2007)	Yes	Yes	Yes	Yes
Initial CBSA Variables?	Yes	Yes	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes	Yes
Year-by-Region Fixed Effects?	No	No	Yes	Yes
Observations	4,221	4,221	4,221	4,221
R-squared	0.160	0.160	0.229	0.229

1. Each column represents a unique specification. The dependent variable is the change in the FMR of CBSA *k* at time *t*. The point estimates of other variables included in both Saiz's model and this model are omitted for the sake of brevity. Robust standard errors clustered by CBSA are reported in parentheses.
2. λ denotes that the point estimate is statistically different from the replication estimates of Saiz (2007) at the 5% level.

Table 2.4: Determinants of Immigrant Shares in Base Year

VARIABLES	(1) Immigrant Share 1995	(2) Immigrant Share 1994	(3) Immigrant Share 1993	(4) Immigrant Share 1992	(5) Immigrant Share 1991	(6) Immigrant Share 1990
Panel A						
Initial FMR (1990)	0.0123**	0.0132**	0.0128**	0.0104**	0.00526**	0.00596**
	(0.00491)	(0.00523)	(0.00526)	(0.00418)	(0.00215)	(0.00248)
% Housing Stock Built Pre-1939 (1990)	0.00391	0.00456	0.00424	0.00421	0.00219	0.00265
	(0.00739)	(0.00736)	(0.00653)	(0.00558)	(0.00282)	(0.00304)
% of Earnings From Farms (1990)	-0.0157	-0.0146	-0.0170	-0.0139	-0.00683	-0.00745
	(0.0111)	(0.0114)	(0.0108)	(0.00890)	(0.00450)	(0.00502)
Per Capita Sales (1992)	0.00798***	0.00802***	0.00762**	0.00611***	0.00303**	0.00339**
	(0.00268)	(0.00286)	(0.00299)	(0.00231)	(0.00120)	(0.00140)
Per Capita Proper Tax Revenue (1997)	0.000364	2.75e-05	-0.000406	-0.000228	-0.000144	-0.000282
	(0.00172)	(0.00185)	(0.00191)	(0.00148)	(0.000768)	(0.000894)
Observations	325	325	325	325	325	325
R-squared	0.103	0.102	0.104	0.102	0.097	0.097
Panel B						
Rent Growth (1980-90)	0.0199**	0.0210**	0.0202**	0.0166**	0.00841**	0.00956**
	(0.00875)	(0.00920)	(0.00896)	(0.00723)	(0.00373)	(0.00424)
% Housing Stock Built Pre-1939 (1990)	0.0102	0.0112	0.0106	0.00944	0.00484	0.00566
	(0.00968)	(0.00977)	(0.00881)	(0.00745)	(0.00379)	(0.00414)
% of Earnings From Farms (1990)	-0.00534	-0.00351	-0.00625	-0.00515	-0.00241	-0.00246
	(0.00848)	(0.00863)	(0.00819)	(0.00675)	(0.00338)	(0.00374)
Per Capita Sales (1992)	0.0093***	0.0094***	0.0090***	0.0072***	0.0036***	0.0040**
	(0.00298)	(0.00322)	(0.00340)	(0.00262)	(0.00136)	(0.00160)
Per Capita Proper Tax Revenue (1997)	0.000348	3.41e-05	-0.000385	-0.000226	-0.000143	-0.000284
	(0.00162)	(0.00175)	(0.00183)	(0.00140)	(0.000730)	(0.000853)
Observations	325	325	325	325	325	325
R-squared	0.107	0.105	0.107	0.105	0.101	0.101

Table 2.5: Alternate Proxies for Initial Economic Conditions

	(1)	(2)	(3)	(4)
	FMR Growth	Med Gross Rent	Commute	Price/Rent
VARIABLES	Δ FMR	Δ FMR	Δ FMR	Δ FMR
Immigration Impact	0.486	0.0367 $^{\lambda}$	0.0741 $^{\lambda}$	0.236 $^{\lambda}$
	(0.455)	(0.530)	(0.500)	(0.522)
FMR Growth (1983-90)	0.00133			
	(0.00556)			
Initial Median Gross Rent (1990)		0.0150**		
		(0.00586)		
Average Commute (1990)			0.000816***	
			(0.000206)	
Price-to-Rent Ratio (1990)				0.00538*
				(0.00301)
Per Capita Sales (1992)	0.00277	0.00209	0.00257	0.00242
	(0.00178)	(0.00184)	(0.00166)	(0.00173)
Per Capita Proper Tax Revenue (1997)	-0.000741	-0.00229*	-0.000356	-0.000572
	(0.00114)	(0.00122)	(0.00110)	(0.00114)
% Housing Stock Built Pre-1939 (1990)	0.0107	0.0196***	0.00897	0.00946
	(0.00663)	(0.00741)	(0.00631)	(0.00655)
% Total Earnings from Farms (1990)	0.0162	0.0216	0.0341**	0.0159
	(0.0166)	(0.0162)	(0.0154)	(0.0162)
% Pop with at least Bachelor's (1990)	-0.0154	-0.0265***	-0.0139	-0.0166*
	(0.00991)	(0.0102)	(0.00969)	(0.00966)
Observations	4,221	4,221	4,221	4,221
R-squared	0.228	0.229	0.229	0.228

1. All specifications use the full preferred model. Other point estimates are omitted for the sake of brevity.
2. Robust standard errors, clustered by CBSA, are reported in parentheses.
3. λ denotes that the point estimate is statistically different from the replication estimates of Saiz (2007) at the 5% level.

Robust standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table 2.6: Impact of Predicted Employment Growth on Rents

	(1)	(2)	(3)
VARIABLES	Δ FMR	Δ FMR	Δ FMR
Predicted Employment Growth (t-1)	0.516***	0.422***	0.465***
	(0.101)	(0.108)	(0.108)
FMR (1990)		0.00923***	
		(0.00347)	
Rent Growth (1980-90)			0.0170***
			(0.00515)
Per Capita Sales (1992)		0.00227	0.00285*
		(0.00166)	(0.00153)
Per Capita Property Tax Revenue (1997)		-0.000791	-0.00102
		(0.00113)	(0.00115)
% Housing Stock Built Pre-1939 (1990)		0.00889	0.0137**
		(0.00670)	(0.00649)
% Total Earnings from Farms (1990)		0.0195	0.0144
		(0.0160)	(0.0150)
% Pop with at least Bachelor's (1990)	-0.000759	-0.0223**	-0.0249***
	(0.00808)	(0.00929)	(0.00946)
Observations	4,225	4,221	4,221
R-squared	0.158	0.231	0.231

1. All specifications use the full preferred model. Other point estimates are omitted for the sake of brevity.
2. Robust standard errors, clustered by CBSA, are reported in parentheses.

Robust standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table 2.7: Housing Affordability			
	(1) Average Wages Per Job, (BEA)	(2) Average Wages, (QCEW)	(3) Good Producing Industries, (QCEW)
VARIABLES	$\left(\frac{Rent}{Avg\ Wage}\right)$	$\left(\frac{Rent}{Avg\ Wage}\right)$	$\left(\frac{Rent}{Avg\ Wage}\right)$
Immigration Impact	-0.349	-0.287	-0.677
	(0.522)	(0.460)	(0.697)
Unemployment Rate (t-1)	-0.0231	-0.00314	-0.0569
	(0.0360)	(0.0350)	(0.0455)
Δ Per Capita Income (t-1)	-0.0811***	-0.0789**	-0.0425
	(0.0298)	(0.0314)	(0.0401)
Rent Growth (1980-90)	0.0110**	0.0143**	0.0216***
	(0.00555)	(0.00584)	(0.00636)
Per Capita Sales (1992)	0.00663***	0.00514***	0.00727***
	(0.00213)	(0.00197)	(0.00226)
Per Capita Proper Tax Revenue (1997)	-0.00102	-0.000883	4.49e-05
	(0.00114)	(0.00117)	(0.00141)
% Housing Stock Built Pre-1939 (1990)	0.0211***	0.0142*	0.0190**
	(0.00713)	(0.00739)	(0.00930)
% Total Earnings from Farms (1990)	-0.00230	-0.00126	0.0339*
	(0.0146)	(0.0133)	(0.0181)
WRLURI	-0.0232**	-0.0242**	-0.0267**
	(0.00933)	(0.00952)	(0.0117)
% Pop with a Bachelor's (1990)	-0.000116	-8.26e-05	0.000146
	(0.000632)	(0.000661)	(0.000813)
Observations	4,225	4,216	4,216
R-squared	0.306	0.303	0.232
Immigration Impact (Baseline Model)	**0.815****	**0.746****	**1.002****
	(0.390)	**(0.345)**	**(0.489)**

Robust standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

3. Immigration and Native Wages: A New Look

3.1 Introduction

According to labor theory, the question of how immigration impacts native wages seems like a straightforward one. Using a simple labor market model of supply and demand it is easy to show that as labor supply increases, the average market wages will fall, *ceteris paribus*. While economic theory suggests a clear cut answer, empirical evidence rarely supports the theory. In fact, most empirical work suggests immigration has a negligible negative impact, or even a slight positive impact, on the wages of demographically comparable natives.[26] Several arguments can be made as to why the empirics fail to match the economic theory. First, immigrant location decisions are endogenous, such that characteristics of local labor markets may be driving immigrant location decisions. This endogeneity may take several forms. Immigrants may choose to locate in high wage cities, natives may respond to immigrant inflows by moving, or firms may reallocate capital to high-immigrant cities in order to take advantage of the abundance of cheaper labor. To alleviate this concern, Borjas et al. (1997) suggested that the analysis move away from analyzing local labor markets; rather, researchers should use national-level data and treat the entire US as one labor market. Second, Aydemir and Borjas (2011) suggest that sampling error leads to attenuation bias. Due to the nature of the model, even small levels of measurement error can have large impacts on the estimated coefficients.

Even when one treats the US as a single labor market, past studies fail to compare immigrants to demographically comparable natives that will directly compete in the labor market. It is in this area that the present paper will contribute to the existing literature. It has become standard in the literature to analyze the impact of immigration on similarly skilled natives within cohorts defined by education and work experience. This approach, pioneered in the immigration literature by Borjas (2003), implicitly assumes that within these cohorts, immigrants and natives

[26] Borjas (1994) and Kerr and Kerr (2011) provide comprehensive reviews of this literature.

are perfect substitutes. Recently, however, the assumption of perfect substitutability has been challenged, and estimates suggest that a degree of *imperfect* substitutability exists between immigrants and natives within these cohorts (Card, 2009; Ottaviano and Peri, 2012; Manacorda et. al, 2012). As pointed out by Ottaviano and Peri (2012), this fact is nontrivial. If immigrants and natives are imperfect substitutes, then any wage effect of immigration would be concentrated on existing immigrants, not natives.

We claim that the incidence of imperfect substitutability arises due to the empirical model employed in previous studies – education is an imperfect proxy for overall skill level. To see this, consider three empirical regularities. First, there is a small literature examining the differential impacts of immigration on natives by race. In this literature, researchers stratify labor markets by education and race and find that immigration has a differential impact on black wages relative to white wages, but the evidence is mixed. Using the national labor market approach, Borjas et al. (2010) find that the impact of immigration is 33% lower on black men relative to white men. Altonji and Card (1991), who examine the impact of immigration on the wages of less-skilled (educated) workers using the area approach, find the opposite. Their first-differenced results (row 4 of Tables 7.8 and 7.9) suggest that a 10% immigration shock has a (roughly) 70% larger (more negative) effect on the average wage of less-skilled blacks than less-skilled whites. Though the results differ in the direction of the differential impact (which is likely due to differences in methodology and/or sample selection), it is clear that the impact of immigration is not constant across races within education groups. If education is a good proxy for overall skill, then one would expect the impact of immigration to be constant across all workers within an education group. The differential effects on black wages estimated in this literature, however, suggest whites and blacks are not perfect substitutes within education groups; thus, calling into question the use of education to stratify labor markets.

Second, there is significant wage dispersion *within* education groups (Levy and Murnane, 1992; Murnane, Willett, and Levy, 1995; Ingram and Neumann, 2006). This suggests that skills other than educational attainment are being rewarded in the labor market. Third, immigrants earn less than similarly educated natives (Bratsberg and Terrell, 2002; Bratsberg and Ragan, 2002; Ferrer and Riddell, 2008; Friedberg, 2000). This fact has been attributed to differing employment distributions across occupations and a lower return to education for immigrant workers. A similar argument is found in the geography literature when discussing the disparate value of "credentialized cultural capital" in determining immigrant/native wage gaps in Canada (Bourdieu, 1977; Reza, 2006). In this literature, credentialized cultural capital refers to the level of educational attainment. Although immigrants may have more credentialized cultural capital (higher educational attainment), domestic employers do not value education earned abroad as highly as education earned domestically.

Several feasible scenarios exist for the above differentials in returns to education. First, US employers may be simply discriminating against immigrants and either underpaying for their skills or refusing to hire immigrant workers (Borjas, 1990). While feasible, Bucci and Tenorio (1997) decompose the wage gaps between white natives and immigrants and find that the majority of the wage differential is simply US employers overvaluing native skills, not undervaluing immigrant skills. Similarly, Reimers (1983) documents that while discrimination may play a minor role in the wage gaps of Hispanic immigrants; differences in observable characteristics (i.e. language proficiency) explain the majority of the wage differences. Second, immigrants face differential returns to education because they are being "misplaced" in the labor market. That is, immigrants enter the US and are pushed toward jobs in which they possess too much education than the average worker. One reason for under-placement is that educational attainment is a subjective measure between countries and over time within countries. Peracchi (2006) notes that years of schooling or the schooling level may reflect varying levels of literacy in different countries. As researchers are interested in the effects of immigration on demographically comparable natives and many immigrants receive the entirety of their education abroad, stratifying labor markets by education may not identify immigrants and natives that directly compete in the labor market.

Because of differences in education standards across countries, immigrants may be misplaced because skills learned in the host country are not transferrable to the US labor market. While many cases of skilled immigrants taking unskilled jobs are reported in the national media, this fact is supported by the data (Mattoo et al., 2008; Neagu, 2009). Figure 3.1 confirms this phenomenon for low-skill occupations. The figure plots the percentage of native and immigrant workers with a high school degree or some college that work in low-skill occupations. Holding educational attainment constant, immigrants are more concentrated in less-skilled occupations and the gap is widening over time. Thus, it seems reasonable to assume that these workers will not directly compete in the labor market.

Further evidence of this phenomenon can be seen in Table 3.1 below. Table 3.1 presents the percent of workers that are classified as over-educated for their current job. Here, we define over-educated as having significantly more education relative to others working in the same occupation (more detail below). Table 3.1 uses occupation-specific education requirements from the ONET and matches these data to US Census micro-data from 1970-2010. Specifically, we use O*NET data for the required level of education needed to adequately perform the job. These data give a value of 1-100 for 12 education groups, which map directly to the percentage of the total employment in each occupation that holds said level of education. We collapse these 12 education groups into 7 categories: less than high school, high school graduate (or equivalent), some college – no degree, Associate's Degree, Bachelor's Degree, Master's Degree, and Doctorate/Professional Degree. We are interested in the share of the population who possess above average education for their current job. That is, they work in an occupation for which they hold significantly more education than the rest of the labor force in the given occupation. Using the data on required education, we group occupations based on the level at which the worker would be considered over-educated: over-educated if holding at least a bachelor's degree, over-educated if holding at least a master's degree, over-educated if holding a doctorate/professional degree, or never over-educated. We do not consider the case in which someone is over-educated for a job if they hold an associate's degree or some college but no degree. This follows from the wage structure literature which suggests that high school dropouts and high school graduates are perfect substitutes (Katz and Murphy, 1992).[27] The table presents over-education rates for natives, all immigrants, and immigrants who have been in the US for less than 5 years.

The differences in over-education rates by nativity are significant, especially for those persons holding advanced degrees. For all occupations, immigrants are nearly twice as likely to be over-educated for their job compared to natives. In occupations that generally require a bachelor's degree, 15.18% of the immigrant workers hold an advanced degree compared to 6.18% of natives. Column (3) displays over-education rates for newly arriving immigrants. Unsurprisingly, new immigrants have higher over-education rates than the entire immigrant population, which likely reflects the lack of transferability in immigrant skills upon entry (i.e. language skills). From the immigrant assimilation literature however, we would expect this rate to decline significantly as immigrants remain in the US. Figure 3.2 plots the over-education rates for immigrants across all occupations by length of time in the US and region of birth. Contrary to the assimilation hypothesis, the over-education rate for the entire immigrant population (solid line) is relatively constant over tenure in the US, around 10%. Because assimilation is affected by English proficiency and cultural similarities, we also plot over-education rates by region of birth. The constant over-education rate persists for immigrants from Central and South America

[27]Similarly, when grouping workers into high- and low-education groups, the authors allocate a share of the "some college, no degree" group to the low-education group. Thus, we follow this reasoning and assume that workers with less than a bachelor degree are not over-educated if they work in lower-skill jobs that typically do not require any college education.

(dotted line) and Asia (dashed line). Though the magnitudes are different, the underlying trend is the same. For European immigrants (dash-dot line) however, over-education rates are decreasing over time, consistent with positive occupational mobility associated with assimilation. While decreasing, the over-education rate for the longest tenured immigrants is still roughly 9%.

If it is the case that many immigrants are being “misplaced” in the labor market on the basis of education, then previous studies analyzing wage impacts within education-experience cells may not tell the whole story. That is, immigrants and natives with the same education-experience profile may not be directly competing in the labor market, which would explain the negligible impacts found in the existing literature. While the under-placement scenario is the main focus, the discrimination scenario is not without merit. As Reimers (1983) indicated, discrimination plays a minor role in the immigrant-native wage gap. Thus, if this discrimination is in the form of employers preferring to hire native workers, this may force more immigrants into occupations for which they are over-educated.

For these reasons, we argue a better measure of labor market competition is to stratify the labor market by occupation. While this seems like a logical empirical test, existing studies incorporating occupations as a proxy for skill are relatively sparse. To my knowledge, only three such studies exist. Camarota (1997) uses one CPS cross-section to estimate the impact of immigration on wages within occupations and finds that a 1% increase in immigration will decrease the wages of the average native worker by 0.5%. However, the use of a single cross-section and small within-occupation sample sizes, make causal inference difficult. Card (2001) estimates city-specific impacts of immigration on occupational wages for 175 cities using 1990 US Census data and finds that the immigration inflows of the 1980’s decreased wages in low-skilled occupations in high-immigration cities by no more than 3%. Orrenius and Zavodny (2007) use CPS data from 1994 – 2000 and INS immigration data to estimate the impact of immigration on native wages in 3 broad occupation categories. The authors estimate that the change in immigrants over the data period decreased wages in low-skilled, manual occupations 0.8% and had no impact for medium-skilled and high-skilled occupations.

The present study improves upon past research in several ways. First, following Borjas and Katz (1997) and Borjas (2003), we move away from the area studies of Card (2001) and Orrenius and Zavodny (2007) and treat the U.S. as one national labor market. Area studies have been criticized because they implicitly assume that native labor and capital do not adjust across labor markets in response to immigration. If the existing population relocates inputs to areas (or occupations) less affected by immigration, then the impact of immigration will be underestimated. Second, we construct occupation groups defined using skill data from the O*NET. Previous studies using occupations have relied on broad Census-defined occupation groups. The advantage of using the O*NET data is that we are able to construct occupation groups with a greater degree of homogeneity in overall skill level, regardless of nationality and citizenship status, than those using either education groups or broad occupation classifications.

The rest of the paper is structured as follows. Section 3.2 outlines the data and the methodology used to define occupation groups. Section 3.3 outlines the potential problems with stratifying labor markets by education when analyzing the impact of immigration on native wages. We first analyze differences in employment shares of immigrants and natives along skill distributions. The results suggest that immigrants are underrepresented (overrepresented) in communicative (manual/physical) task intensive occupations. This result holds for the entire population and *within* education groups. Next, we analyze the differences in the rate of return to education paid to natives and immigrants. We show that immigrants are paid a lower rate of return than natives and this leads to a heavier concentration of immigrants in low-wage jobs. As discrimination has been shown to play only a minor role in immigrant-native wage gaps, this suggests that similarly educated immigrants and natives work in different jobs. Section 3.4 presents the empirical methodology and results similar to those in Borjas (2003). The results confirm the intuition above. When we stratify labor markets by occupations, the impact of immigration is nearly twice as large as those found in the existing literature. This result is robust to several different definitions of occupation groups and when we control for selection problems associated with occupations. In section 3.5, we address the concern that the use of occupation-defined skill groups may introduce bias. Using the traditional education-experience skill cohorts, we show that the impact of immigration on the wages of demographically comparable natives within *education* groups is quantitatively similar to the estimated impact when using cohorts defined by occupational skill. As such, the impact on wages is muted because immigrants and natives are imperfectly substitutable within education groups. Section 3.6 concludes.

3.2 Data

We draw from several data sources in this paper. Labor supply and wage data are from the 1960, 1970, 1980, 1990, and 2000 PUMS of the U.S. Census, and the 2009, 2010, and 2011 PUMS of the ACS. The ACS data are pooled together to form a single 2010 cross-section. Following the work of Borjas (2003), we restrict our sample to men, aged 18-64, who earned positive wage income. A full description of both the employment and wage samples can be found in the Data Appendix.

We sort workers into skill groups based on potential experience and occupation. As is customary in this literature, we calculate potential experience based on educational attainment. It is assumed that workers with less than a high school diploma enter the labor market at 17 years old, workers with a high school diploma or GED enter the labor market at 19, workers with some college enter the labor market at 21, and those with a college degree enter the labor market at 23. Following Borjas (2003), we limit the sample to men who have 1-40 years of potential experience and group workers into 5-year potential experience groups (i.e. 1-5 years of potential experience, 6-10 years, etc.).

3.2.1 Occupation Groups

The occupation groups constructed in this paper follow generally from a recent paper by Peri and Sparber (2009). We assume that occupations are distinguished by two occupation-specific indices of task intensity: manual task intensity and communicative task intensity. Individual occupations are then grouped based on their relative communicative-to-manual task intensity.

Occupation-specific task indices are constructed using the Department of Labor's O*NET survey, which provides comprehensive data on characteristics of occupations. The O*NET content model is partitioned into several different domains, each providing different worker-specific and occupation-specific data. Unlike Peri and Sparber (2009), we make use of *both* worker-specific data on abilities, knowledge, and skills *and* occupation-specific data on work activities to generate these task intensity indices (throughout the rest of the paper, we will refer to all four of these measures as "skill groups").[28] Table A1 of the Appendix lists each skill used in constructing the task intensity indices.

One challenge when working with occupations over this many Census years is that occupation classifications change over time. Additionally, O*NET data are assigned to 2000 SOC (standard occupation classification) occupations. To remedy this problem, we use a modified occupation classification developed by Autor and Dorn (2013) (AD classification, hereafter). This occupation classification system creates a consistent, balanced panel of occupations across all years. To construct the occupation groups used in this paper, we merge skill data from the O*NET survey to the AD classification and group occupations on the basis of their occupation-specific skills.

[28] Peri and Sparber (2009) rely solely on "abilities" from the O*NET survey.

The O*NET data assigns each skill a score for importance (I) with a range of 0-5 and a score for level (L) with a range of 0-7 for each occupation.[29] To create the occupation-specific skill index, we first standardize the importance and level scores such that each has a range of 0-100. Then, we create a normalized "task-intensity score" (TS) for each skill by multiplying the standardized importance score and standardized level score – a higher task-intensity score suggests a given task is more important to performing a given occupation. We then calculate the average manual and communicative task-intensity score for each skill group and occupation. For example, within the worker ability domain, both physical abilities and psychomotor abilities are classified as manual abilities. Thus, for each occupation, we calculate the average manual task-intensity score by averaging the task-intensity of physical and psychomotor abilities. Lastly, the final manual (communicative) task-intensity score is the average of all skill group specific manual (communicative) task-intensity scores. Analytically, the manual task intensity index for each occupation (j) is calculated as[30]:

$$(1) \qquad M_j = \frac{1}{n}\sum_i \left(\overline{TS}_{ij}\right) \quad \forall \ i = (Ability, Knowledge, Skill, Work\ Activity).$$

For each occupation in the AD classification, we create the ratio of communicative task intensity to manual task intensity, which is the basis for defining our occupation groups. From this ratio, we construct three occupation classifications based on the distribution of this skill ratio across occupations: 1) a four occupation group classification where each group is a quartile of the distribution, 2) a five occupation group classification where each group is a quintile of the distribution, and 3) a six occupation group classification where each group is a sextile of the distribution.

---

[29] Importance and Level scores measure different aspects. There are occupations in which a given skill is equally important; however, one occupation needs to use the skill at a much higher level. An example from the O*NET is speaking ability for lawyers and paralegals. Speaking is important in both occupations; however, lawyers need a high level of speaking skills to argue cases, while paralegals simply need an average level of speaking skill (https://www.onetonline.org/help/online/scales).

[30] Construction of the communicative task intensity index is constructed analogously.

As the above classifications are rather crude treatments of the data, we construct a fourth occupation classification that allows the data to determine the optimal cutoffs. One concern with the above classifications is the definition of manual skills. There are obvious occupations that require significant manual tasks relative to communicative tasks (i.e. construction laborers, miners, etc.); however, there are other occupations (i.e. dancers and performers) that have similar values of manual task intensity that are clearly not competing with construction laborers for jobs. While we attempt to control for this by using both the importance score and level score above, another feasible way to alleviate this problem is to first classify occupations into blue-collar and white-collar occupations. Then, we use cluster analysis to determine the optimal number of occupation groups.[31]

3.3 Occupation Groups vs. Education Groups

The concern of the present research is that by stratifying labor markets by education, researchers do not compare immigrants and natives that will directly compete in the labor market because 1) immigrants are under placed in the labor market and 2) immigrants and natives work in different occupations. Below, we present two empirical exercises that illustrate this point.

3.3.1 Misplacement of Immigrants in the Labor Market

To illustrate the first point, we provide an empirical analysis in the spirit of Dustmann et al. (2012). Specifically, we compare across the native wage distribution the actual immigrant earnings distribution to a counterfactual immigrant earnings distribution. The counterfactual distribution is the share of immigrants along the native wage distribution if immigrants were paid the same rates of return to observable characteristics as natives.

[31] It is determined that a five group occupation classification is optimal (based on maximizing the Bayesian Information Criterion (BIC)): two clusters in the blue-collar sector and three clusters in the white-collar sector. We also use several other methods and in almost all cases, the methods agree on the optimal number of clusters. These results are available upon request.

We construct the employment distributions using micro-data from the 2000 U.S. Census (IPUMS). Sample criteria are discussed in the Data Appendix. First, we estimate the rates of return to observable characteristics for *native* workers via a typical log wage model[32]:

$$(2) \qquad w_i = X_i\beta + \theta_k + \varepsilon_i;$$

where w_i is the log hourly wage for individual i; X_i is a vector of demographic variables including categorical variables for education and experience, an interaction of education and experience, race, and marital status; and θ_k is a vector of state fixed effects controlling for wage differentials across states. Next, the estimated coefficients are used to predict the wage for each *immigrant* in the sample. In other words, we predict the wage an immigrant would have earned had they received the same rates of return as a native worker. Once we have obtained the predicted wage, each immigrant in the sample is ranked according to their actual and predicted wage in the native wage distribution in year *t.*

Figure 3.6 below plots the kernel estimates of the *relative* density of the log odds ratio along the native wage distribution.[33] As we plot relative densities, the horizontal line at one represents the actual native density; thus, if the immigrant density is above one, immigrants are overrepresented in this portion of the native wage distribution (and vice versa). The dashed line represents the observed relative density for immigrant wages. The plot of observed wages suggests that immigrants are overrepresented below the 35th percentile of the native wage distribution. The dotted line represents the plot of the counterfactual relative density. The plot illustrates the potential problems with defining skill cohorts based on demographics. The differences in the actual density and the predicted density are significant and confirm the

[32] The model is estimated on male workers only. The regression is weighted by the person weight from the Census and robust standard errors are clustered by education and potential experience. Also, hourly wage is "Winsorized" such that the lower bound of hourly wage is 75% of the federal minimum wage in year t and the upper bound is 50 times the minimum wage in year t (Card, 2009).

[33] Because the variable of interest, the position of immigrants along the native wage distribution, is bounded between 0 and 1, kernel estimates on the untransformed variable would give misleading estimates at the extreme (Dustmann et al., 2012). To mitigate this concern we 1) estimate the kernel on the log odds ratio and 2) report the kernel estimates for the 10th-90th percentiles only.

discussion on misplacement of immigrants in the labor market with regards to educational attainment. First, based on observable demographics, too many immigrants reside in the lower tail of the native wage distribution. Second, while we actually observe immigrants in the bottom 35% of the native wage distribution, the counterfactual distribution suggests immigrants should be clustered from roughly the 20th to 60th percentiles.

Two plausible scenarios exist for the differences in the distributions in Figure 3.3. First, either U.S. employers undervalue foreign education or overvalue domestic education. While Figure 3.3 does not allow differentiation between these two scenarios, either one would lead to under-placement of immigrants in the labor market. Second, omitted variables are driving the differences. Namely, we are unable to control for English speaking ability in (2). Because we estimate (2) on the *native* population, English proficiency cannot be included as it does not vary within the native sample. While omitted variables are a threat to the interpretation of the *differences* in the distributions above, they would not alter the interpretation that stratifying the labor market via educational attainment is problematic in the context of immigration. To see this, consider two workers. One is a U.S. native who recently graduated with a bachelor's degree while the other is an immigrant with a recent bachelor's degree but limited English proficiency. It is not hard to imagine a scenario in which these two workers accept drastically different occupations although they have similar education and work experience. This fact would explain their relative positions along the native wage distribution, but it would not change the fact they do not compete in the labor market despite equal educational attainment and work experience. As such, we take Figure 3.3 as support for our claim that education-specific skill groups are problematic in the context of immigration.

3.3.2 Differences in Immigrant and Native Employment Distributions

Peri and Sparber (2009) suggest that immigrants have comparative advantage in manual/physical tasks while natives have comparative advantage in communicative tasks. As such, immigrants and natives sort into and specialize in occupations intensive in the task for which they have comparative advantage. If this occupational sorting exists *within* education groups, it may explain the negligible impacts of immigration estimated in previous models.

To test this, we examine the employment distribution of immigrants and natives along the distribution of occupation-specific skills. Figure 3.4 plots the percentage of total hours worked by immigrants and natives from 1970-2010 along the distribution of the ratio of the communicative task intensity index to the manual task intensity. The differences in employment are striking and make clear that immigrants and natives are distributed differently across occupation-specific skills. Relative to natives, immigrants are overrepresented in jobs that require more manual tasks and underrepresented in those jobs that require more communicative tasks.

While informative, this fact is only important in the context of this analysis insomuch as these differences persist within education groups. Figure 3.5 shows the distribution of employment shares for each of the four education groups typically found in the immigration literature (less than high school, high school graduate or equivalent, some college, college graduate with at least a bachelor's degree). For all four education groups, the result is the same: immigrants are overrepresented in manual task intensive occupations relative to natives while underrepresented in communicative task intensive occupations.

While the same general result holds within education groups, the differences between immigrant and native employment shares are modest. This result is unsurprising as the immigrant population is significantly more heterogeneous than the native population with respect to educational attainment and education quality. Countries differ in terms of school quality, curriculum, resources available to schools, and teacher standards (Peracchi, 2006). As such, one would expect the transferability of general education skills to differ based on an immigrant's country of origin. Figure 3.6, which plots employment shares along the skill distribution by region of birth, confirms this phenomenon.[34] Employment outcomes differ widely by region of birth and these differences are likely attributable to the English proficiency. European immigrants (dashed line) face similar labor market experiences as the native population (solid line); however, Asian and Central and South American immigrants face significantly different employment outcomes and are driving the differences in Figures 4 and 5. Asian immigrants (dotted line) are clustered around the median of the distribution (e.g. occupations within the service industry), while Central and South American immigrants (dash-dot) are concentrated at the lower tail of the distribution (e.g. manual task intensive occupations).

Ultimately, the results in this section complement the findings in the previous section. Education is a subjective measure of skill. Simply stratifying labor markets by education does not necessarily compare immigrants and natives who will directly compete in the labor market. Immigrants and natives cluster in occupations in which they have the comparative advantage. This holds within education groups and across the immigrant population. Stratifying labor markets by occupation will form labor market cohorts with a greater degree of homogeneity with respect to skill in which immigrants and natives are perfect substitutes.

3.4 Empirical Methodology and Results

3.4.1 Empirical Model

As we are estimating the impact of relative labor supply of different skill groups on the structure of wages, the empirical model is derived from a theoretical framework of the demand side of the labor market. Assuming output is produced using a CES production function where labor and capital are separable, the relative wage of a given skill group is a function of 1) the

[34] For the sake of brevity, we only display the high school graduate and some college education groups. However, the general result holds for the other two groups as well. These figures are available upon request.

population share within the group and 2) a group specific productivity component.[35] Following Borjas (2003), this group-specific productivity component is absorbed by a collection of fixed effects:

$$(3) \qquad w_{ijt} = \beta s_{ijt} + \theta_i + \varphi_j + \tau_t + (\theta_i * \tau_t) + (\varphi_j * \tau_t) + (\theta_i * \varphi_j) + \varepsilon_{ijt}.$$

Here, w_{ijt} is the mean of the log weekly wage of natives in occupation group *i* and experience group *j* at time *t*. s_{ijt} is the share of immigrants in occupation group *i*, experience group *j* at time *t*, making β the coefficient of interest. The share of immigrants in a skill group (i,*j*) is represented as the percent of total hours worked by immigrants. The remaining controls are vectors of linear fixed effects for occupation group (θ_i), experience group (φ_j) and year (τ_t) to control for differences in average wages across occupation groups, experience groups, and over time. The interaction of occupation fixed effects with time ($\theta_i * \tau_t$) and experience group fixed effects with time $(\varphi_j * \tau_t)$ control for the fact that the impact of occupation or experience on average wages may change over time. Lastly, the interaction of occupation fixed effects and experience group fixed effects $(\theta_i * \varphi_j)$ controls for any differences in the impact of experience on average wages across occupation groups. Thus, the impact of immigration on native wages is identified by variation in immigrant shares within occupation groups and experience groups over time.

Equation (3) is estimated via OLS and the estimated coefficients are reported in Table 3.2. Table 3.2 is structured as follows. Each column/row represents a different specification of (3). The columns differ by skill group classification (i.e. Education-Experience, Occupation (4 group)-Experience, etc.). Row 1 reports the weighted estimates, where the weights are the number of observations used to calculate the average wage within a cell. Row 2 reports the corresponding elasticities from the estimated coefficients in row 1.[36] Rows 3 and 4 are

[35] For derivation of the model in the context of immigration, I refer interested readers to Card (2001) or Borjas (2003).
[36] The share of immigrants within a skill group (s_{ijt}) in Eq. 3 is not in log form rather an approximation. As such, we calculated the corresponding elasticities as in Borjas (2003).

specification checks. Row 3 presents unweighted estimates, while row 4 reports estimates when we include native labor force as an explanatory variable. Because the key explanatory variable is simply the immigrant share of total hours worked within a skill group, an increase in s_{ijt} would occur from either an increase in immigrant labor supply *or* a decrease in native labor supply. As such, the estimates in row 4 report the impact of s_{ijt} holding native labor supply constant.

First, column (1) reports estimates of (3) using the traditional education-experience classification found in the existing literature.[37] The baseline results are slightly lower than those found by Borjas (2003).[38] Focusing on the estimated elasticity in row 2, the results suggest that a 10% supply shock (an inflow of immigrants that increases total hours worked within an education-experience cohort by 10%) will reduce native wages by a modest 1.9%. Columns (2) – (6) use different occupation classifications in the estimation of (3). Columns (2) – (4) use occupation groups defined by the distribution of the communicative-to-manual task intensity ratio. When we group workers based on occupation-specific skills, the estimated impact of immigration is much larger. Again, focusing on the elasticities in row 2, the results suggest a 10% supply shock within a given occupation-experience cohort will decrease native wages by 7.2%, 5.6%, and 6.1%, respectively. Column (5) uses the clustered classification that first separates workers by white-collar/blue-collar status then groups workers based on occupation-specific skill. In this specification, the estimated impact of immigration is similar to those above and suggests that a 10% increase in the number of immigrants within a cohort will decrease the average native wage by 5.4%.

The results support the hypothesis that defining skill groups on the basis of education may attenuate the effects of immigration. By grouping workers into skill groups defined by

[37] In this specification, we use the four-group classification described above (Less than HS, HS grad, some college, college grad).

[38] Borjas (2003) estimates a point estimate of -0.572; however, this estimate does not use data from 2010 and uses CPS data for 2000. We used the methodology above and the same data described in Borjas (2003) and produced a very similar result. Thus, the methodology used above is consistent with the past literature.

occupation, the estimated impact on native wages is 2-3 times larger depending on specification. From rows 3 and 4, the results are not sensitive to using weights or controlling for native labor supply. What is not clear from the estimates in columns (2)-(5) is why the results are larger when using the occupation-defined skill groups. Is it the fact that skill groups are defined on the basis of occupation-specific skills or are the estimates driven by the use of occupation-defined skill groups in general?

To test this, we estimate (3) using the occupation classification system developed by Autor and Dorn (2013). The results are reported in column (6). Recall that these occupation groups mirror the typical occupation classifications used in the U.S. Census and are not defined based on occupation-specific skills.[39] If the results are biased downward simply because we use occupations to define skill groups, we would expect the impact of immigration to be similar to columns (2)-(5). When using this skill group classification however, the impact of immigration is significantly lower and similar in magnitude to the estimates when using education-based skill groups. This is unsurprising as AD rely on average educational attainment when constructing these groups, not occupation-specific skills.[40] To see this in the data, Figure 3.7 plots the share of total hours worked along the distribution of our skill ratio within AD occupation groups. Panels A and B are white-collar jobs (i.e. management occupations, etc.) and panels C and D are low-wage blue-collar jobs (i.e. construction). Though labor supply is skewed in the expected direction for each occupation group (white-collar occupations are skewed to the right hand side of the distribution, and vice versa), the variance is quite high. Because of this variability, it is reasonable to assume that, similar to skill groups defined by educational attainment, not all workers will directly compete in the labor market. Thus, we take the result in column (6) as

[39] The occupation groups are as follows: 1) Management/Professional/Technical/Financial/Public Security, 2) Administrative Support and Retail Sales, 3) Low-Skill Services, 4) Precision Production and Craft Occupations, 5) Machine Operators, Assemblers, and Inspectors, and 6) Transportation/Construction/Mechanics/Mining/Agricultural.
[40] In describing one of the occupation groups, the authors claim: “Technical, sales, and administrative support occupations cover a workforce that is on average better educated than any other occupation group apart from managers and professionals”.

support for the claim that occupation-specific *skills*, not occupations themselves, are the important component in constructing skill groups for which labor market competition is high.

3.4.2 Robustness Checks

While the estimates in column (6) of Table 3.2 suggest that occupation-specific skills are what are important when defining skill groups, at least two concerns arise when stratifying labor markets by occupation. First, we only observe those individuals who are presently working in a given occupation, not all workers who *could* work in these occupations given a change in local labor market conditions. Second, as occupational choice is conditional on labor market conditions, we would expect natives to switch occupations in response to an immigrant inflow. In both cases, these selection issues would cause us to overstate the impact of immigration on wages. Following Card (2001), one can alleviate these two concerns by treating a worker's occupation as a probabilistic outcome that depends on observable characteristics. In other words, each worker has some probability (π_j), based on observable characteristics, of working in occupation group 1,..., J. Then, total labor supply in a given occupation group is simply the sum of these probabilities.

To incorporate this idea into the above analysis, we first estimate the probability that an individual would work in a given occupation group using a flexible multinomial logit model for each year and for immigrants and natives separately. For both the native and immigrant specification, we control for potential experience, race, marital status, education, an indicator for living in a high-immigration state, and region fixed effects in all models. In the immigrant specification, we also control for country of birth and years in the U.S.[41] Next, we calculate the average log weekly wage of all workers who could work in a given occupation group, which is a weighted average using the predicted probabilities ($\hat{\pi}_j$) as weights. We then re-estimate (3) using

[41] A full description of these models and methodology can be found in the Data Appendix.

this measure of labor supply and wages and data from 1970-2010. The results are reported in Table 3.3.

Again, the estimated coefficients from the weighted regression are reported in row 1 and the corresponding elasticities in row 2. Column (1) of Table 3.3 reports estimates using the education-experience classification as a benchmark[42]. The benchmark elasticity is around -0.25. As expected, the estimated wage effect is lower (less negative) in columns (2) – (4) relative to the estimates in Table 3.2. While selection did bias the estimates in Table 3.2, the bias is small as the estimated impact of immigration is quantitatively similar to those in Table 3.2. Thus, when we account for the selection issues of occupational choice, we still conclude that a 10% immigrant supply shock will reduce average native wages by around 5%.

3.5 Who Competes With Whom?

The question of "who competes with whom?" in the labor market is the motivation for this paper. The motivation for stratifying the labor market into skill cohorts is to estimate the impact of immigration on the wages of demographically comparable natives. To this point, we have argued that occupation-experience cohorts are superior to education-experience cohorts because we define skill groups for which immigrants and natives directly compete in the labor market. That is, immigrants and natives with similar work experience are perfect substitutes within occupations while imperfect substitutes within education groups. While this has been shown to be true above, two additional concerns arise from the above methodology. First, there may be some concern regarding the seeming arbitrariness with which we define the number occupation groups.[43] Second, occupational choice of immigrants is likely endogenous. On one hand, immigrants may choose occupations based on favorable labor market conditions. If so, the

[42] The slight differences in the point estimates in Tables 2 and 3 stem from the loss of 1960 data.
[43] While this is a legitimate concern, we have estimated the above model using occupation classifications with as many as 10 occupation groups (dividing the skill distribution by centiles) and the underlying result does not change. These results are available upon request.

estimates in Table 3.2 would be biased upward. On the other hand, if immigrants are systemically under placed in the labor market and forced into lower wage jobs, then the estimates in Table 3.2 would be biased downward. It is this last concern that influenced the use of education-experience cohorts in the early literature.

An alternate way to approach the question of "who competes with whom?" is to let the data determine which native workers are demographically comparable to immigrants. In this section, we return to the standard education-experience skill cohort. The use of education-based skill cohorts in this section is advantageous for two reasons. First, switching occupations is significantly easier than switching education groups. As discussed above, there may be doubt as to whether the estimates in Table 3.2 result from defining more homogeneous skill groups or bias introduced by using occupations. Second, this analysis provides a test to our claim that imperfect substitutability within education groups is the primary force behind the counterintuitive results seen in the previous literature.

To identify demographically comparable natives, we begin by modeling the relationship between observable characteristics and the nativity of the worker. We first estimate, using the same data as above less the 1960 census[44], the following probit model on male workers for each year separately:

$$(4)\quad \Pr(I_i = 1) = \Phi(\beta X_i + \gamma OCC_i + \delta GEOG_i)$$

where I_i is a dummy variable equal to 1 if the worker is an immigrant; X_i is a vector of worker demographics including education, marital status, race, disability status, and a quadratic in potential experience; OCC_i is a vector of occupation-specific controls including AD occupation group fixed effects and industry fixed effects; $GEOG_i$ is a vector of geographic location controls

[44] The 1960 Census data does not have as rich of a set of demographics as the later Census'

including metropolitan status, state fixed effects, and a state-by-metro interaction.[45] We use the estimated coefficients to predict the probability of being an immigrant for all *natives* in the sample. We assume that native workers who more closely resemble immigrants in the data are also more likely to compete with immigrants in the labor market.

Table 3.4 below reports the average labor market and demographic characteristics of native workers in each of the four quartiles that reflect the intensity with which they will compete with immigrants in the labor market (i.e. Quartile 1 are the native workers least like immigrants in the data). Hours worked, weeks worked, potential experience, and the percentage of workers who are part-time are all fairly constant across quartiles. Perhaps counterintuitively, average weekly wages are *higher* among natives that are *more* likely to compete with immigrants in the data. However, this confounding result can be explained by the fact that those in quartiles 3 and 4 are much more likely to reside in metropolitan areas where wages are higher. In addition, native minorities are much more likely to compete with immigrants—the proportion of white workers decreases uniformly across the quartiles. Lastly, the differences across education, occupation, and industry groups are as expected. Native workers who are more likely to compete with immigrants are those with less education and work in low-skill occupations that require less communicative skills.

To estimate the impact of immigration on the native wages, we estimate the same reduced-form model in equation (3). The lone difference is the dependent variable is now the average log weekly wage of demographically comparable immigrants within a given education-experience cohort. The results are presented in Table 3.5 below. As a baseline, column (1) reports the estimates from above using education-experience cohorts. Again, the estimated elasticity is around -2. Columns (2) – (5) report the estimated impact on the wages of each

[45] I also estimated a more flexible specification of this model including a quartic in potential experience and a full set of education-by-demographic interactions and the results are quantitatively similar. These results are available upon request.

intensity quartile. For example, the dependent variable in column (2) is the average log weekly wage of natives in the lowest competition intensity quartile. Recall that by modeling skill groups on the basis of education and experience, the implicit assumption is that all workers within these skill groups are perfect substitutes. In theory, we would expect the impact of immigration on the wages to be the same across all columns because all natives should compete equally with immigrants in the labor market. From the estimates in Table 3.5, we see that the theory does not hold. The impact of immigration is increasing uniformly across intensity quartiles. The impact of immigration is strongest on the wages of quartile 4 – the native workers most likely to compete with immigrants in the labor market. The elasticity suggests that a 10% immigration shock would decrease the wages of these natives by 4.3%. The estimated elasticity is quantitatively similar to the estimates using occupation-experience groups in section 3.4. Therefore, it is not endogeneity of occupational choice that is driving the estimates in section 3.4; rather, it is the construction of a more homogeneous group of perfectly substitutable workers that directly compete in the labor market.

3.6 Conclusion

"Who competes with whom?" is an important question when trying to understand the impact of immigration on native wages. The existing literature assessing the impact of immigration on native wages has yielded contradictory results. The majority of these studies find little evidence that immigration has adversely affected labor market outcomes of natives. In this paper, we attribute these counterintuitive results to the fact that previous attempts have failed to compare immigrants and (demographically comparable) natives who directly compete in the labor market. We show that education is an imperfect proxy for skill in the labor market. Because immigrants and natives specialize in different skills and immigrants are often under placed in the labor market, immigrants and natives tend to cluster in different occupations.

When stratifying labor markets by occupation groups constructed based on occupation-specific skills, the estimated impact of immigration on native wages is 2-3 times larger than those using education-experience cohorts. The results are robust to changes in occupation classification and controlling for potential selection issues that arise when dealing with occupational choice. Overall, the estimates in section 3.4 suggest a 10% immigrant labor supply shock will decrease native wages by about 5%.

Lastly, we confirm that the impact of immigration on wages is muted when one uses education-experience skill groups. When we estimate the impact of immigration on the wages of demographically comparable natives *within* education-experience groups, the effect is quantitatively similar to those found when using occupation-experience groups. As such, the assumption found in the existing literature—that immigrants and natives are perfect substitutes within education-experience groups—fails to hold.

While the estimates suggest a nontrivial impact on native wages, these are in fact partial equilibrium effects ignoring potential cross-cohort effects of immigration. While immigrants may be perfect substitutes with native within occupation-experience cohorts, they are certainly complements in production to other skill cohorts. Because the degree of complementarity across skill cohorts will have potentially large effects on the general equilibrium effects of immigration on wages, future research should work to include the above into a general equilibrium framework to understand the total wage effect of immigration.

Figures and Tables

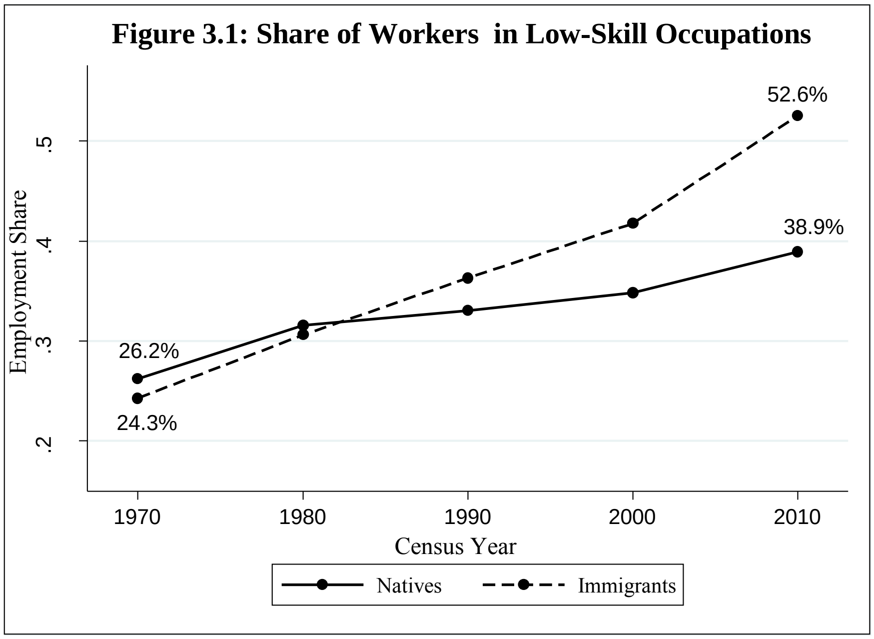


Figure 3.2: Over-Educated Workers, by Years in US and Region of Birth

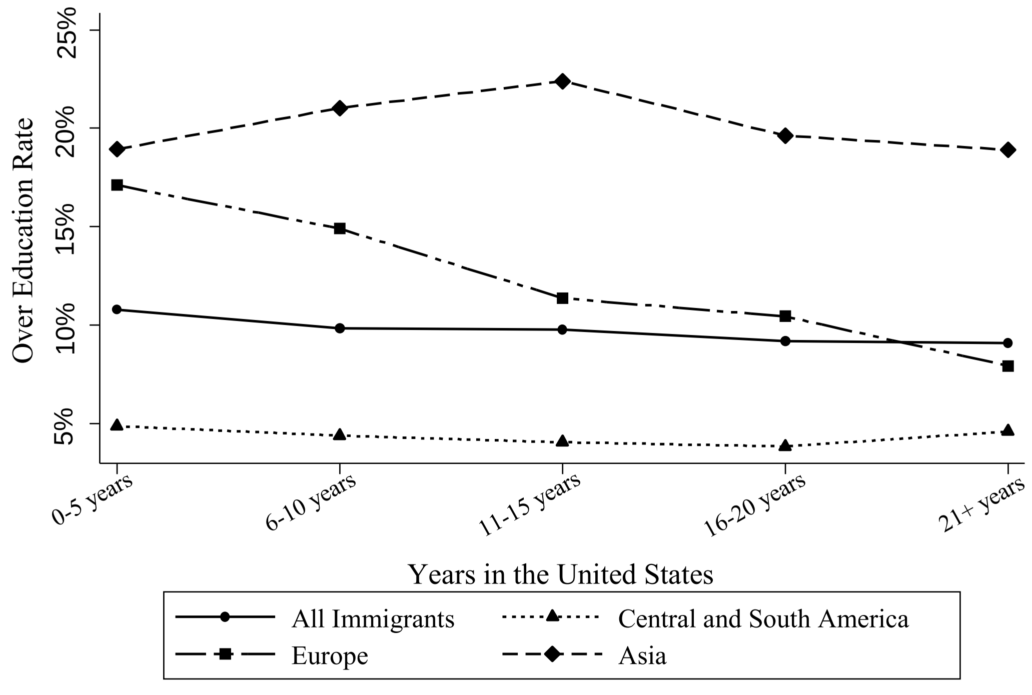


Figure 3.3: Actual vs. Predicted Positions of Immigrants Along Wage Distribution

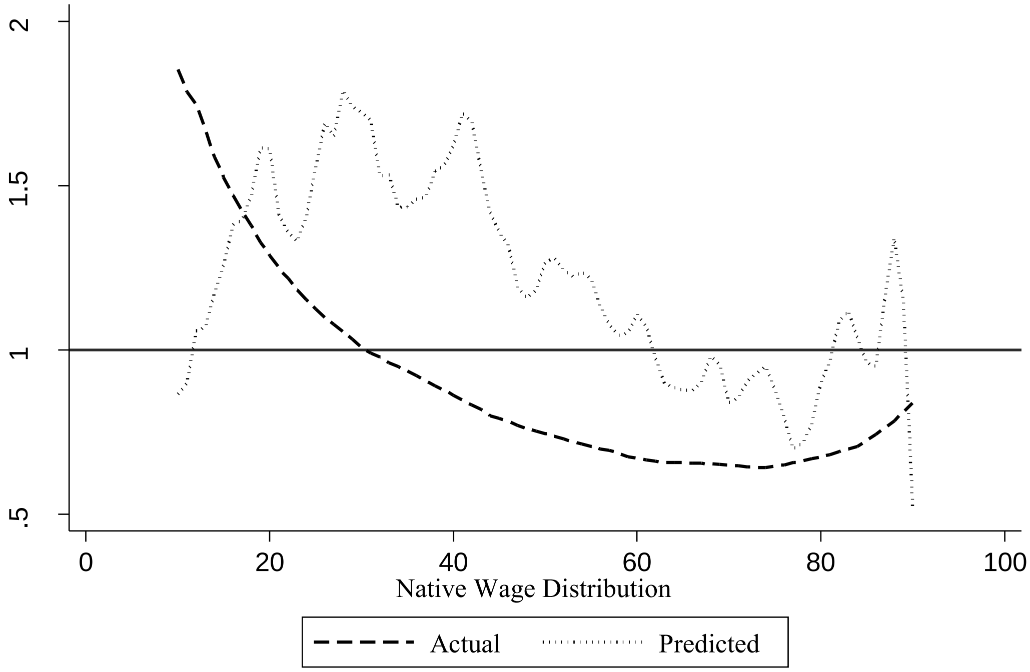
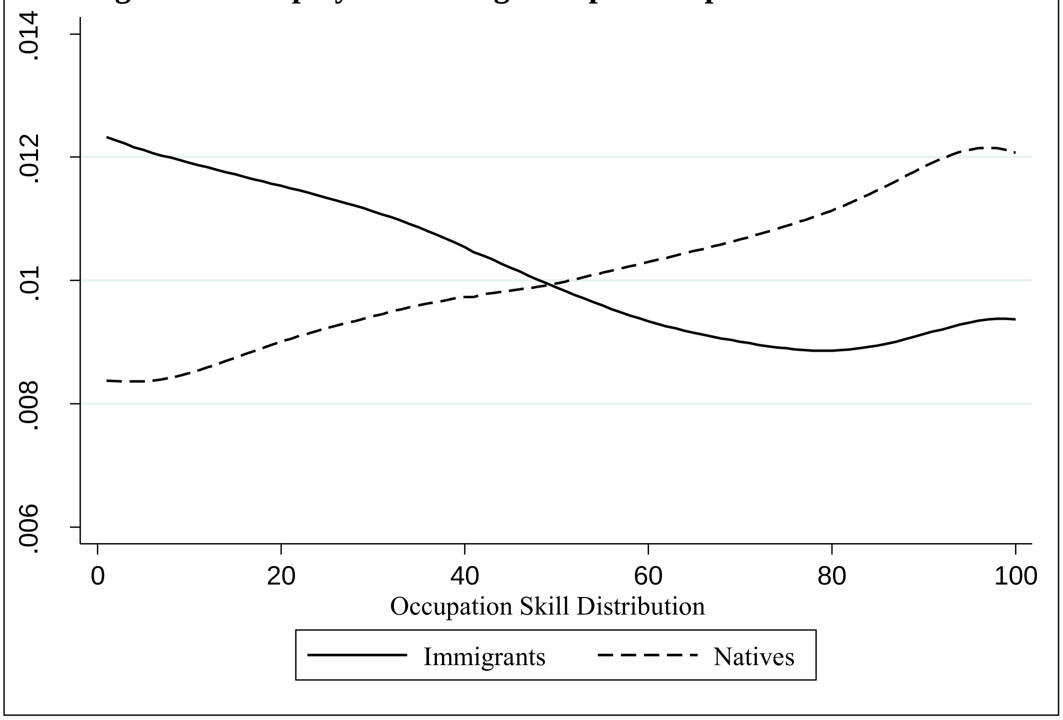


Figure 3.4: Employment Along Occupation-Specific Skill Distribution



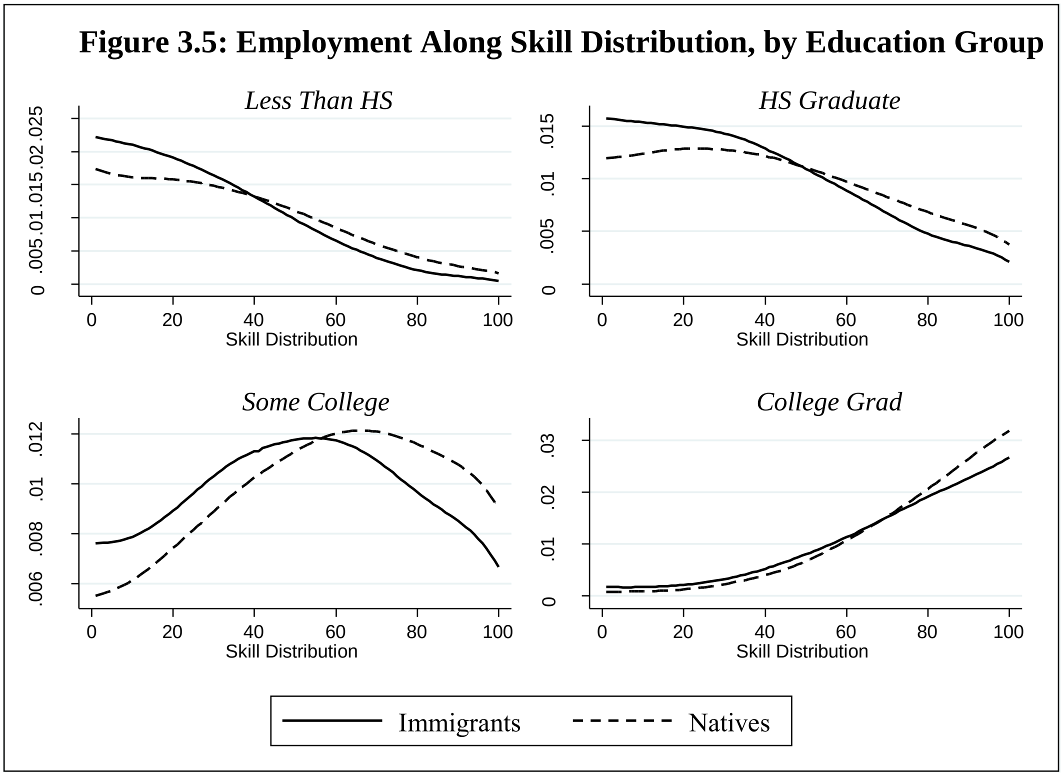


Figure 3.5: Employment Along Skill Distribution, by Education Group
Less Than HS
0 .005.01.015.02.025
0 20 40 60 80 100
Skill Distribution
HS Graduate
0 .005 .01 .015
0 20 40 60 80 100
Skill Distribution
Some College
.006 .008 .01 .012
0 20 40 60 80 100
Skill Distribution
College Grad
0 .01 .02 .03
0 20 40 60 80 100
Skill Distribution
Immigrants
Natives

Figure 3.6: Employment Along Skill Distribution, by Nativity

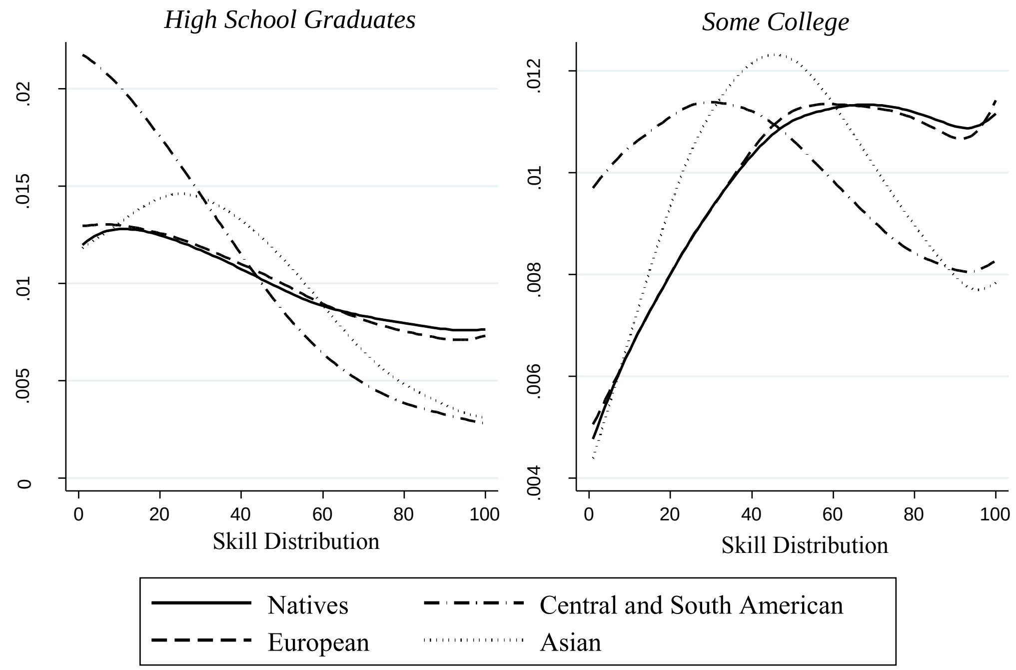


Figure 3.7: Employment Along Communicative-to-Manual Skill Ratio

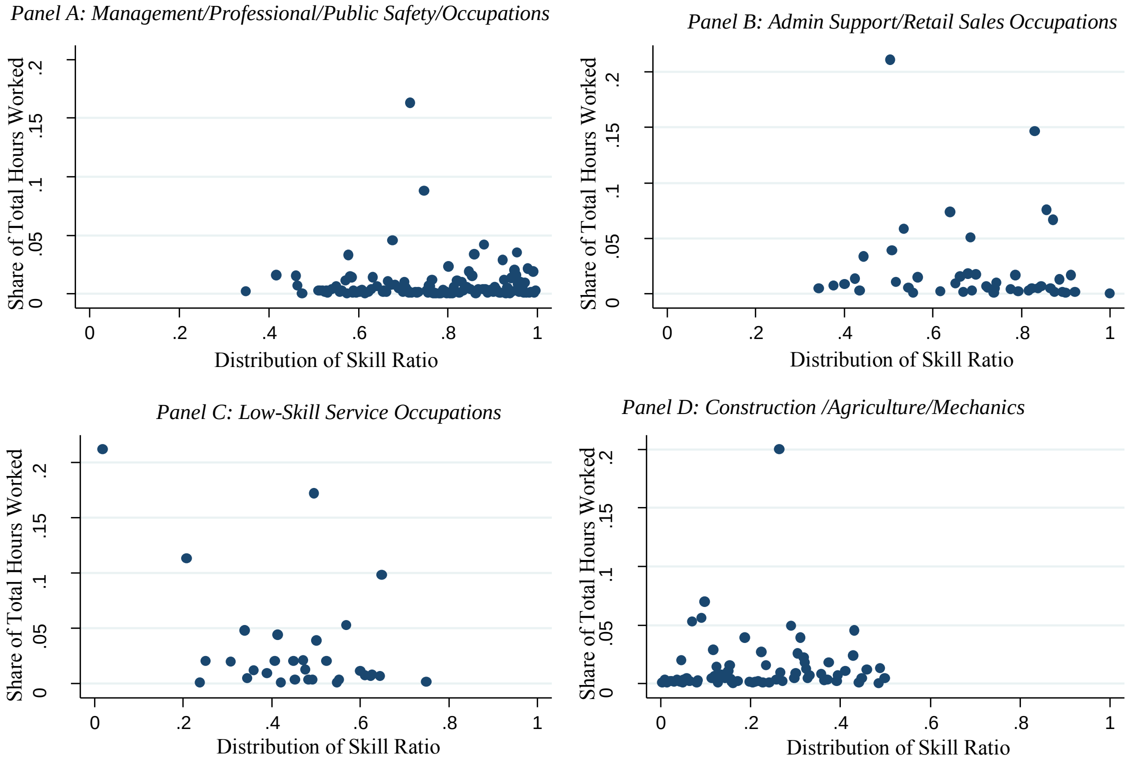


Table 3.1: Over-Educated of Natives and Immigrants, 1970-2010			
Occupation Group	**(1) % Over-Educated Natives**	**(2) % Over-Educated Immigrants**	**(3) % Over-Educated Immigrants (in US for less than or equal to 5 years)**
All Occupations	5.36% (6.33%)	9.25% (10.89%)	9.59% (11.06%)
Occupations where one is over-educated when holding at least a Bachelor's Degree	5.17% (6.67%)	7.55% (9.37%)	7.91% (10.02%)
Occupations where one is over-educated when holding at least a Master's Degree	6.70% (7.04%)	15.86% (17.81%)	18.95% (22.86%)
Occupations where one is over-educated when holding at least a Doctoral/Professional Degree	4.28% (4.43%)	12.74% (13.43%)	13.98% (14.75%)
Occupations where one is over-educated when holding at least a Masters or a Doctoral/Professional Degree	6.18% (6.48%)	15.18% (16.81%)	17.78% (20.74%)

1) Hours weighted averages reported in parentheses.

Table 3.2: Reduced Form Estimates of s_{ijt}

	(1) Educ-Exp	(2) Occ-Exp (Quartile)	(3) Occ-Exp (Quintile)	(4) Occ-Exp (Sextile)	(5) Occ-Exp (Cluster)	(6) Occ-Exp (Dom)
VARIABLES	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}	w_{ijt}
Weighted	-0.259*	-0.978***	-0.760***	-0.826***	-0.736***	-0.254
	(0.134)	(0.147)	(0.267)	(0.193)	(0.255)	(0.174)
Elasticities	-0.190	-0.718	-0.558	-0.606	-0.540	-0.186
Unweighted	-0.354***	-0.908***	-0.811***	-0.839***	-0.689**	-0.454***
	(0.103)	(0.171)	(0.252)	(0.161)	(0.334)	(0.149)
Includes Native Labor Force	-0.213**	-0.909***	-0.685***	-0.864***	-0.724***	-0.293
	(0.099)	(0.130)	(0.247)	(0.165)	(0.209)	(0.243)

1) Each column and row represents a unique specification. Each column differs based on the definition of skill (education or one of the occupation groups), while each row differs based on the label – weighted regression of (3), the corresponding elasticities of the weighted regressions, unweighted regression of (3), and the weighted specification including the native labor force as a regressor. The dependent variable is mean of the log weekly wage of natives in each skill group. The independent variable of interest is the share of total hours worked by immigrants in a given skill group. All specifications include year fixed effects, occupation (or education in column 1) fixed effects, experience group fixed effects, and interactions of all fixed effects. Robust standard errors clustered by skill group are reported in parentheses.

2) Weighted estimates in row 1 and 4 are weighted by the total number of natives used to calculate the average wage in each cohort.

Table 3.3: Robustness Check, Impact of Immigration (1970-2010)

VARIABLES	(1) Educ-Exp w_{ijt}	(2) Occ-Exp (Quartile) w_{ijt}	(3) Occ-Exp (Quintile) w_{ijt}	(4) Occ-Exp (Cluster) w_{ijt}
Immigrant Share (s_{ijt})	-0.307**	-0.741***	-0.681***	-0.623**
	(0.126)	(0.1105)	(0.1621)	(0.2661)
Elasticity	-0.255	-0.544	-0.500	-0.457
Observations	160	192	240	240
R-squared	0.997	0.999	0.998	0.999

1) Each column represents a unique specification. Each column differs based on the definition of skill (education or one of the occupation groups). The dependent variable is mean of the log weekly wage of natives that *could* work in a given skill group. The independent variable of interest is the share of total hours worked by immigrants that *could* work in a given skill group. All specifications include year fixed effects, occupation (or education in column 1) fixed effects, experience group fixed effects, and interactions of all fixed effects. Robust standard errors clustered by skill group are reported in parentheses.
2) All specifications are weighted using the total number of natives used to calculate the average wage in each cohort as weights.

Table 3.4: Native Worker Characteristics by Intensity of Competition with Immigrants				
	Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**
Observations (N)	**660,275**	**660,503**	**660,775**	**661,228**
Weekly Wage	$435.98	$479.31	$522.62	$491.26
Hours Worked per Week	40.59	40.95	41.15	40.93
Weeks Worked per Year	48.26	48.95	48.94	48.87
Part-Time Workers	21.08%	18.66%	17.87%	18.90%
Potential Experience	17.69	18.77	19.09	19.44
White	91.90%	87.54%	84.14%	62.11%
African-American	8.10%	12.43%	15.38%	16.54%
Live in Metropolitan Area	35.54%	77.17%	91.43%	95.11%
Education Groups				
Less Than High School	3.17%	4.32%	5.06%	8.25%
High School Graduate (or GED)	35.64%	39.31%	38.17%	43.85%
Some College	27.09%	26.74%	25.77%	27.33%
College Graduate	34.10%	29.63%	31.00%	20.57%
Occupation Groups (AD)				
Management & Professional	44.25%	43.22%	43.11%	37.63%
Administrative Support & Retail Sales	42.18%	36.70%	33.74%	30.56%
Low-Skill Services	8.27%	11.65%	12.83%	19.00%
Precision Production & Craft	1.27%	1.75%	2.15%	2.58%
Machine Operators & Assemblers	1.87%	3.87%	5.11%	6.36%
Transportation, Construction, Mining, Agricultural	2.16%	2.82%	3.07%	3.86%
Select Industry Groups				
Manufacturing	8.65%	11.74%	12.46%	13.66%
Business and Repair Services	2.61%	4.05%	4.94%	5.62%
Personal Services	0.95%	1.87%	2.70%	5.44%
Professional Services	42.38%	39.58%	37.84%	34.45%
Public Administration	9.63%	5.45%	5.38%	2.84%
Occupation-Specific Skill Ratio	6.14	6.05	6.07	5.50

Table 3.5: Impact on Demographically Comparable Natives					
	(1)	(2)	(3)	(4)	(5)
	All Natives	Quartile 1	Quartile 2	Quartile 3	Quartile 4
VARIABLES	w_{ijt}	w_{ijt}^{Q1}	w_{ijt}^{Q2}	w_{ijt}^{Q3}	w_{ijt}^{Q4}
Immigrant Share (s_{ijt})	-0.307**	0.099	-0.349**	-0.385***	-0.587***
	(0.126)	(0.144)	(0.134)	(0.137)	(0.104)
Elasticity	*-0.225*	*0.072*	*-0.256*	*-0.282*	*-0.431*
Observations	160	160	160	160	160
R-squared	0.997	0.997	0.998	0.998	0.999

1) Each column represents a different specification. The dependent variable is the in column (1) is the mean log native wage in a given education-experience group. The dependent variables in columns (2) – (5) are the mean log wages of natives in competition intensity quartile *j* in each education-experience group. The independent variable of interest is the share of total hours worked by immigrants in each education-experience group. Robust standard errors clustered by skill group are reported in parentheses.
2) All regressions are weighted. The weights are the sample size used to create the average log weekly wage in a given cohort.

4. Differential Impacts of Immigration Within Cities

4.1 Introduction

The impact of immigration on the housing market is an important one because housing expenditures are a large portion of the budget for most Americans. Even a modest increase in prices due to immigration can have significant impacts on the native population. Much of the existing literature analyzing immigration and the housing market has identified the impact of immigration on rents using metropolitan statistical area (MSA) median gross rents, treating the entire MSA as one homogenous "city" (Saiz 2003, 2007).[46] Ignoring the heterogeneity of neighborhoods within a MSA has led to an unsurprising consensus in the literature: immigrant inflows into an MSA lead to an increase in housing prices and rents. Because an inflow of immigrants is a positive shock to housing demand and we assume an upward sloping supply curve, one would expect increases in housing prices in the short-run. The present research expands on the existing literature and analyzes the impact of immigration *within* a metropolitan area.

The motivation for examining the more local effect of immigration on rents is two-fold. First, settlement patterns of immigrants in the U.S. are unique. We know that immigrants cluster in only a handful of states and certain cities within these states (Bartel, 1989). This clustering behavior has been explained as immigrants forming ethnic enclaves that provide cultural amenities to its residents. The explanation in the literature cited above is that it is this clustering behavior that bids up rents in high-immigration cities. Assuming the desire to reside in these ethnic enclaves is strong enough, the increased willingness to pay of immigrants leads to higher rents in the city. What is typically ignored, however, is that immigrants also cluster *within* cities.

Immigrant clustering within cities is illustrated in Figures 4.1 and 4.2. Figure 4.1 depicts census tract-level immigrant population shares for the Los Angeles and New York City CBSA's.

[46] This is also the methodology used in Chapter 2 of this dissertation.

The darker areas are tracts with higher shares of immigrants. In both Los Angeles and New York City, pronounced immigrant clustering is exhibited around the central cities and decreasing immigrant density in the suburbs.[47] Similarly, Figure 4.2 demonstrates immigrant clustering is consistent over time. Figure 4.2 illustrates tract-level immigrant shares for the years 2000 and 2010 for the Los Angeles CBSA. Again, the same pattern emerges: immigrants cluster near the city-center, and high-immigrant neighborhoods in 2000 were still high-immigrant neighborhoods in 2010. If increases in rents are driven by the preferences of immigrants to reside near ethnically similar households, Figures 4.1 and 4.2 suggest that the impact of immigration should not be uniform across cities. Instead, the increase in rents should be concentrated on these high-immigrant neighborhoods as new immigrants enter the housing market and bid up rents in these areas.

A second omission from the existing literature is the acknowledgement that households are mobile. As immigrants cluster within cities, natives may have incentives (which are discussed in more detail below) to move away from high-immigration areas of the city. Schelling (1972) was among the first to document the "tipping point" at which white populations abandon neighborhoods with growing black populations for the suburbs. This tipping point is measured as the share of the population which is black. If white populations feel similarly about immigrant neighborhoods, then the clustering of immigrants in the same neighborhoods may spur mass out-migration of white populations as these neighborhoods exceed this tipping point. If natives migrate from high-immigrant areas to other non-immigrant neighborhoods within the same city, we ignore an important dynamic when treating a metropolitan area as one homogenous unit. If this out-migration from high-immigration neighborhoods is severe enough, it is possible that the

[47] As Los Angeles and New York City are 1) the two CBSA's that receive the greatest annual immigrant inflows and 2) two of the largest cities in the US, one may be concerned that immigrant settlement behavior is different in these cities relative to other small CBSA's. To reconcile this, I also provide illustrations of immigrant clustering in two smaller, lower-immigration CBSA's (Lexington, KY and Louisville, KY) in Figure 4A.1 of the Appendix. The clustering of immigrants is equally pronounced in these cities as well.

impact of immigration on housing rents is lower in high-immigration neighborhoods relative to other low-immigrant neighborhoods.

The primary focus of this paper is to disentangle the impact of immigration on CBSA-level rents found in the existing literature. Because of the unique clustering of immigrants, differential preferences of natives and newly arriving immigrants for living in high-immigrant neighborhoods may segment the housing market within a CBSA. The presence of unique housing submarkets within a metropolitan area is well documented in the literature. Submarkets within metropolitan areas may occur due to either supply or demand-related factors (Goodman and Thibodeau, 1998). Across these unique submarkets, the implicit price of housing market characteristics or neighborhood amenities may not be constant (Goodman, 1978; Goodman, 1981). Metropolitan housing markets may be segmented along several different dimensions. King and Mieszkowski (1973) show that housing submarkets exist along racial lines. Schnare and Struyk (1976) argue that submarkets occur when household demand for a particular neighborhood characteristic (i.e. proximity to immigrants) is highly inelastic and these preferences are common among a large number of households within a metropolitan area. I argue that the inelastic demand of newly arriving immigrants to live near other immigrants will segment the housing market within CBSA's and the impact of immigration on prices will differ across these submarkets.

In this paper, I document the differential impact of immigration within a metropolitan (CBSA) housing market in two ways. First, I assume that markets are segmented by different characteristics of high-immigrant neighborhoods: high shares of foreign-born populations, low income, and low rent neighborhoods. Using census tract-level data, I show that an immigrant inflow into a city has a nonlinear effect within a CBSA. Specifically, the impact of immigration on rents is, on average, negative in high-immigration tracts. This differential effect is even more negative if I focus on high-immigration CBSA's.

Second, using a quantile regression framework, I analyze the impact of immigration along the rent distribution within a CBSA. The use of quantile regression is appropriate here due the settlement patterns of immigrants. Due to the clustering of immigrants in certain neighborhoods within cities, we also observe clustering along the distribution of housing rents. To see this, Figure 4.3 plots the share of immigrant households and the share of native households along the distribution of rents in 2000.[48] Relative to native households, immigrants are overrepresented from roughly the 10^{th} percentile to the 60^{th} percentile. With no out-migration of native households, one would expect the impact of immigration to be larger in this area of the rent distribution. If natives do respond by moving, however, the increase in housing demand associated with immigration (and corresponding increase in rents) would also be seen in the low-immigrant areas of the rent distribution. The results suggest the latter and confirm the findings using tract-level data. Immigration has a smaller effect on rents in portions of the rent distribution where immigrants cluster. While immigrant inflows are shown to have a positive impact on rents across the distribution, the impact of immigration on rents takes a U-shape. In fact, the quantile graph of the effect of immigration is roughly the inverse of the immigrant curve in Figure 4.3, which suggests that the impact is largest in areas with more native households.

Lastly, I show that decreased impact on rents in high-immigration portions of the rent distribution is due to out-migration of native households. Using census tract-level data for NYC, I show that immigrant inflows into NYC cause out-migration of white households from tracts with rents below the median, while higher-rent tracts experience growth in white households.

Just as economists have been concerned with the formation of the "black ghetto" over the last century, white flight out of high-immigration areas may suggest the formation of an "immigrant ghetto". Segregation among immigrants into ethnic enclaves can have positive short

[48] This plot uses household data from the 2000 decennial Census for all observations living in a CBSA. To construct this figure, I first generate a cumulative rent distribution within each CBSA. Then, I aggregate all immigrant and native households in each percentile of the rent distribution. The plot illustrates the share of total households in each percentile, by nativity.

term economic impacts on immigrants (Cutler et al., 2007). As the authors note, ethnic enclaves decrease the needed assimilation time by offering job opportunities and transportation. On the other hand, increased segregation of immigrants may have harmful economic effects in both the short and long term, especially for low-skill or less educated immigrants. These negative consequences include lower earnings (Cutler et al., 2007; Sousa, 2013), decreased human capital accumulation for immigrant children (Cascio and Lewis, 2012), and decreased English proficiency and decreased access to jobs and quality public services (Cutler et al., 2007). As each successive immigration wave has become less and less skilled, increased segregation due to white flight may have tremendous effects on overall economic outcomes for these immigrants.

The rest of the paper is structured as follows. Section 4.2 outlines the conceptual framework underlying the empirical analysis. This discussion is framed within the context of a residential segregation model in the spirit of Yinger (1976) and Boustan (2010). Section 4.3 provides supporting evidence into the differential impact of immigration within metropolitan areas. Specifically, I show that the impact of immigration within a CBSA is smaller in census tracts that had higher initial immigrant populations, lower incomes, and lower rents. Section 4.4 presents the quantile regression analysis, discusses potential data issues, and presents the results. Section 4.5 relates the quantile regression results to the out-migration of native households. Section 4.6 concludes.

4.2 Native Out-Migration and Segregation

White flight and urban segregation has been heavily researched area in economics, sociology, and demography. In the majority of this work, researchers examine the incidence of white flight in response to black migration and the segregation of black and white residents within an urban community.[49] Recently, however, a growing literature has emerged discussing

[49] This literature is far too large to cite all of the relevant papers. Schelling (1971), Yinger (1976), and Courant and Yinger (1977) provide seminal work in the area of racial segregation within an urban community. Bradford and

the incidence of white flight in response to immigration. As discussed above, immigrants display a unique and predictable settlement pattern across cities in the U.S. Because immigrants cluster within cities, the growing concentration of immigrants within neighborhoods has been shown to spur white (or native) flight.

To see how immigration may spur native out-migration and its impact on housing prices, I apply a simple residential segregation model (Yinger, 1976; Boustan, 2010).[50] To start, consider a city with a fixed number of native households. The city has both a city center and a suburban outer ring. Due to free mobility, utility of a native household cannot fall below $\bar{u}$, the utility of a native household living in the suburbs. Native household utility is written as:

$$U^N(p, i, z) = \bar{u}. \tag{1}$$

Utility is a decreasing function of both housing prices (p) and weakly decreasing in the share of the city population that is foreign-born (i). I do not specify the nature of the disutility associated with i, but discuss potential sources in more detail later in the paper. z is a demand shifter that represents local amenities. Housing prices in the city are a function of the total number of households in the city (N) and the sensitivity of housing prices to changes in N is determined by the elasticity of housing supply. Utility for immigrant households is defined as in (1) except immigrant household utility is increasing in (i). This follows from the discussion above regarding the clustering of immigrants to achieve cultural amenities. Spatial equilibrium is achieved when all native and immigrant households weakly prefer their present location to all other locations in the city and construction firms earn zero profits. The equilibrium housing price is denoted p^* and the equilibrium share of immigrants in the city is i^*.

Kelejian (1973) model white flight. In sociology, a good overview of the white flight hypothesis, I direct interested readers to Crowder (2000).

[50] Yinger (1976) defines a complete model of residential segregation. So as to not be redundant, the following model follows a more short-hand model similar to that found in Boustan (2010).

When new immigrants move into the city, the impact on housing prices and the number of native households that move out of the city will depend on the marginal utility with respect to *i* for native households. First, consider the case where native households do not receive disutility from immigrant households ($U_i' = 0$). Assuming supply is not perfectly elastic, an immigrant inflow will increase prices in the short-run to $\tilde{p}$. This increase in prices will induce some native households to flee to the suburbs and they will continue to do so until housing prices in the city return to p^*. Because p is solely a function of N, in order to maintain equilibrium it must be the case that each immigrant household into the city displaces exactly one native household. Thus, if natives do not show distaste for living near immigrants, immigrant inflows will displace native households at a rate of one-for-one and the long-run impact on housing prices in the city will be zero.

Now, consider the case where native households show distaste for living near immigrants ($U_i' < 0$). As before, the new immigrant inflow to the city will increase housing prices to $\tilde{p} > p$ and increase the share of immigrants in the city to $\tilde{\imath} > i$. Again, native households will respond to the increase in price and move to the suburbs until spatial equilibrium is restored ($U^N(p^*, i, z) = \bar{u}$). When natives receive disutility from increased prices *and* disutility from living near immigrants, the marginal native would still prefer the suburbs to living in the city even at equilibrium price levels as $U^N(p^*, \tilde{\imath}, z) < \bar{u}$. In this scenario, native householders will continue to move out of the city and total population falls below equilibrium. Thus, assuming housing supply is not perfectly elastic, native distaste for immigration, white flight will cause housing prices in the city will fall below equilibrium in the short-run.

In the discussion above, I do not specify the nature of the distaste associated with immigrants and how it may spur out-migration of native households. Crowder et al. (2011) outlines three main theories to explain the out-migration of natives in response to growing immigrant concentration. While each theory describes a different mechanism through which native out-migration is achieved, the underlying results are the same: large immigrant concentrations spur out-migration on native populations. The first theory, referred to as the ethnic flight theory, suggests immigrant inflows induce out-migration because immigrant inflows change the ethnic composition of a neighborhood (Clark and Blue, 2004; Saiz and Wachter, 2011). The premise behind this theory is purely racial and can be thought of as traditional "white flight". If native households prefer to live near culturally and racially similar households, the response of natives to immigrant inflows is purely racial.

The second theory is called the socioeconomic context theory. Like the ethic flight theory above, white flight occurs because of the proximity to large immigrant populations. Contrary to the ethnic flight theory, however, the social context theory suggests natives respond to changes in socioeconomic conditions of neighborhoods brought on by a large immigrant inflow, not the racial sentiment toward immigrants themselves. As pointed out by the authors, immigrants tend to be less educated with a higher incidence of poverty. As such, an increased concentration of immigrants in a neighborhood would lead to lower average income and if this decrease in income is correlated with neighborhood conditions (i.e. school quality, crime, etc.), then native populations flee high immigrant neighborhoods.

The last theory of white flight, the housing competition model, is related to the willingness to pay story told in the previous section. Upon entering a neighborhood, immigrants may change local housing market conditions. In the short-run, immigrant inflows into a neighborhood will cause an increase in prices which, in turn, may push natives out of the neighborhood in search for more affordable housing. Similarly, immigrant inflows may affect other aspects of the local housing market. It is widely known that homeownership rates are far lower for immigrants relative to natives. If immigrant inflows have an effect on rental/owner-occupied mix within a neighborhood and this is a source of disutility for native homeowners, natives may flee the neighborhood.

It should be noted that I do not differentiate between these theories in the analysis below. The data do not allow one to speak to the exact mechanism that spurs out-migration of native households. While identifying the motive for out-migration is not possible, the above discussion does provide ample support for the prior that immigrant inflows should have some effect on the migration decisions of native households in a neighborhood. Furthermore, the above theories have different implications for the impact of immigration on rents. If the housing competition model is the main mechanism that spurs out migration, then the impact on rents should be near zero in high-immigrant tracts. This corresponds directly to the case where natives show no distaste for living near immigrants discussed above ($U_i' = 0$). If out-migration is racially motivated or due to changes in socioeconomic conditions, then the impact of rents will be negative ($U_i' < 0$).

4.3 Differential Impact of Immigration Within Cities

This section examines the average impact on rent at the census tract level and finds that the impact is non-linear, supporting a model where there is negative utility for native households living near immigrants. The empirical model follows loosely from the model of Saiz and Wachter (2011). I estimate the impact of a CBSA-level immigrant inflow when accounting for the heterogeneity of neighborhoods. Here, as is customary in the literature, I use census tracts as a proxy for neighborhoods. Specifically, the model is:

(2) $$\Delta \ln\left(R_{j,k,t}\right) = \alpha I_{k,t} + \beta(I_{k,t} * X_{j,k,t-1}) + \delta H_{j,k,t} + \gamma Z_{j,k,t-1} + \theta_t + \varepsilon_{jkt}$$

$R_{j,k,t}$ is the average gross rent in a given tract (neighborhood) *j* within a CBSA *k* at time *t*. $I_{k,t}$ denotes the CBSA-level immigration impact variable, which is defined as the change in foreign-born population in year *t* divided by the CBSA population in year *t-10*. The interaction term $(I_{k,t} * X_{j,k,t-1})$ represents the interaction of the CBSA-level immigration impact and an initial neighborhood level characteristic that differentiates between high and low-immigrant tracts. I estimate four variants of the model with different definitions for $X_{j,k,t-1}$: two specifications include a measure of immigrant concentration, a third is an indicator equal while the third is an indicator for below average rents. As such, β is the coefficient of interest. Because $X_{j,k,t-1}$ are characteristics of high-immigrant neighborhoods, $\beta < 0$ would suggest the impact of immigration is lower in high-immigration neighborhoods (and vice versa).

$H_{j,k,t}$ is a vector of tract-level rental housing market characteristics including controls for age of structures, units in structures, rental vacancy rate, initial rent level in 1980, and other physical characteristics of the housing unit. Following Saiz and Wachter (2011), I include both lagged levels and changes in average housing characteristics. $Z_{j,k,t-1}$ is a vector of lagged neighborhood socioeconomic characteristics including the share of the population that is black, the share of the population with at least a bachelor's degree, among others. θ_t are year fixed effects.

Summary statistics are presented in Table 4.1 for all tracts, high-immigrant tracts, and low-immigrant tracts. High-immigrant tracts differ widely along housing unit characteristics, neighborhood characteristics, and demographics. High-immigrant tracts have significantly fewer single family units, housing units tend to be smaller, and average rents are lower. Similarly, the high-immigrant neighborhoods tend to be less desirable as there is less new construction and above average values of the neighborhood disadvantage index (NDI). The NDI is comprised of four individual parts: the unemployment rate among working-aged males in the neighborhood, the percent of total households that are female heads of household with children under 18 years old, the inverse of median household income, and the poverty rate (Hannon, 2005).[51] Less desirable neighborhoods have higher values of NDI. Lastly, high-immigrant tracts differ significantly along demographic lines. Households in these neighborhoods tend to be more

[51] To calculate this measure, each of the four components is standardized to mean 0 with a standard deviation of 1. Then, the NDI is simply the average of these 4 standardized components.

mobile. Larger shares of renter-occupied households, younger householders, and a smaller share of households with tenure greater than 10 years in their current dwelling are all characteristics of more mobile households (Quigley and Weinberg, 1977; Weinberg, 1979). The relative mobility of the households in high-immigrant neighborhoods lends credence to the white flight hypothesis in the previous section. Because newly arriving immigrants cluster in existing high-immigrant neighborhoods (Figures 4.1 and 4.2), these inflows will be concentrated on a more mobile population, increasing the likelihood of significant out-migration of native households.

4.3.1 Instrumental Variable

Estimating Eq. (2) via OLS will produce biased and inconsistent estimates because immigrant inflows into cities and neighborhoods are endogenous. As shown by Chapter 2 of this dissertation, immigrants locate in CBSA's that provide them the best economic opportunities. Because immigrants are locating in thriving cities rich in amenities and public goods, housing prices will increase irrespective of immigration. In this case, OLS estimates will be biased upwards. To deal with this endogeneity, I use an instrumental variable strategy based on country-of-origin similar to the one presented in Saiz (2007). I use INS data on newly arriving immigrants and source country-level data that are exogenous to CBSA-specific amenities to predict the number of new immigrants to the U.S. from each country in each year. To predict immigrant inflows from country *i* in year *t*, I estimate the following panel random effects model:

(3) $$m_{it} = \alpha X_{i,t-1} + \beta Z_{i,t-2} + \gamma V_t + \theta_i + \mu_{it}.$$

Here, m_{it} is the migration rate from country *i* to the U.S. in time *t*. $X_{i,t-1}$ is a vector of lagged source country-level characteristics including real GDP (relative to U.S. GDP), a measure of poverty defined as the inverse of per capita income, the share of the population that is between 15-19 years old, and the average annual immigrants sent to the U.S. over the previous 5 years. $Z_{i,t-2}$ is a vector of country-specific variables describing the political instability of the source country and military conflicts. Specifically, I include a dummy variable equal to 1 if the country underwent a regime change, a dummy variable equal to 1 if the country was involved in a major military conflict in year *t-2*, and a dummy variable equal to 1 if there was genocide in year *t-2*.

While similar to the instrument defined in Saiz (2007), the advantage of the present instrument is that Eq. (3) is more grounded in migration theory. Following Clark et al. (2007), I also control for changes in U.S. immigration policy that would directly affect the number of immigrants arriving from a given source country through the vector V_t. Specifically, I account for the number of refugee visas and diversity visas allotted to a given source region and the mass legalization of immigrants in the early 1990's that stemmed from the Immigration Reform and Control Act.

I present the estimates of the panel random effects model in Table 4A.1 of the Appendix and variable descriptions in Table 4A.2. All of the variables have the expected impact on migration rates. Countries with higher shares of young population, who are war torn, or experiencing a regime change all experience increased migration. The variables describing migration policy also have significant effects on migration. Eligibility for diversity and refugee visas has significant positive impacts on migration. This is important because some countries do not have complete data throughout the panel. For these countries, Saiz (2007) estimates the panel random effects model on country random effects and lagged migration. Here, with the addition of the immigration policy variables, I am able to include these variables in addition to lagged migration for these counties.

To construct the predicted migration rate from country *i*, I exclude the estimated random effects. As Saiz (2007) explains, these random effects may be correlated with factors that made it attractive to locate in cities where immigrants of that nationality clustered in previous years. Next, I convert the predicted migration rate into prediction immigration inflows.

Once I have backed out the number of imputed immigrants from each country and year ($\hat{M}_{i,US,t}$), I follow the traditional shift-share approach found in the literature to construct imputed immigrant inflows into each CBSA that are exogenous to local market conditions. To do this, I first calculate the number of newly arriving immigrants from each country *i* that located in each CBSA *k* in 1980 ($\omega_{i,k}^{1980}$). Because immigrants cluster in a predictable manner, I assume that CBSA *k* will receive the same share of total (imputed) immigrants from country *i* in every year after 1980. Using this initial share ($\omega_{i,k}^{1980}$) and the imputed immigrants ($\hat{M}_{i,US,t}$), I calculate the number of imputed immigrants from each source country *i* to CBSA *k* for every year after 1980. Then, the total imputed inflow of immigrants into a CBSA is simply the sum of the inflows from each country. Analytically, the annual imputed total immigrant inflow into CBSA *k* is calculated as:

(4) $$\hat{M}_{k,t} = \sum_{i=1}^{N} \left(\omega_{i,k}^{1980} * \hat{M}_{i,US,t} \right)$$

4.3.2 Estimation and Results

I estimate (2) using tract-level data from the U.S. Census, Summary Tape 3 from 1990-2010. Because tract definitions change over time, I use a publicly available crosswalk file from the US2010 Project to construct consistent 2010-defined tract-level data over time. Due to data limitations, I focus on the 1990-2010 period.[52]

As a baseline, I first estimate Eq. (2) without the interaction term via OLS and report the estimates in Column (1) of Table 4.2. The OLS estimates suggest that an immigrant inflow into CBSA equal to 1% of the total population will increase neighborhood rents by 0.58%, on average.

[52] While the crosswalk files match the data reasonable well in 1990 and 2000, these files do not perform as well for the earlier data There are roughly 30,000 more tracts in 2010 than in 1980 and before. The crosswalk file uses weights to aggregate the earlier tracts to the 2010 definitions. However, in 1980, I routinely calculate tracts with populations of 10 or less when using these weights. As such, the 1980 tracts are not comparable and cannot be used in the national setting. I do however use these 1980 data later in the paper when the analysis is restricted to only a few CBSA's. For these select CBSA's, I am able to match all of the tracts throughout the sample period.

Next, I estimate (2) via 2SLS (again, without the interaction) using the instrument described above and report the estimates in column (2). As expected, the OLS estimates were biased upward. Once I instrument for endogenous location choices of immigrants, the estimated impact of an immigrant inflow equal to 1% of the population is roughly half, around 0.27%. It is worth pointing out that this estimate is similar in magnitude to the estimates in Chapter 2 of this dissertation using CBSA-average rents and a similar time period. Columns (3) – (5) of Table 2 report the 2SLS estimates of the interaction specifications. Columns (3) and (4) report the estimates when CBSA-level immigrant inflows are interacted with indicators for above average immigrant concentration. In column (3), $X_{j,k,t-1}$ is a dummy variable equal to 1 if the tract share of linguistically isolated households is greater than the CBSA average. In column (4), $X_{j,k,t-1}$ is a dummy variable equal to 1 if the lagged foreign-born share of the neighborhood exceeds 10%.[53] I use two definitions of high-immigration tract because the share of foreign-born population may be confounded by the fact that children of immigrants are classified as natives in the data. The use of linguistically isolated households should mitigate this problem. Lastly, in column (5), $X_{j,k,t-1}$ is a dummy variable equal to 1 if the average tract rent is below the CBSA average in the previous period.

The results suggest that the impact of immigration on rents is nonlinear. In all four columns, the coefficient on the interaction term is negative and in most cases highly significant at the 1% level. In fact, in columns (3) and (4), the total impact of immigration in high-immigration tracts is negative. The negative effect of immigration is exacerbated if I limit the sample of tracts to those in the 100 CBSA's that received the largest share of immigrants over the sample period.[54] Table 4.3 presents estimates when I limit the sample to these CBSA's. For these high-

[53] This definition of immigration concentration follows from the tipping point models *a la* Schelling (1972). Specifically, Card et al (2008) show that for the majority of cities, the tipping point that will spur native out-migration is a minority share between 5-20%.
[54] This approach is common in the literature (see Saiz and Watcher, 2011). Because immigrants cluster in very few CBSA's, the variation in immigrant flows is much smaller in CBSA's that receive few immigrants.

immigrant CBSA's, the 2SLS estimates in column (2) suggests a negative impact on rents, on average. Though the average effect is negative, columns (3) – (6) again suggest this negative impact is driven by large negative effects in high-immigration tracts. The interaction term is highly statistically significant and negative when I use the foreign-born share of the population variables and the low-rent variable as characteristics for high-immigrant tracts.

The estimates in Tables 4.2 and 4.3 are in line with Saiz and Watcher (2011), who estimate the impact of a change in the neighborhood-level immigrant share of the population on the evolution of housing prices. The authors find that increasing the share of immigrants in a neighborhood by 1% is associated with a decrease in housing prices of around 0.25 log points. Because we know that new immigrants will locate in already high-immigrant tracts, the negative effect on rents is suggestive of native out-migration brought on, *in part*, by racial or socioeconomic factors.

4.4 Quantile Regression Framework

The estimates in section 4.3 suggest that immigrant inflows have a differential effect on rents within cities and the effect is actually negative (or marginally positive in one specification) in high-immigration neighborhoods. An alternate method for assessing the differential impact of immigration within a city is to use quantile regression, which estimates the impact of immigration along the distribution of rents. This approach has several advantages over the previous analysis. First, because I use micro-data from the U.S. census, I am able to better control for the quality of individual housing units. Although census tracts are fairly homogenous by definition, it is likely that rental units differ by quality within these tracts. If immigrant inflows are negatively correlated with housing quality, then the previous estimates will be biased downward. Second, and most importantly, the results in the previous section use arbitrary cutoff points to denote high-immigration tracts. Though many specifications suggested a negative effect of immigration in high-immigrant tracts, the results were inconclusive in other tracts because of insignificant main effects and/or interaction effects. In the quantile regression framework I do not have to use proxies for high-immigrant neighborhoods.

4.4.1 Empirical Model and Data

I start by modelling the rental price of housing similar to hedonic studies of the housing market. Rents are assumed to be a function of physical housing characteristics and neighborhood characteristics. Additionally, the neighborhood characteristics are decomposed into immigration inflows and other neighborhood characteristics. A linear model of this relationship is:

$$(5) \qquad r_{jkt} = \alpha W_{jt} + \beta Z_{kt} + \gamma I_{kt} + \theta_t + \varepsilon_{jkt};$$

where r_{jkt} is the log of reported gross rent of housing unit j in neighborhood k, W_{jt} is a vector of physical unit characteristics of the j^{th} unit, I_{kt} is the immigrant inflows into neighborhood k, Z_{kt} are all other neighborhood characteristics, and θ_t are year fixed effects.

Before I discuss the individual components in (5), I first discuss the data and potential problems that may arise. I use micro-data from the 1990 and 2000 from the U.S. Census (5% sample files) for the New York City CBSA only (described in more detail below). There are advantages and disadvantages to using Census micro-data in this analysis. While these data have the benefit of large sample sizes and more localized geographic data, the controls for housing unit characteristics and neighborhood amenities are limited. This concern could be alleviated by using the American Housing Survey (AHS); however, the sample size of the AHS is significantly smaller and the lowest level of identifiable geography is the MSA. Because I analyze a single CBSA, the use of AHS data is not feasible as there would be no variation in immigrant inflows.

I define neighborhoods as the state/county of residence. In a traditional hedonic framework, a neighborhood is typically defined as a census tract or census block group. In the more recent versions of the Census micro-data however, more local geographic data are omitted.

In these data, the lowest level of geography available is either the county of residence or PUMA. Because this analysis focuses on the New York City CBSA (NYC, hereafter), I choose to define neighborhoods at the county level as there are more identifiable counties than PUMA's. I am able to identify 24 individual counties within NYC, which provides sufficient variation in I_{kt}.[55] A second related problem in using these data are omitted variables due to a lack of data on unit quality and the broad definition of neighborhood.

Because of these issues, it should be noted that the model in (5) is not a traditional hedonic regression. In the traditional hedonic framework, the researcher is interested in estimating the implicit prices of housing market characteristics presumably to estimate either a constant-quality price index or consumer demand for housing (Sheppard, 2003). As such, parameter estimates for individual neighborhood effects are crucial. The primary concern of the model herein, however, is to effectively isolate the causal impact of immigration on rents that is independent of housing unit characteristics or quality and other neighborhood effects. From (5), if one believes that Z_{kt} sufficiently describes neighborhood conditions, then γ should indicate the pure neighborhood effect of immigration on rents. However, if key explanatory variables are omitted from W_{jt} or Z_{kt} and these are reflected in γ, then the estimated impact of immigration on rents is biased (Rubin, 1993). Due to the broad definition of a neighborhood, the main concern for the present analysis is disentangling the effect of immigration from other neighborhood effects. In a typical hedonic model, one controls for neighborhood effects by including control variables such as crime, proximity to parks, school quality, or other amenities of the neighborhood; however, I cannot explicitly control for such neighborhood amenities as census-tracts are not identifiable in the data. While county-level "neighborhood" characteristics are included, these are averages of tract-level characteristics and will disguise the variation in neighborhood amenities at the tract-level. Additionally, from the analysis in section 4.3, these

[55] The next highest count for a CBSA was 5 individual counties.

tract-level neighborhood effects are important. Because high-immigrant neighborhoods are less desirable on average (Table 4.1), omitting these variables from the above model will bias γ downward. As the vector Z_{kt} of county-level variables alone will not adequately control for the heterogeneity of census tracts within these counties, I make use of the within-county variation in individual demographics (detailed below) to control for these omitted variables.

To this end, the available controls are as follows. Immigrant inflows (I_{kt}) are defined as the change in the foreign-born population in the neighborhood from year *t-10* to year *t* divided by the total population in year *t-10*. Thus, γ is interpreted as: an immigrant inflow over the prior 10 years equal to 1% of the total population in the prior period causes rents to increase by γ%. The vector W_{jt} includes all physical unit characteristics available in the IPUMS. These variables include the age of the dwelling, the number of bedrooms, a dummy variable equal to 1 if the unit is a single family detached home, a dummy variable equal to 1 if the unit is in a building with 10 or more units, and indicator variables for lacking complete plumbing or kitchen facilities.

The vector Z_{kt} includes four county-level variables that control for economic and socioeconomic conditions of the county. First, I include for the neighborhood disadvantage index (NDI). Because the NDI describes the economic climate within a city and is shown to be correlated with crime, poverty, and unemployment, higher values of NDI should lead to lower rents. Second, I include the lagged share of the population that is black. Third, I include the lagged percent of the population with at least a bachelor's degree. Glaeser and Saiz (2004) show that cities with a more educated population experience increased growth over time due to productivity shocks. Last, I include a dummy variable equal to 1 if the county resides in the city center. This variable is included to pick up any omitted cross-county differences in housing prices such as average housing unit characteristics, proximity to public transportation, and lower commuting costs, among others.

In order to alleviate the concern of omitted neighborhood characteristics, I use householder demographics as a proxy for unobserved differences in neighborhood and housing unit quality. Because households of similar demographic characteristics tend to cluster within cities, any unobserved across-tract differences in neighborhood characteristics will be picked up by these demographic variables. These demographics include marital status, an indicator for being black, an indicator for being Hispanic, and a categorical variable for education attainment (less than HS, HS graduate, some college, and college graduate).

Figures 4.4 and 4.5 provide evidence that people cluster by education and race within New York City, supporting the inclusion of these demographics as proxies for unit and neighborhood quality. Figure 4.4 plots the share of total population with less than a high school diploma in Panel A and the share of total population with at least a bachelor's degree for census tracts in the 4 largest counties in NYC.[56] Similarly, Figure 4.5 plots these population shares by race. Both figures provide initial support for the use of demographics as proxies for unobservable differences in neighborhoods. Within counties, the population is very much segregated on both racial and educational lines.

In order for these controls to mitigate the effects of omitted variables, however, these demographics must also proxy for differences in housing quality. To see this, I make use of the rich data provided in the AHS. Table 4.4 reports average neighborhood and unit characteristics by educational attainment (columns 1-4) and race (columns 5-7). Each cell represents the average response for a given characteristic for all renter-occupied housing units residing in a metropolitan area. Prior to calculating the average response, I standardize the responses within metropolitan areas to be mean 0 and have a standard deviation of 1. Table 4.4, demonstrates that both neighborhood and unit characteristics differ in expected ways across both education and

[56] These counties include Bronx County, Kings County, New York County, and Queens County. I originally plotted the 5 main boroughs of NYC, but the inclusion of Richmond County (Staten Island) made the graphs illegible as they were too big to adequately see the sorting.

race. In most cases, respondents with low educational attainment and black respondents report significantly larger incidents of both neighborhood disamenities and unit attributes associated with low quality.[57]

As these demographic variables seem to be sufficiently correlated with differences in unit quality and neighborhood amenities *within* counties, I rewrite the linear model including the vector of householder characteristics of unit j (X_{jt}) as:

(6) $$r_{jkt} = \alpha W_{jt} + \theta X_{jt} + \beta Z_{kt} + \gamma I_{kt} + \theta_t + \varepsilon_{jkt}.$$

Least squares estimates the conditional *mean* of r_{jk} in (6); however, I am interested in the effect of an immigrant inflow at different points along the rental distribution. Quantile regressions –which minimize weighted absolute loss instead of squared loss—estimate the condition *quantiles* (i.e. median or 25th percentile) of r_{jk} given the explanatory variables. Using the same relationship described above, the quantile regression model is written as below and the coefficient of interest is $\gamma(\tau)$. Here, the impact of immigration on rents (γ) is allowed to vary across quantiles (τ).

(7) $$r_{jkt} = \alpha(\tau) W_{jt} + \theta(\tau) X_{jt} + \beta(\tau) Z_{kt} + \gamma(\tau) I_{kt} + \theta_t + \varepsilon_{jkt}(\tau).$$

4.4.2 Two-Stage Quantile Regression

As discussed previously, immigrant inflows into a neighborhood are endogenous to housing prices. This is particularly important as the dependent variable is housing rent *levels*, not *changes*. The primary concern here is that immigrants may be attracted to areas with lower housing prices (or less desirable neighborhoods and/or lower housing unit quality). If so, γ will be biased downward. To correct for the endogeneity, I use the same instrument described in section 4.3. Recall that this instrument used source country-level variables that are exogenous to

[57] If I cut the sample by marital status or Hispanic origin, the results are similar.

local market conditions in the U.S. to predict inflows to CBSA's. In this section, I use the same model and estimating strategy but predict inflows to counties instead of CBSA's.

Several methods have been adopted for estimating quantile regressions with endogenous explanatory variables.[58] The estimator most appropriate for this analysis is a two-stage estimator as in Kim and Muller (2004).[59] In the first stage, I estimate a quantile regression of the endogenous immigration impact variable (I_{kt}) on the exogenous covariates included in (6) and the imputed immigration inflow instrument (M_{kt}):

(8) $$I_{kt} = \alpha_1(\tau)W_{jt} + \alpha_2(\tau)X_{jt} + \alpha_3(\tau)Z_{kt} + \alpha_4(\tau)M_{kt} + \theta_t + \varepsilon_{jkt}(\tau);$$

I then estimate the impact of immigration on rents using the fitted values of the dependent variable in (8), $\widehat{I}_k$, as the independent variable of interest:

(9) $$r_{jkt} = \alpha(\tau)W_{jt} + \theta(\tau)X_{jt} + \beta(\tau)Z_{kt} + \gamma(\tau)\widehat{I}_{kt} + \theta_t + \varepsilon_{jkt}(\tau).$$

4.4.3 Results

I start by estimating the least squares model (6) via OLS and 2SLS. The results are reported in columns (1) and (2) of Table 4.5, respectively. The OLS estimates suggest that an immigrant inflow equal to 1% of the lagged population leads to an increase in rents of 0.48%. The 2SLS estimates are nearly twice as high as the OLS estimates and suggest that the same immigrant inflow will increase rents by 0.90%. An increase in the point estimate after instrumenting for immigrant inflows is in stark contrast to the previous section (and Chapter 2 of this dissertation). Though different, this is not unexpected, as I address a very different question in this section. In both section 4.3 above and chapter 2 of this dissertation, the variation in immigrant inflows is *across* CBSA's. Here, the variation in immigrant inflows is *within* a CBSA. In chapter 2, I showed that immigrants cluster in the largest metropolitan areas that are rich in

[58] See Lee (2007) for a comprehensive overview of these methods.
[59] Also described as the "fitted values" approach by Blundell and Powell (2003).

amenities and provide the best economic opportunities. In the case of national data, immigration inflows are spuriously positively correlated with rent growth. Here, when focusing *within* a single metropolitan area, one should expect immigration to be negatively spuriously correlated with rent levels. This stems from the fact that immigrants tend to live in less desirable neighborhoods with smaller housing units and units of lesser quality (Table 4.1). Thus, if immigrants are locating in areas with otherwise lower rents, controlling for this spurious correlation should lead to an increase in the estimated impact of immigration on rents.

Taken at face value, the 2SLS estimates in Table 4.5 would lead one to conclude that immigration increases rents within a city. However, as noted above, immigrants tend to cluster along the rent distribution. To see this, I plot kernel density estimates of the relative position of immigrant households along the rent distribution (similar to Chapter 3 of this dissertation) in Figure 4.6. Again, because the horizontal line at 1 represents the location of native households, the plot will be above 1 when immigrants are more concentrated than natives (and vice versa). Figure 4.6 shows that immigrants cluster in the middle of the rent distribution with the largest relative share from about the 30^{th} – 60^{th} percentiles. This figure will provide a nice comparison when relationship between immigration inflows, rents, and native mobility. If the estimated impact of immigration along the rent distribution is shaped similarly to Figure 4.6, then the willingness to pay story holds. If the impact of immigration is lower in this portion of the rent distribution, then the results suggest the willingness to pay of native households for living away from high-immigrant neighborhoods is greater than the willingness to pay of immigrants to live in high-immigrant neighborhoods. In other words, native households respond to immigrant inflows by moving away from high-immigrant areas.

I present the quantile regression results for all covariates in the quantile regression specification and the IV quantile regression specifications in Tables 5.6 and 5.7, respectively. For the sake of brevity, I report the estimates of the full model for select quantiles. To see the impact across the entire distribution, I present the estimated impact of immigration graphically along the rent distribution in Figure 4.7. I will focus on this figure primarily in the discussion.

Panel A of Figure 4.7 presents the quantile regression results without accounting for the endogeneity of immigrant location decisions. The results suggest that the impact of immigration on rents is decreasing uniformly across the rental distribution and is actually negative at roughly the 75th percentile. Again, this is not unexpected insomuch as immigrants cluster in lower cost (or quality) units in undesirable neighborhoods. If immigrants cluster in these areas of the rent distribution, then Panel A supports the willingness to pay story above. Because immigrants are seeking ethnic enclaves that provide cultural amenities, they are willing to outbid natives for these properties. When we account for endogenous location decisions, however, the story changes. Panel B of Figure 4.7 reports the IV quantile regression results. While the impact of immigration is positive across the distribution, it is U-shaped and closely resembles the distribution of immigrant households along the rent distribution. The impact of immigration on rents is lower in portions of the rent distribution where immigrants tend to cluster (the 30th-60th percentiles from Figure 4.6). In fact, the effect of immigration in these areas of the rent distribution is minimal. From Table 4.7, the estimated impact of immigration on rents is 0.26% at the 40th percentile

Similar to the tract-level analysis above, the quantile results suggest the impact of immigration estimated in previous studies is driven by rent increases in low-immigration areas. Therefore, it is not the willingness to pay of immigrants that increases rents in a city that is driving up rents; rather, it is the increased willingness to pay of *natives* to live in low-immigrant neighborhoods. To see this, I estimate the least squares model separately for immigrants, white natives, and black natives and report the results in Table 4.8. In comparing columns (1) – (3), the estimated impact of immigration on rents is nearly twice as high for native householders, on average. These estimates explain the increase in rents seen in the tails of the distribution. Figure

4.8 plots the kernel estimates for the relative position of black households along the rent distribution. The plot shows that black households are significantly overrepresented in the bottom quartile of the rent distribution. As discussed previously, white households are more likely to live in the upper tail of the distribution. Furthermore, the differential impact in the tails of the distribution can be explained by the fact that significantly more white native households live in NYC relative to black households (more than twice as many in the data). Because immigrants cluster with other immigrants, we would expect an immigrant inflow to have a larger effect on immigrant households if it was the immigrant inflow alone driving the price increase. However, the larger impact on rents of native households suggests they are willing to pay more for comparable housing outside of high-immigration areas.

4.5 Native Out-Migration in New York City

Figures 4.6 and 4.7 suggest that the effect of immigration on rents is lower in the portion of the rent distribution where immigrants are clustered relative to natives. From the discussion in section 4.2, this suggests that natives are moving out of high-immigration tracts. To test this, I use census tract-level data from 1990-2000 for all tracts in the New York City CBSA. I estimate the impact of a CBSA-level immigrant inflow on the change in the native white population of a tract and allow the impact of immigration to differ along rent quartiles of the CBSA:

$$\Delta w_{j,NYC,t} = \alpha X_{j,NYC,t-1} + \beta(I_{NYC,t} * r^{q}_{NYC,t}) + \varepsilon_{j,NYC,t}. \tag{10}$$

Here, $\Delta w_{j,NYC,t}$ is the change in the native white population of tract j in the New York City CBSA at time *t*. The theory in section 4.2 discussed the more broadly defined "native flight" instead of white flight. This would call for changes in the native born population as the dependent variable; however, children born to immigrant parents are natives themselves. Thus, if native out-migration is motivated by attitudes of native-born populations towards immigrants, using changes in the overall native population would confound the analysis. As such, changes in the white, non-immigrant population serve as a proxy for changes in the native born population. $X_{j,NYC,t-1}$ is a vector of lagged tract-level variables that control for other factors that may cause population changes within a tract. First, to control for neighborhood conditions, I include the neighborhood disadvantage index (as described earlier), the share of the population with at least a bachelor's degree, vacancy rates, and population density. As described above, higher shares of college graduates are correlated with future growth of a city (Glaeser and Saiz, 2004). As such, I expect this to positively influence migration rates. Lagged vacancy rates are expected to have a positive impact on future migration rates as vacant units act as a pull factor that attracts in-migrants. Population density is a proxy for housing supply constraints and is expected to have a negative impact on changes in white population. Next, I control for characteristics of the population residing in the tract at time *T-10* that may describe future migration decisions. These variables include the share of the population that is married, the share of households that have resided in their current dwelling for at least 10 years, the share of the population that is black, and the share of occupied units that are renter-occupied. Higher shares of married households and households with 10 years of tenure are expected to be negatively correlated with future migration rates, while the share of renter-occupied units is expected to positively impact future migration rates. These expected impacts follow from the migration literature (Quigley and Weinberg, 1977; Weinberg, 1979). Married households and households with longer tenure in their current home are less mobile, *ceteris paribus*; however, renter households are more mobile, *ceteris paribus*.

The main explanatory variable is the interaction of $I_{NYC,t}$ and $r^q_{NYC,t}$. $I_{NYC,t}$ is the immigrant inflow (as described in section 4.3) into NYC at time *t*. $r^q_{NYC,t}$ is a dummy variable equal to 1 if the tract-level average rent at time *t* falls in the q^{th} quartile of the CBSA rent distribution. For each year, I calculate the 25^{th}, 50^{th}, and 75^{th} percentiles of CBSA rent from tract-level rent data.[60] Then, I assign each tract into the relevant quartile of the rent distribution based on *current* period average rents.

Given the quantile results, how should β differ across the CBSA rent distribution? Panel B of Figure 4.7 shows that the least squares estimates are driven by the impact in the upper tail of the distribution. The impact of immigration is decreasing along the rent distribution up to (roughly) the median rent level, then the increasing thereafter. If native out-migration is the motivating factor, we would expect an immigrant inflow into NYC to cause white populations to flow from high-immigration tracts to low-immigration tracts. Thus, β should be negative in the 1st and 2nd quartiles and positive in 3rd and 4th quartiles.

I first estimate (10) via OLS and 2SLS without the interaction terms and report the results in columns (1) and (2) of Table 4.9, respectively. The OLS estimates suggest that an immigrant inflow equal to 1% of the total population leads to an increase in the white population by roughly 0.4%. If immigrant location choices are correlated with local economic conditions, then the OLS estimate is biased. In Chapter 2 of this dissertation, I argue that immigrants are locating in areas that provide them with the best economic opportunities and these same areas are rich in amenities that attract both new immigrants and natives. If so, the impact on white population flows is biased upward. To remedy this, I again use predicted immigrant flows based on country of origin push factors as an instrument for actual immigration inflows.[61] The 2SLS estimates are significantly lower than the OLS estimates and show that immigrant inflows have zero impact on white population flows, on average. This result is remarkably consistent with the theory derived in section 4.2 when natives do not have distaste for living near immigrants ($U_i' = 0$). When natives do not receive disutility from living near immigrants and the out-migration is purely for

[60] Using the number of rental housing units in a tract as weights.
[61] Because the independent variable of interest in this analysis is at the tract-level, the instrument is also calculated at the tract-level. In this case, I assume that each tract receives the same fraction of immigrants as it did in 1980. This seems like a reasonable assumption given Figure 2 which shows the clustering of immigrants over time by tract is relatively constant.

economic reasons, each incoming immigrant displaces exactly one native to the suburbs. In this analysis, I estimate the impact on *all* tracts within NYC, which includes tracts in *both* the central city *and* suburbs. Thus, a net impact of zero is consistent with this story.

I then estimate the interaction specifications via OLS and 2SLS in columns (3) and (4) respectively. The omitted quartile in both specifications is the 2nd quartile because this is the portion of the rent distribution with the lowest impact of immigration from the quantile estimates. The difference in the OLS and 2SLS estimate is significant. This large reduction in the point estimate suggests that new immigrants are locating in neighborhoods where white populations are otherwise increasing. Again, this is consistent with the findings in chapter 2 of this dissertation.

The 2SLS estimates confirm native out-migration as a possible explanation for the differential effect of immigration on rents within cities. Because the 2nd quartile is the omitted category, the point estimate on the immigration impact variable is the effect of immigration on white population flows in the 2nd quartile. The effect, though not statistically different from zero, is negative. Relative to the 2nd quartile, an immigrant inflow into NYC has a positive effect on the growth of white populations in the 3rd and 4th quartiles of the rent distribution. It is hard to definitively say how large these impacts are as the main effect is not statistically significant. What can be said is the effect is modest in the 3rd quartile and large in the 4th quartile. This result is consistent with the quantile result - the impact of immigration on rents is largest in the upper tail of the rent distribution. Table 8 shows that it is white population flows driving this increase in rents in the 4th quartile of the rent distribution.

The insignificant point estimate in the 1st quartile is unsurprising given the 2SLS estimates in column (2). From column (2), the zero impact of immigration suggests that native out-migration is not driven by distaste for living near immigrants. If immigration displaces natives due to economic reasons, natives will migrate to other areas of the city that provide better economic opportunities (i.e. more access to jobs, increased amenities, etc.). As these amenities are capitalized into rents, these high amenity areas demand higher rents. Thus, in response to an immigrant inflow, natives are fleeing to these high amenity areas, not to any area with other native households.

A second explanation stems from the fact that the model only considers the effect of immigration on white population flows. As shown in Figure 4.8, the overrepresentation of native households in the bottom quartile of the rent distribution is driven by black households. Black households are significantly more likely to reside in the bottom quartile of the rent distribution. Because white populations also tend to flow away from black populations and the relatively small number of white households living in this area of the rent distribution, the insignificant and modest impact in the 1st quartile is expected.

While the theory holds in regards to native out-migration at the tract level, the theory does not match the quantile results. Given that natives have no distaste for living near immigrants, the theory predicts immigration should have no impact on long-run housing prices. The positive impact across the distribution of rents then is likely attributed to the data problems discussed above. Because I am only able to identify county of residence, I do not observe the significant heterogeneity of individual neighborhoods within these counties.

4.6 Conclusion

The impact of immigration on the rental housing market is an important question for policy. Immigrants cluster within cities while native populations are mobile, thus immigration is an important factor in the formation of neighborhoods and potentially immigrant ghettos. Although a consensus has yet to be formed on the true impact of immigrant ghettos on future economic outcomes, there is reason to believe that the long-run effect is negative. As economic activity leaves the central city, immigrants will be isolated from jobs and live near lower quality public services. Similarly, while ethnic enclaves ease the cost of assimilation for many immigrants, decreased English proficiency will decrease job prospects. If natives flee high-immigration areas and further isolate immigrants within a city, these effects may be exacerbated.

The main contribution of this paper was to show that immigration has a differential effect within cities. First, using national census tract-level data, I show that the effect of an immigrant inflow into a metropolitan area is lower in high-immigrant tracts. The effect of immigration was marginally positive and, in some cases, negative in high-immigrant neighborhoods. This result held for several proxies for high-immigrant neighborhoods. Furthermore, this result was in direct contrast to the explanation in the existing literature which suggests that immigrant inflows lead to higher rents because immigrants are willing to pay more for housing in high-immigrant tracts.

Second, I show that the effect of immigration on rents is nonlinear across the rent distribution in the New York City CBSA. After correcting for endogenous location decisions of immigrants, the effect of immigration is U-shaped. Similar to the national tract-level results, the effect is lower in the portion of the rent distribution where immigrants cluster. Lastly, I link the quantile regression results to the native out-migration hypothesis developed in this paper. The analysis confirms out-migration of native households as a likely explanation for the differential quantile effects. White population flows out of tracts in the 2nd quartile of the rent distribution into neighborhoods in the 3rd and 4th quartiles.

The results of this paper provide the first detailed analysis of the impact of immigration within cities. While the results suggest out-migration as a possible explanation, more research in this area is needed. However, due to the data issues outlined above, more detailed data are needed to provide a definitive answer. Restricted access Census data would provide the necessary local geographic data to satisfactorily control for neighborhood effects in the quantile regression framework. Similarly, the analysis focuses solely on the NYC CBSA. While this is one of the major immigrant gateways, the results are not generalizable. Future research should look to expand the present analysis to other immigrant gateway cities.

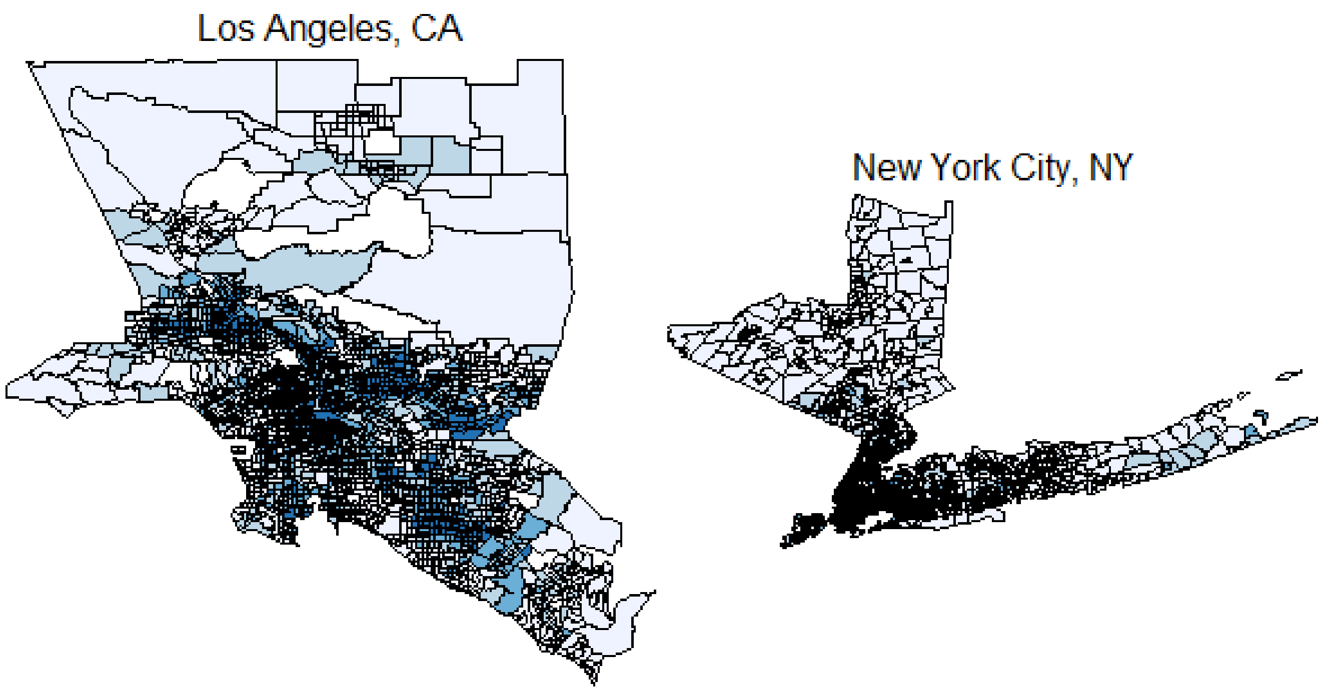


Figure 4.1: Immigrant Clustering Within Metropolitan Areas
High-Immigrant Metropolitan Areas

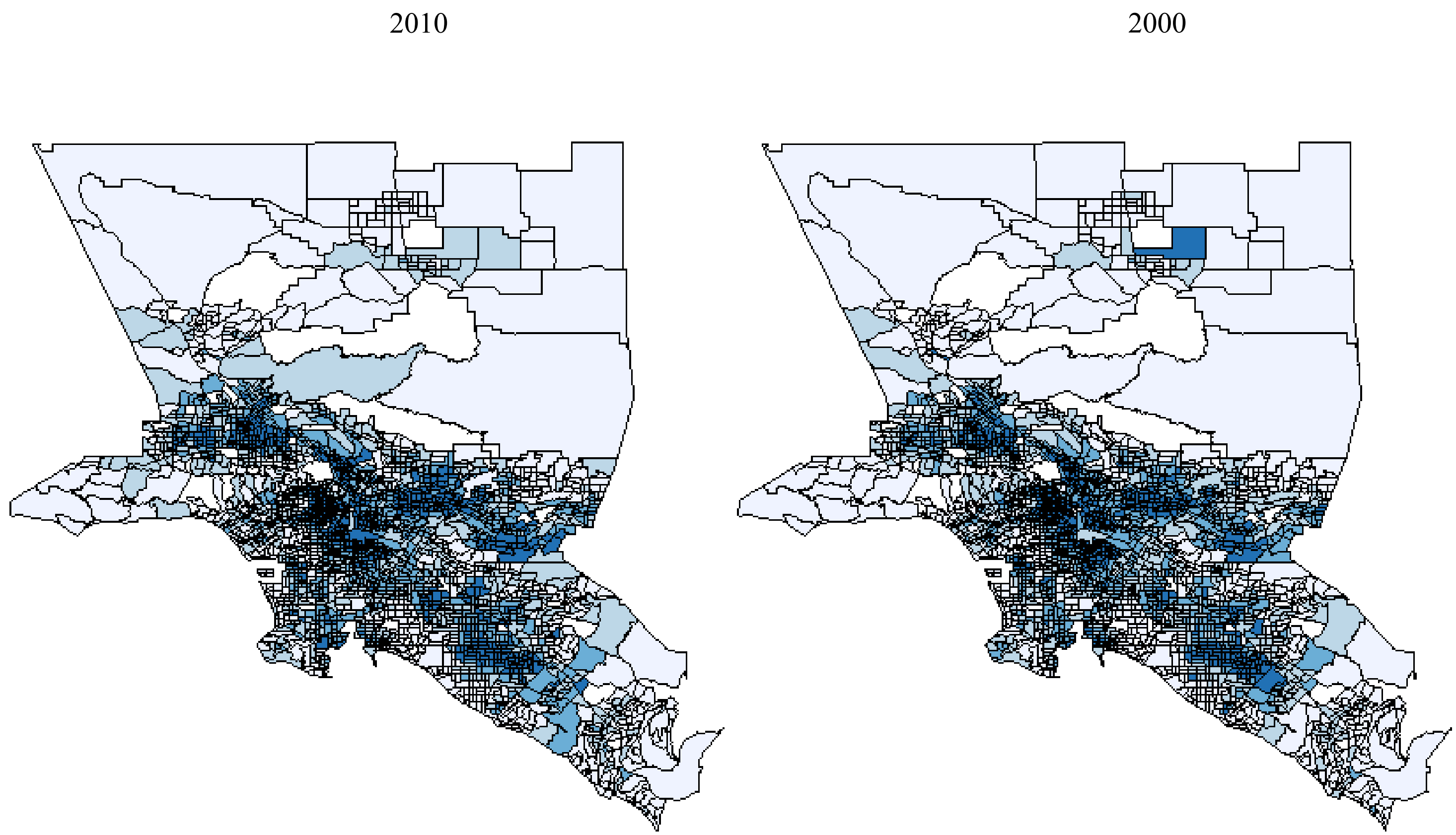
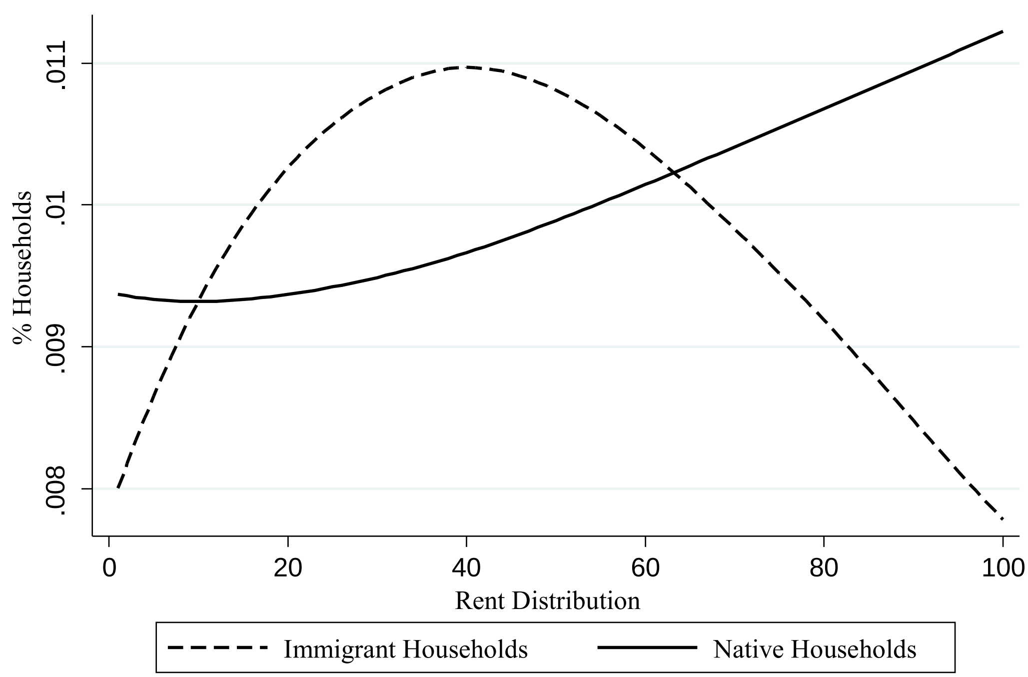


Figure 4.2: Immigrant Clustering Over Time
Los Angeles, CA

Figure 4.3: Households Along Rent Distribution, by Nativity



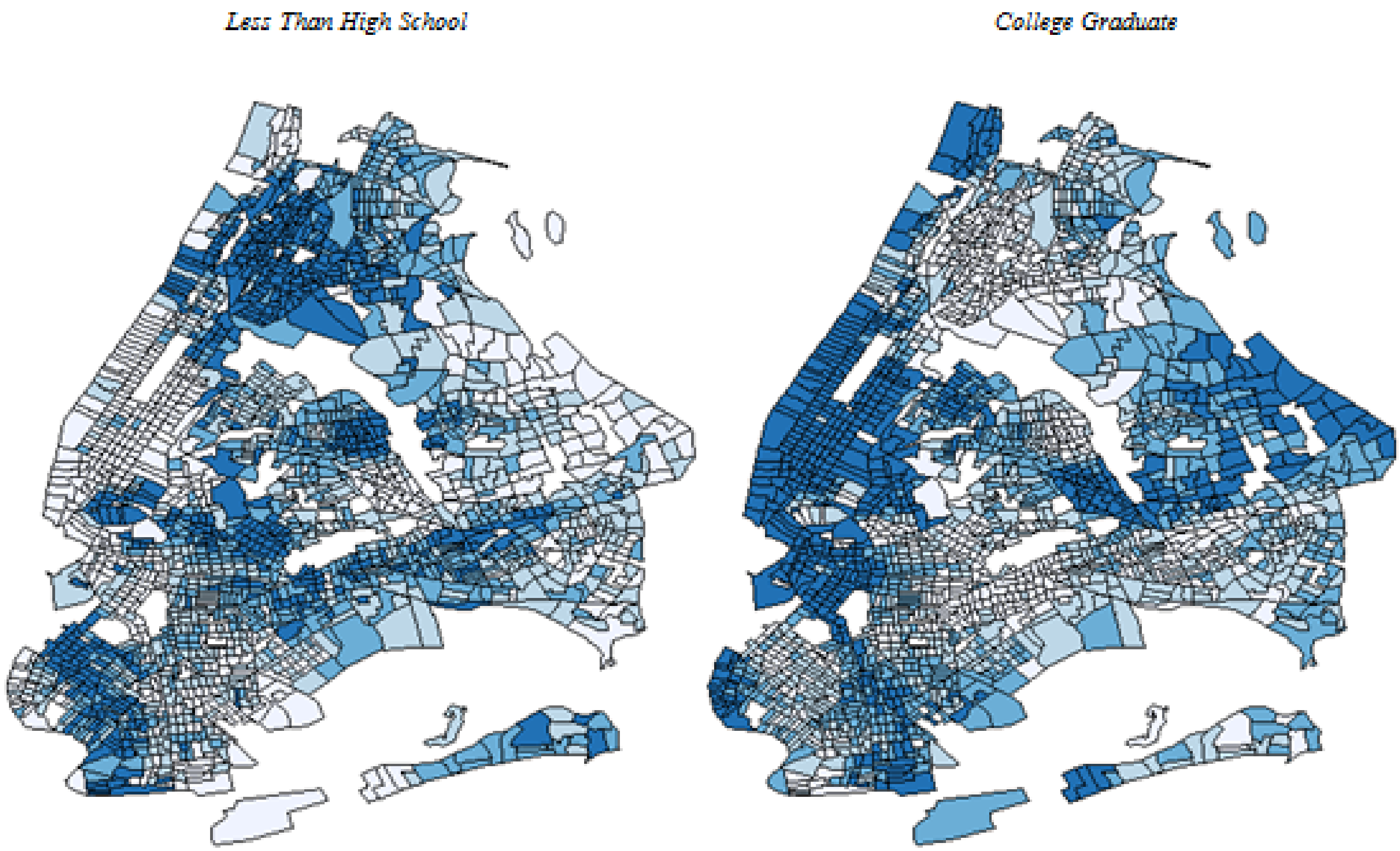


Figure 4.4: Clustering by Education

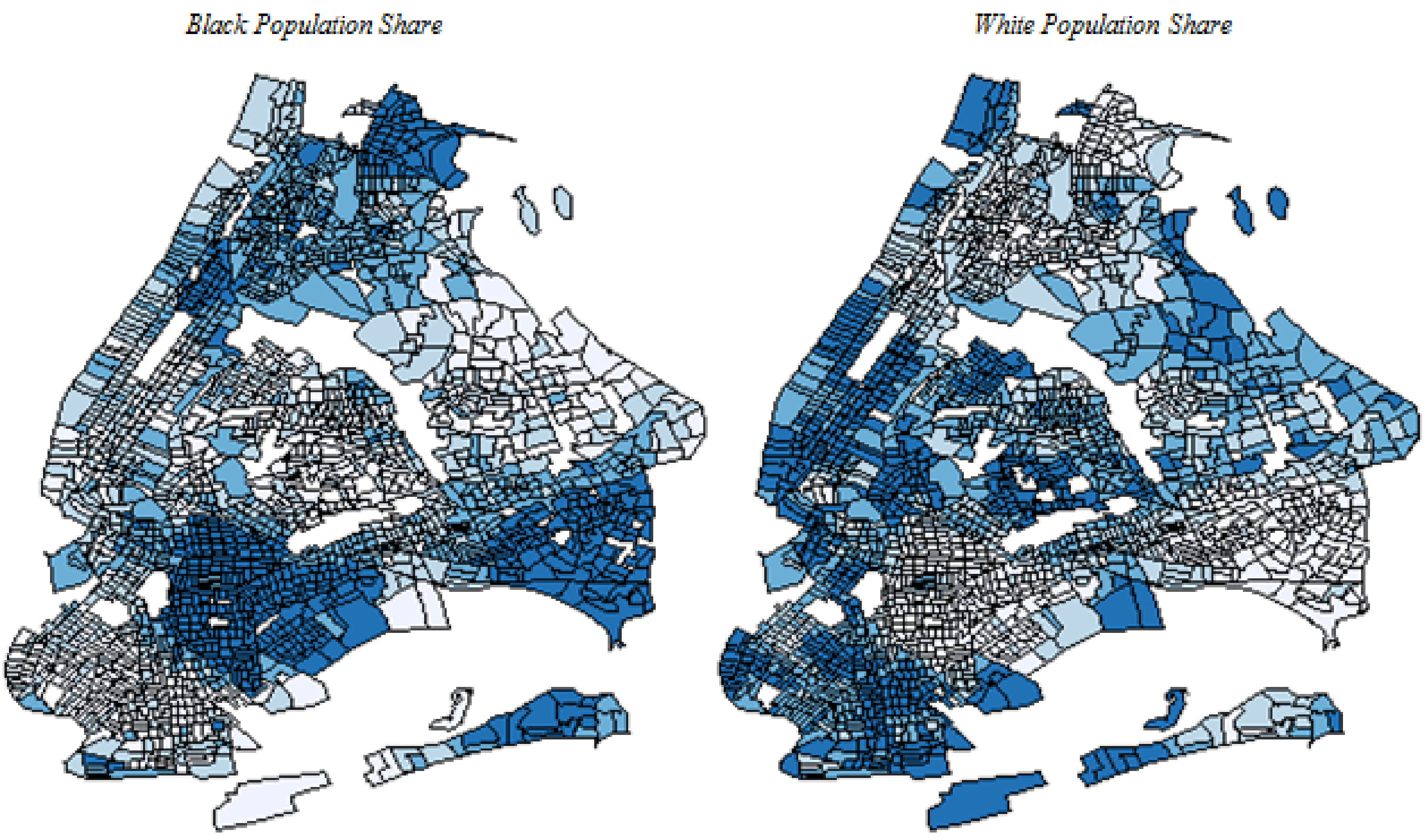
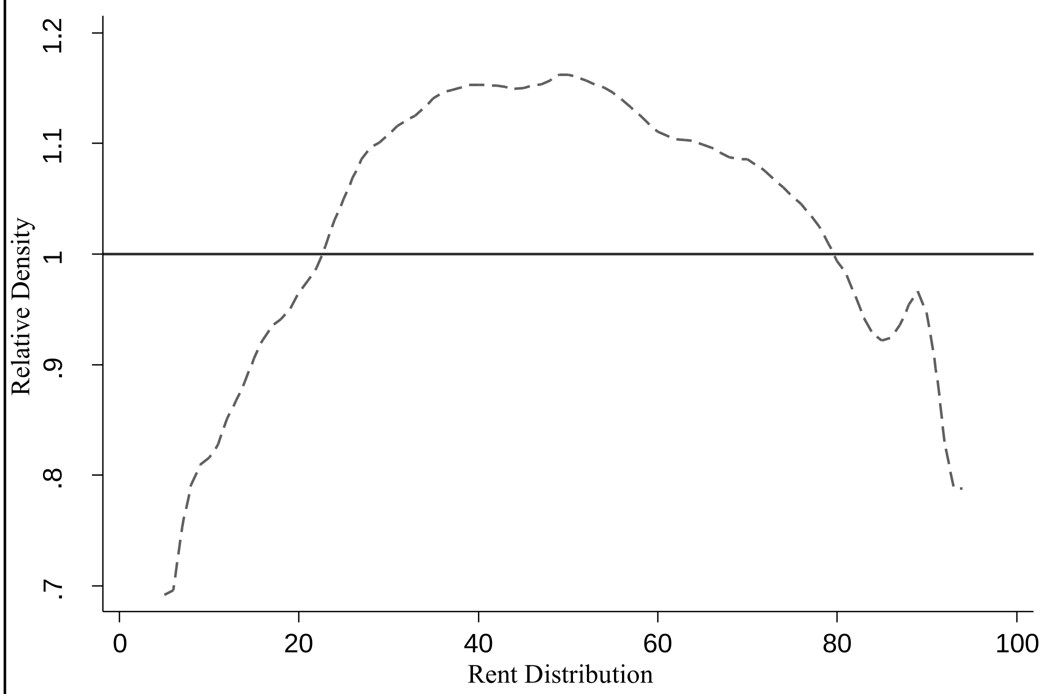


Figure 4.5: Clustering by Race

Figure 4.6: Position of Immigrant Households Along Rent Distribution



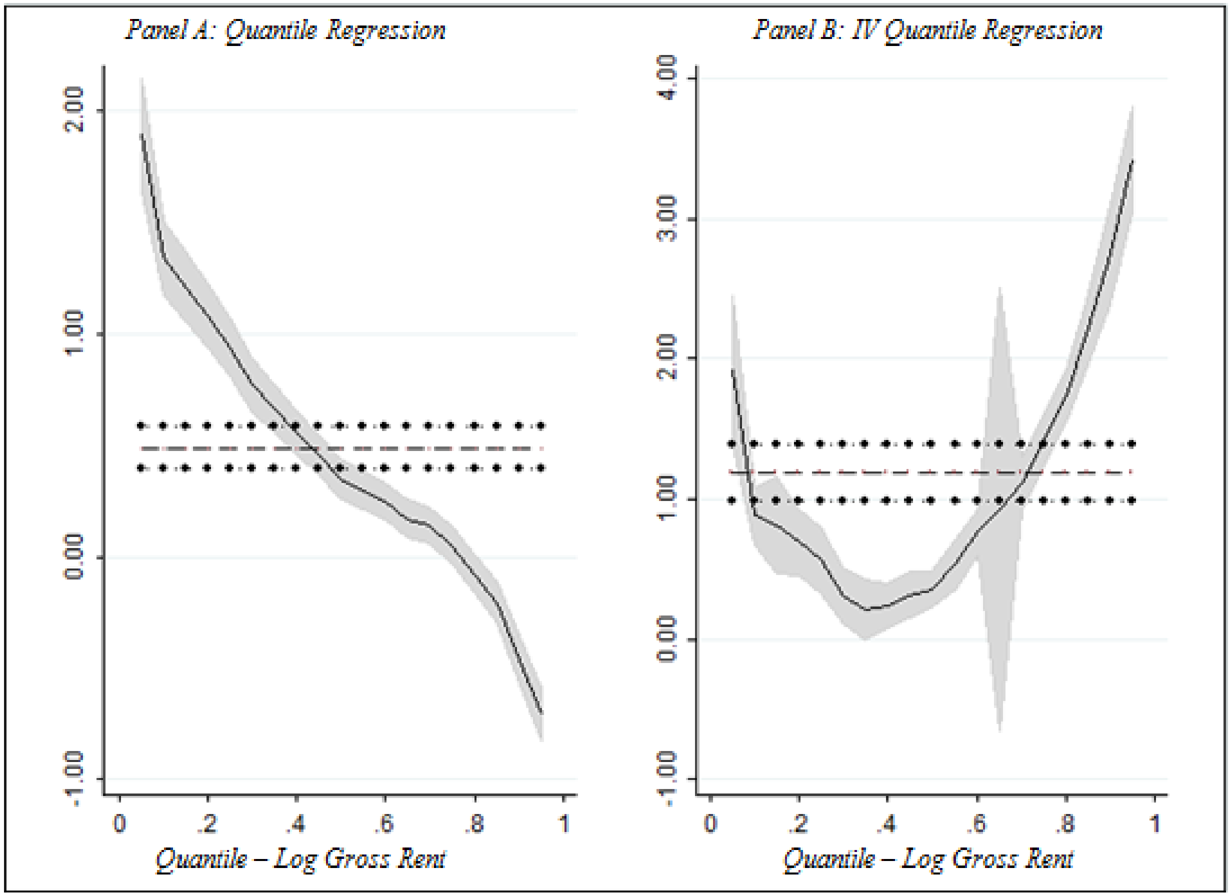


Figure 4.7: Quantile Estimates, Immigration Impact Variable

Figure 4.8: Position of Black Households Along Rent Distribution

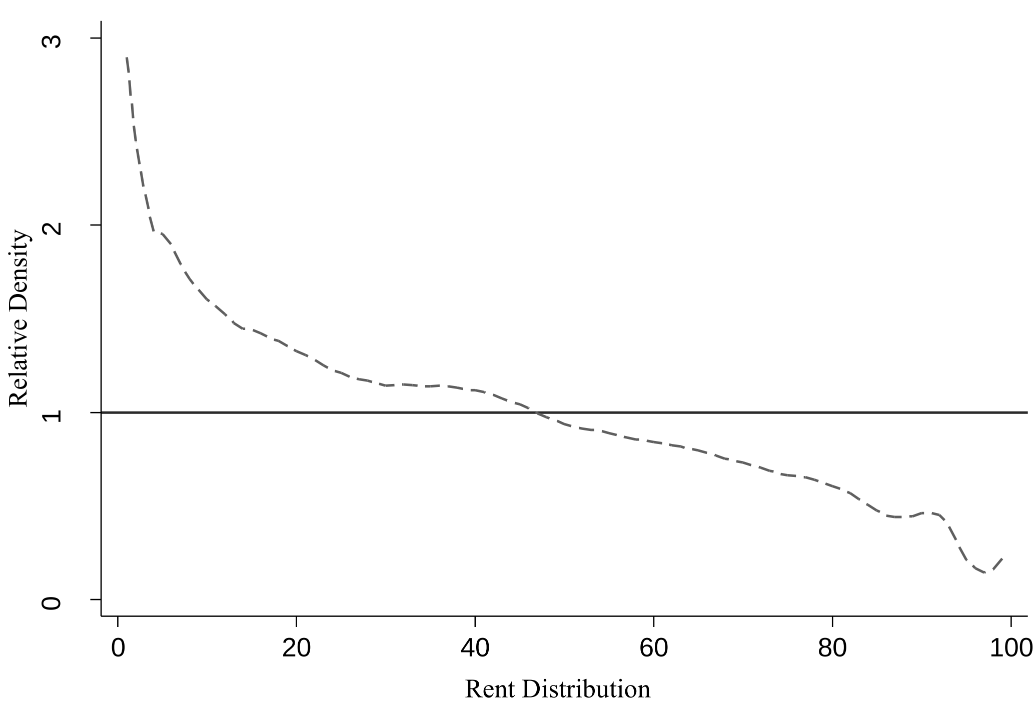


Table 4.1: Summary Statistics, Tract-Level Analysis (2000)			
	All Tracts	High-Immigrant Tracts	Low-Immigrant Tracts
Mean Tract Rent	\$651.29	\$604.08	\$675.88
% Population Foreign-Born	12.05%	20.57%	7.61%
% Population Black	14.09%	14.87%	13.69%
% Population with at least Bachelor's Degree	25.27%	20.71%	27.65%
Household Income	\$53,426.38	\$44,085.23	\$59,051.78
Unemployment Rate	6.23%	7.92%	5.34%
% Householders younger than 25 years old	5.30%	7.44%	4.18%
% Householders older than 64 years old	19.95%	18.85%	20.52%
% Households moved in more than 10 years ago	33.91%	30.66%	35.60%
% Households Married	61.54%	59.15%	62.78%
% Households Renter-Occupied	35.38%	49.19%	28.18%
Rental Vacancy Rate	7.92%	7.79%	7.99%
New Building Permits (as % of Housing Stock)	0.1566	0.1367	0.1669
Neighborhood Disadvantage Index	0.000	0.201	-0.105
% Housing Units 1-Unit Detached	34.07%	25.16%	38.47%
% Housing Units 10+ Units	24.49%	30.89%	21.33%
% Housing Units Mobile Homes	5.84%	3.97%	6.77%
% Housing Units Built Pre-1939	13.99%	15.01%	13.48%
% Housing Units with 0 Bedrooms	5.26%	8.09%	3.86%
% Housing Units with 1 Bedrooms	25.68%	30.57%	23.26%
% Housing Units with 2 Bedrooms	37.98%	37.64%	38.15%
% Housing Units with 3 Bedrooms	24.02%	19.01%	26.49%
% Housing Units with 4 Bedrooms	5.87%	3.92%	6.84%
% Housing Units with 5 Bedrooms	1.20%	0.77%	1.41%
% Housing Units, Lack Complete Plumbing	0.84%	1.14%	0.69%
% Housing Units, Lack Complete Kitchen	1.16%	1.31%	1.08%

Table 4.2: Impact of CBSA Immigration Inflows on Tract Rents

VARIABLES	(1) OLS Δr_{jkt}	(2) 2SLS Δr_{jkt}	(3) 2SLS High Foreign-Born Share Δr_{jkt}	(4) 2SLS High Foreign-Born Share Δr_{jkt}	(5) 2SLS Low-Income Δr_{jkt}	(6) 2SLS Low-Rent Δr_{jkt}
Immigration Impact	0.575***	0.273*	0.679***	0.888***	0.187	1.136***
	(0.0354)	(0.147)	(0.235)	(0.279)	(0.161)	(0.192)
*Immigration Impact * High-Immigration Tract*			-0.952***	-1.754***	-0.432	-0.923***
			(0.283)	(0.328)	(0.390)	(0.287)
High-Immigration Tract			0.0335***	0.132***	0.001	0.144***
			(0.0126)	(0.0176)	(0.017)	(0.0132)
% African-American (T-10)	0.00186	0.00368	-0.00395	0.00799*	-0.00394	-0.00576
	(0.00393)	(0.00401)	(0.00452)	(0.00460)	(0.00414)	(0.00395)
Unemployment Rate (T-10)	0.0962***	0.115***	0.122***	0.0710**	0.0425	0.0281
	(0.0298)	(0.0312)	(0.0311)	(0.0321)	(0.0312)	(0.0307)
% Renter Occupied (T-10)	0.0566***	0.0652***	0.0733***	0.0276***	0.00813	0.0137
	(0.00777)	(0.00886)	(0.00913)	(0.0104)	(0.00778)	(0.00937)
% Population with Bachelor's Degree (T-10)	0.0422***	0.0274**	0.0276**	0.0751***	0.148***	0.154***
	(0.00882)	(0.0111)	(0.0113)	(0.0148)	(0.00901)	(0.0106)
Log Household Income (T-10)	0.110***	0.118***	0.115***	0.0956***		0.0852***
	(0.00684)	(0.00792)	(0.00805)	(0.00951)		(0.00769)
Log Tract Rent (1980)	-0.238***	-0.232***	-0.236***	-0.253***	-0.193***	-0.197***
	(0.00571)	(0.00633)	(0.00696)	(0.00833)	(0.00603)	(0.00676)
New Building Permits/Housing Units (T-10)	0.0609***	0.0952***	0.0801***	0.0471	0.112***	0.0521***
	(0.0100)	(0.0188)	(0.0213)	(0.0297)	(0.0194)	(0.0188)
Observations	116,811	116,669	116,669	116,669	116,708	116,669
R-squared	0.164	0.163	0.161	0.168	0.156	0.182

1) Each column represents a unique specification that differs by estimation technique and the high-immigrant tract characteristic used in the interaction specification. The dependent variable in each specification is the change in log average rent for each tract j in CBSA k at time t. The independent variable of interest is the change in foreign-born population of the CBSA k at time t. Robust standard errors clustered by tract are reported in parentheses.
2) Columns (3) – (6) differ by the variable used in the interaction specification. Columns (3) and (4) both use a measure of foreign-born share to differentiate markets. In column (3), a high-immigration tract is one where the number of linguistically isolated households exceeds the CBSA

Table 4.3: Impact of CBSA Immigration Inflows on Tract Rents, High-Immigration CBSA's

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	2SLS	2SLS High Foreign-Born Share	2SLS High Foreign-Born Share	2SLS Low-Income	2SLS Low-Rent
VARIABLES	Δr_{jkt}	Δr_{jkt}	Δr_{jkt}	Δr_{jkt}	Δr_{jkt}	Δr_{jkt}
Immigration Impact	0.288***	-0.672***	-0.220	-0.189	-0.845***	0.901***
	(0.0498)	(0.247)	(0.366)	(0.486)	(0.271)	(0.307)
*Immigration Impact * High-Immigration Tract*			-0.972**	-0.909**	-0.650	-1.356***
			(0.403)	(0.417)	(0.603)	(0.438)
High-Immigration Tract			0.0561**	0.0725***	0.0162	0.197***
			(0.0262)	(0.0249)	(0.0394)	(0.0285)
Observations	68,057	67,915	67,915	67,915	67,950	67,915
R-squared	0.192	0.184	0.184	0.191	0.176	0.210

1) Each column represents a unique specification that differs by estimation technique and the high-immigrant tract characteristic used in the interaction specification. The dependent variable in each specification is the change in log average rent for each tract *j* in CBSA *k* at time *t*. The independent variable of interest is the change in foreign-born population of the CBSA *k* at time *t*. Robust standard errors clustered by tract are reported in parentheses.
2) Columns (3) – (6) differ by the variable used in the interaction specification. Columns (3) and (4) both use a measure of foreign-born share to differentiate markets. In column (3), a high-immigration tract is one where the number of linguistically isolated households exceeds the CBSA average. In column (4), a high-immigration tract is one where the share of foreign-born exceeded 20% in year (T-10). Column (5) the variable interacted with immigration impact is an indicator variable equal to 1 if the lagged tract household income is below the lagged CBSA average household income. In column (6), I interact an indicator variable equal to 1 if the lagged tract average rent is below the lagged CBSA average rent.
3) All specifications include both lagged and changes in tract-level housing characteristics and year fixed effects; however, these point estimates were omitted for the sake of brevity.

Table 4.4: Neighborhood and Unit Characteristics, by Demographics

	Less Than High School	High School Grad (or GED)	Some College	College Graduate	White	Black	Other Race
Neighborhood Characteristics							
Abandoned Buildings	0.118	0.023	0.008	-0.024	-0.045	0.218	-0.017
Trash Accumulation on Street	0.033	-0.009	-0.008	-0.006	-0.042	0.064	0.007
Structures with Barred Windows	0.200	0.055	0.016	-0.044	-0.001	0.233	-0.044
Factories Within	0.070	0.053	0.024	-0.026	0.009	0.079	-0.020
Roads in Need of Repair	0.084	0.089	0.083	-0.048	0.018	0.188	-0.047
Neighborhood Crime is Bothersome	0.025	0.041	0.075	-0.007	-0.025	0.161	-0.002
Overall Rating of Neighborhood	0.048	0.015	-0.007	-0.006	0.103	-0.140	-0.029
Unit Characteristics							
Large Areas of Peeling Paint	0.023	0.013	0.001	-0.003	-0.003	0.031	-0.001
Mice/Rodents Present	0.133	0.016	0.005	-0.024	-0.018	0.138	-0.018
Cracks in Walls or Holes in Floors	0.043	0.014	-0.013	-0.004	-0.022	0.054	0.003
Holes in Roof or Uneven Roof	0.055	0.022	0.013	-0.011	0.008	0.025	-0.007
Broken or Boarded Windows	0.100	-0.009	-0.021	-0.005	0.002	-0.008	0.002
Overall Rating of Unit	0.103	0.036	0.011	-0.026	0.083	-0.053	-0.038
Unit is Inadequate	0.040	-0.020	-0.018	0.004	-0.025	0.019	0.014
No Problems Observed	-0.256	-0.249	-0.227	0.093	-0.223	-0.284	0.127

1. These averages are drawn from the 1999-2009 American Housing Survey. These statistics were calculated from a sample of renter-occupied units that resided in a Standard Metropolitan Statistical Area (SMSA).
2. Before calculating averages in each cell, I first standardize all responses to be mean zero with a standard deviation of 1 within each SMSA.
3. The averages in each cell are weighted averages using "pwt" supplied in the AHS.

Table 4.5: Least Squares Estimates

VARIABLES	(1) OLS $\ln(r_{jkt})$	(2) 2SLS $\ln(r_{jkt})$
Immigration Impact	0.486***	0.902***
	(0.0447)	(0.0695)
Housing Unit, Single Family	0.143***	0.151***
	(0.00546)	(0.00551)
Housing Unit, 10+ Units	-0.176***	-0.175***
	(0.00286)	(0.00287)
Lacks Complete Kitchen	0.0787***	0.0792***
	(0.00153)	(0.00153)
Lacks Complete Plumbing	0.148***	0.147***
	(0.00528)	(0.00528)
Number of Bedrooms	0.327***	0.326***
	(0.00348)	(0.00348)
High School Graduate	0.529***	0.528***
	(0.00360)	(0.00359)
Some College	-0.114***	-0.114***
	(0.0136)	(0.0136)
College Graduate	-0.0378***	-0.0380***
	(0.0140)	(0.0140)
Householder Married	0.153***	0.152***
	(0.00261)	(0.00262)
Householder Hispanic	-0.0728***	-0.0729***
	(0.00335)	(0.00335)
Householder Black	-0.170***	-0.169***
	(0.00349)	(0.00349)
% Population with Bachelor's Degree	0.738***	0.847***
	(0.0234)	(0.0279)
% Population Black	-0.388***	-0.365***
	(0.0163)	(0.0163)
In Central City	0.0330***	0.0178***
	(0.00484)	(0.00509)
Observations	161,243	161,243
R-squared	0.330	0.329

1) Robust standard errors reported in parentheses.
2) Each specification includes year fixed effects and a categorical variable for age of dwelling (9 categories as reported in the IPUMS). These point estimates are omitted for the sake of brevity.

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.6: Quantile Regression Results, New York City

VARIABLES	(1) 10th $\ln(r_{jkt})$	(2) 25th $\ln(r_{jkt})$	(3) 40th $\ln(r_{jkt})$	(4) 50th $\ln(r_{jkt})$	(5) 60th $\ln(r_{jkt})$	(6) 75th $\ln(r_{jkt})$	(7) 90th $\ln(r_{jkt})$
Immigration Impact	1.338***	0.939***	0.557***	0.346***	0.249***	0.0482	-0.465***
	(0.0866)	(0.0661)	(0.0496)	(0.0455)	(0.0415)	(0.0448)	(0.0542)
Single Family Unit	0.0991***	0.0990***	0.123***	0.145***	0.159***	0.175***	0.193***
	(0.0109)	(0.00822)	(0.00615)	(0.00565)	(0.00517)	(0.00559)	(0.00692)
10+ Units	-0.259***	-0.187***	-0.145***	-0.129***	-0.117***	-0.106***	-0.103***
	(0.00545)	(0.00408)	(0.00308)	(0.00284)	(0.00260)	(0.00281)	(0.00346)
Number of Bedrooms	0.0510***	0.0793***	0.0858***	0.0890***	0.0934***	0.100***	0.105***
	(0.00275)	(0.00206)	(0.00151)	(0.00138)	(0.00127)	(0.00138)	(0.00171)
High School Graduate	0.213***	0.250***	0.165***	0.128***	0.105***	0.0823***	0.0619***
	(0.00904)	(0.00686)	(0.00516)	(0.00475)	(0.00436)	(0.00473)	(0.00584)
Some College	0.570***	0.463***	0.311***	0.255***	0.218***	0.178***	0.154***
	(0.00627)	(0.00472)	(0.00354)	(0.00326)	(0.00298)	(0.00323)	(0.00397)
College Graduate	0.777***	0.614***	0.457***	0.405***	0.374***	0.350***	0.357***
	(0.00669)	(0.00498)	(0.00371)	(0.00338)	(0.00306)	(0.00323)	(0.00385)
Householder Married	0.272***	0.184***	0.135***	0.113***	0.0936***	0.0742***	0.0554***
	(0.00502)	(0.00384)	(0.00291)	(0.00269)	(0.00247)	(0.00269)	(0.00333)
Householder Hispanic	-0.0736***	-0.0612***	-0.0532***	-0.0561***	-0.0585***	-0.0613***	-0.0571***
	(0.00598)	(0.00456)	(0.00344)	(0.00317)	(0.00290)	(0.00315)	(0.00389)
Householder Black	-0.196***	-0.175***	-0.146***	-0.131***	-0.122***	-0.116***	-0.111***
	(0.00600)	(0.00459)	(0.00348)	(0.00322)	(0.00296)	(0.00321)	(0.00398)
Bachelor Rate	0.302***	0.427***	0.530***	0.653***	0.887***	1.355***	1.875***
	(0.0442)	(0.0328)	(0.0242)	(0.0220)	(0.0198)	(0.0212)	(0.0251)
% Population Black	-0.488***	-0.488***	-0.442***	-0.410***	-0.338***	-0.216***	-0.142***
	(0.0315)	(0.0233)	(0.0174)	(0.0160)	(0.0145)	(0.0156)	(0.0187)
Observations	161,243	161,243	161,243	161,243	161,243	161,243	161,243

1. Each specification includes year fixed effects and a categorical variable for age of dwelling (9 categories as reported in the IPUMS). These point estimates are omitted for the sake of brevity.

Table 4.7: IV Quantile Regression Results, New York City

VARIABLES	(1) 10th $\ln(r_{jkt})$	(2) 25th $\ln(r_{jkt})$	(3) 40th $\ln(r_{jkt})$	(4) 50th $\ln(r_{jkt})$	(5) 60th $\ln(r_{jkt})$	(6) 75th $\ln(r_{jkt})$	(7) 90th $\ln(r_{jkt})$
Immigration Impact	1.053***	0.559***	0.261***	0.359***	0.521***	0.494***	2.361***
	(0.120)	(0.117)	(0.0909)	(0.0887)	(0.0500)	(0.0586)	(0.120)
Single Family Unit	0.0991***	0.0979***	0.115***	0.145***	0.162***	0.179***	0.216***
	(0.0123)	(0.00659)	(0.00565)	(0.00683)	(0.00773)	(0.00342)	(0.00925)
10+ Units	-0.256***	-0.184***	-0.145***	-0.128***	-0.116***	-0.103***	-0.0978***
	(0.00804)	(0.00340)	(0.00332)	(0.00263)	(0.00204)	(0.00302)	(0.00340)
Number of Bedrooms	0.0506***	0.0795***	0.0861***	0.0893***	0.0937***	0.102***	0.104***
	(0.00321)	(0.00237)	(0.00162)	(0.00133)	(0.000915)	(0.00120)	(0.00222)
High School Graduate	0.217***	0.249***	0.165***	0.129***	0.108***	0.0819***	0.0646***
	(0.0166)	(0.00865)	(0.00627)	(0.00628)	(0.00488)	(0.00517)	(0.00515)
Some College	0.572***	0.462***	0.311***	0.255***	0.219***	0.178***	0.159***
	(0.00940)	(0.00638)	(0.00412)	(0.00376)	(0.00296)	(0.00312)	(0.00382)
College Graduate	0.777***	0.613***	0.457***	0.405***	0.373***	0.346***	0.342***
	(0.00683)	(0.00694)	(0.00401)	(0.00466)	(0.00328)	(0.00261)	(0.00571)
Householder Married	0.273***	0.184***	0.134***	0.113***	0.0935***	0.0739***	0.0547***
	(0.00668)	(0.00384)	(0.00261)	(0.00295)	(0.00205)	(0.00204)	(0.00262)
Householder Hispanic	-0.0753***	-0.0617***	-0.0540***	-0.0568***	-0.0588***	-0.0578***	-0.0502***
	(0.00829)	(0.00350)	(0.00329)	(0.00379)	(0.00269)	(0.00318)	(0.00324)
Householder Black	-0.195***	-0.176***	-0.147***	-0.132***	-0.123***	-0.117***	-0.110***
	(0.00787)	(0.00479)	(0.00353)	(0.00357)	(0.00290)	(0.00292)	(0.00413)
Bachelor Rate	0.290***	0.314***	0.475***	0.604***	0.911***	1.527***	2.613***
	(0.0491)	(0.0391)	(0.0265)	(0.0242)	(0.0293)	(0.0339)	(0.0366)
% Population Black	-0.450***	-0.490***	-0.474***	-0.473***	-0.337***	-0.0639**	0.377***
	(0.0491)	(0.0191)	(0.0165)	(0.0177)	(0.0178)	(0.0278)	(0.0230)
Observations	161,243	161,243	161,243	161,243	161,243	161,243	161,243

1. Each specification includes year fixed effects and a categorical variable for age of dwelling (9 categories as reported in the IPUMS). These point estimates are omitted for the sake of brevity.
2. Bootstrapped standard errors are reported in parentheses. Bootstrapped using 50 replications.

Table 4.8: Willingness to Pay, by Race and Nativity			
	(1)	(2)	(3)
	Immigrants	Whites	Blacks
VARIABLES	$\ln(r_{jkt})$	$\ln(r_{jkt})$	$\ln(r_{jkt})$
Immigration Impact	0.472***	0.904***	0.938***
	(0.113)	(0.0856)	(0.192)
Housing Unit, Single Family	0.171***	0.127***	0.226***
	(0.0105)	(0.00632)	(0.0153)
Housing Unit, 10+ Units	-0.162***	-0.141***	-0.260***
	(0.00440)	(0.00372)	(0.00631)
Lacks Complete Kitchen	-0.0783***	-0.175***	-0.0477*
	(0.0208)	(0.0203)	(0.0263)
Lacks Complete Plumbing	-0.0237	-0.0533**	-0.0178
	(0.0198)	(0.0223)	(0.0252)
Number of Bedrooms	0.0821***	0.110***	0.0610***
	(0.00242)	(0.00206)	(0.00320)
High School Graduate	0.0993***	0.139***	0.164***
	(0.00737)	(0.00750)	(0.01000)
Some College	0.220***	0.331***	0.335***
	(0.00536)	(0.00484)	(0.00705)
College Graduate	0.374***	0.508***	0.514***
	(0.00569)	(0.00486)	(0.00812)
Householder Married	0.117***	0.131***	0.223***
	(0.00412)	(0.00337)	(0.00609)
Householder Hispanic	-0.0173***	-0.0854***	0.0650***
	(0.00474)	(0.00496)	(0.00981)
Householder Black	-0.00852		
	(0.00540)		
% Population with Bachelor's Degree	0.310***	1.543***	-0.410***
	(0.0567)	(0.0339)	(0.0726)
% Population Black	-0.523***	-0.302***	-0.491***
	(0.0334)	(0.0199)	(0.0434)
In Central City	-0.00404	0.0844***	-0.105***
	(0.00899)	(0.00622)	(0.0139)
Observations	54,541	90,958	35,879
R-squared	0.210	0.310	0.243

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Table 4.9: Native Out-Migration, New York City				
	(1)	(2)	(3)	(4)
	OLS	2SLS	OLS	2SLS
VARIABLES	Δw_{jkt}	Δw_{jkt}	Δw_{jkt}	Δw_{jkt}
Immigration Impact	0.389***	-0.000439	1.560***	-0.309
	(0.0227)	(0.0419)	(0.0456)	(0.361)
*Immigration Impact*Rent Quantile 1*			-1.573***	0.273
			(0.0525)	(0.361)
Rent Quantile 1			0.224***	-0.00572
			(0.0175)	(0.0486)
*Immigration Impact*Rent Quantile 3*			-1.279***	0.848**
			(0.0970)	(0.391)
Rent Quantile 3			0.127***	-0.121**
			(0.0198)	(0.0490)
*Immigration Impact*Rent Quantile 4*			-0.698***	2.189***
			(0.104)	(0.481)
Rent Quantile 4			0.0835***	-0.196***
			(0.0191)	(0.0487)
% Population with Bachelor's (T-10)	0.139***	0.0864**	0.194***	0.152***
	(0.0328)	(0.0337)	(0.0338)	(0.0412)
% Population Black (T-10)	0.0662***	0.0517**	0.0685***	0.0309
	(0.0203)	(0.0207)	(0.0194)	(0.0221)
Log Population Density (T-10)	-0.0731***	-0.0760***	-0.0771***	-0.0724***
	(0.00407)	(0.00414)	(0.00392)	(0.00442)
% Households Married (T-10)	0.00422	-0.0258	-0.0583	0.00765
	(0.0504)	(0.0513)	(0.0482)	(0.0543)
% Renter Occupied Units (T-10)	0.0336	0.0561*	-0.0167	0.0464
	(0.0334)	(0.0340)	(0.0323)	(0.0381)
% Households, Tenure>10 years (T-10)	-0.298***	-0.344***	-0.233***	-0.321***
	(0.0386)	(0.0394)	(0.0369)	(0.0471)
NDI (T-10)	0.0114	0.00395	0.00461	0.0135
	(0.0110)	(0.0112)	(0.0107)	(0.0120)
Vacancy Rate (T-10)	0.418***	0.349***	0.382***	0.374***
	(0.0768)	(0.0783)	(0.0732)	(0.0807)
Observations	8,682	8,682	8,682	8,682
R-squared	0.125	---	0.210	---

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusion

The essays of this dissertation provided useful contributions for both academics and policymakers. The underlying theme of this dissertation was inherently methodological. In chapters 2 and 3, I identified two widely accepted results within the immigration literature and showed the fragility of some of the underlying theoretical and methodological underpinnings of past research. In chapter 2, using a more robust empirical model that more readily controls for the endogeneity of immigrant locations, I provide evidence that we should not expect immigrant inflows to have a differential impact on rents than any other one-time population increase. In this essay, the main contribution to the field is the evidence that the widely used shift-share instrumental variable introduces bias when one does not account for the location choices of past immigrants. The evidence in chapter 2 suggests that all immigrants, both past and present, are locating in cities that afford them the best economic opportunities.

While the model used in Chapter 2 is an improvement over past studies, it should be noted that this is partial reduced form model. In an equilibrium model of population growth and wages, we expect *all* population growth to impact prices; however, native population flows are omitted from the model. Thus, the model in Chapter 2 suggests a much broader model, which is a logical extension of the present paper. The partial reduced form model was used for two reasons. First, the main goal of the paper was to address the fragility of the estimates in the existing literature and the possible bias of the shift share instrument. As such, I utilized a model that most closely resembled the existing literature. Second, while native population flows are integral to the evolution of rents, these native populations are more sensitive to economic conditions within cities – they do not display clustering behavior like immigrants. Thus, a valid instrument for these population flows is not readily apparent.

A second modeling consideration, which is briefly mentioned in the text, is the idea of partial adjustment of rents from one period to the next. The literature analyzing the adjustment of rents suggests that significant lags may exist in the response of rents to changes in demand. Several factors are in play here. First, tenants are likely "tied" to their units by lease contracts, making moving more difficult. Second, vacancy rates play a fundamental role in the evolution of rents. Because rental markets are in constant disequilibrium, these inefficiencies may hinder market clearing. In the context of Chapter 2, this implies that the effect of immigration on rents may be muted in the short-run. A partial adjustment model of the following general form was considered and estimated:

$$r_{kt} = (1 - \lambda) r_{kt-1} + \lambda I_{kt} + \lambda u_{kt}.$$

Here, λ is the adjustment coefficient. If $\lambda=1$, then rents fully adjust between each period. If $\lambda<1$, then rents partially adjust from one period to the next. The results of the partial adjustment model suggest that rent (or at least FMR) fully adjust from one year to the next as λ was essentially 1. As such, the static model is appropriate. One concern, however, stems from the above – the existing literature suggests that the rental market does not clear instantaneously. The full adjustment result is likely due, in part, to the way the FMR for a city is calculated. To calculate the FMR for each year, the HUD uses the most recent data from the decennial Census or American Community Survey to *update* the value of FMR from the previous year, not estimate the new value. Thus, the adjustment process is more predictable and the slow, partial adjustment expected in the rental market is not picked up in the model.

From a policy perspective, the results are potentially more important. Over the last 5 years, some policymakers have considered immigration as a policy tool to help "bring back" the housing market. On the other hand, the results of Saiz (2007) and similar studies have been widely cited in the national media and by policymakers to argue against immigration reform. The results of chapter 2 however, cast doubt on the arguments of either side. Immigrant inflows are not inherently different from native population flows. The difference is that the majority of immigrant inflows are into the largest metropolitan areas that face increased housing prices irrespective of immigration.

In chapter 3, I again challenge the consensus in the existing literature and propose a new framework with which to analyze the wage effects of immigration. Because immigrants are often misplaced in the labor market with respect to educational attainment and immigrants and natives specialize in different skills, I propose stratifying the labor market by occupation instead of education. To my knowledge, I am the first to use occupation-specific skills to define homogenous labor groups (with respect to skill) within the context of immigration. When stratifying the labor market across occupations, I estimate a nontrivial impact of immigration on average native wages. I also provide ample evidence to support the claim that larger wage effect is due to increased substitutability between workers within skill groups, not endogeneity of occupation choice. Furthermore, Chapter 3 leads to a rather obvious extension for future research. While the estimates are significant, both statistically and economically, I should reemphasize that these effects are partial equilibrium effects. In order to inform national policy, one must also speak to the total wage effect of immigration on wages – accounting for within-occupation and across-occupation effects on native wages.

In chapter 4, I return to the rental housing market and assess the impact of immigration within metropolitan areas. Specifically, I show that immigration has a differential impact within cities at both the national level and with a single metropolitan area and can provide initial evidence that differences across the rent distribution is driven by native out-migration. Overall, because the impact of immigration on rents is lower in high-immigrant neighborhoods, I conclude that it is not the willingness to pay of immigrants that bid up rents in the city; rather, it is the willingness to pay of natives to *not* live in these high-immigration areas.

In Chapter 4, I outline three widely accepted theories in the sociology literature that explain why native households leave high-immigrant tracts. While the results show that native mobility is an important factor in determining the evolution of rents in a city, I am unable to identify the mechanism driving this out-migration. While I cannot speak definitively to the mechanism, certain specifications allow for conjecture. The tract-level analysis suggests immigrant inflows are associated with decreases in rents. According to the conceptual framework established in section 4.2, this is consistent with a scenario where native receive disutility from living near immigrants. Thus, these negative point estimates are consistent with either the ethnic flight hypothesis or the socioeconomic context hypothesis.

In addition to the extensions mentioned above, these papers provide solid footing for related research and extensions of the ideas therein. I envision several extensions from Chapter 4. Ultimately, I see chapter 4 as two standalone papers: the tract-level analysis and the quantile regression. The tract-level analysis provides the perfect setup for a spatial analysis of immigration. In order to accurately identify white flight out of neighborhoods, one must consider the effects of immigrant inflows into neighboring tracts on the mobility decisions of native households. For the quantile analysis section, restricted-access micro-data of the Census or AHS would provide the necessary geographic data to completely isolate true neighborhood effects. Additionally, I foresee myself moving beyond the case study of NYC to a more representative sample of cities.

Appendix 1 (Chapter 2)

Table A2.1: Determinants of Immigrant Share, Alternate Proxies

VARIABLES	(1) Share 1995	(2) Share 1995	(3) Share 1995	(4) Share 1995
FMR Growth (1983-90)	0.00703			
	(0.00740)			
Log Med Gross Rent (1990)		0.0190**		
		(0.00736)		
Average Commute (1990)			0.00220**	
			(0.00104)	
Price-to-Rent Ratio (1990)				0.0152**
				(0.00751)
Per Capita Sales (1992)	0.0110***	0.00661***	0.00526*	0.00655***
	(0.00368)	(0.00216)	(0.00269)	(0.00235)
Per Capita Prop Tax Rev (1997)	0.00165	-0.00194	0.00182	0.00116
	(0.00173)	(0.00182)	(0.00173)	(0.00170)
% Housing Stock Built Pre-39 (1990)	0.00455	0.0162	0.0137	0.00410
	(0.00753)	(0.0112)	(0.0108)	(0.00739)
% Total Earnings from Farms (1990)	-0.00502	-0.0116	0.0333*	-0.0199
	(0.0106)	(0.00937)	(0.0181)	(0.0137)
Observations	325	325	325	325
R-squared	0.083	0.117	0.232	0.122

1. All specifications use the full preferred model. Other point estimates are omitted for the sake of brevity.
2. Robust standard errors, clustered by CBSA, are reported in parentheses.

Robust standard errors in parentheses
***** p<0.01, ** p<0.05, * p<0.1**

Table A2.2: Determinants of Predicted Employment Growth

VARIABLES	(1) $\hat{E}_{kt}$	(2) $\hat{E}_{kt}$
Rent Growth (1980-90)	-8.31e-05	
	(0.00268)	
FMR (1990)		0.00345*
		(0.00179)
% Housing Stock Built Pre-1939 (1990)	-0.00479	-0.00502
	(0.00350)	(0.00342)
Per Capita Sales (1992)	0.00159	0.000638
	(0.00127)	(0.00133)
Per Capita Proper Tax Revenue (1997)	0.000256	-0.000174
	(0.000861)	(0.000864)
% Total Earnings from Farms (1990)	0.00272	-0.00118
	(0.0103)	(0.0104)
Observations	4,225	4,225
R-squared	0.001	0.002

Table A2.3: Variable Descriptions and Sources

Variable	Description	Table
FMR	The FMR is reported at the county-level by the HUD. The CBSA-level data are population-weighted averages of the corresponding county data. Prior to aggregating to the CBSA-level, all county-level data are adjusted (as described in section 2.3) to 40% FMR estimates.	T2-A2
Rent-to-Income Ratio	The change in the log of rent-to-income ratio from time *t-1* to time *t*. Here, the FMR in city *k* is divided by one of three income measures.	T6
Immigrants (1999-2011)	Customized data from the Department of Homeland Security. These data were aggregated to 2013 CBSA definitions.	T2 – T4, T6, A1
Per Capita Personal Income	County-level data from the Bureau of Economic Analysis' (BEA) Regional Economic Information System (REIS).	T2 – T4, T6
Average Wages (BEA)	County-level data from the Bureau of Economic Analysis' (BEA) Regional Economic Information System (REIS).	T6
Average Wages (QCEW)	County-level data from the Quarterly Census of Employment and Wages (QCEW). Aggregated to 2013 CBSA definitions.	T6
Average Wages (Goods-Producing)	County-level data from the Quarterly Census of Employment and Wages (QCEW). Aggregated to 2013 CBSA definitions.	T6
Unemployment Rate	County-level employment data from the Bureau of Labor Statistics (BLS) aggregated to 2013 CBSA definitions.	T2, T4-T6, A1
January Average Temperature	The average temperature (measured in Fahrenheit degrees) over the years 1941–1970. From the United States Department of Agriculture (USDA) Economic Research Service (ERS) Natural Amenities Scale Database. County-level data is aggregated to CBSA.	T2, T4-T6, A1
July Average Humidity	The average relative humidity over the years 1941–1970. From the United States Department of Agriculture (USDA) Economic Research Service (ERS) Natural Amenities Scale Database. County-level data is aggregated to CBSA.	T2, T4-T6, A1
CBSA Land Area	County-level data derived from the US Census Bureau Censtats database, aggregated to 2013 CBSA definitions.	T2, T4-T6, A1

% of population with a Bachelor's degree	County-level data derived from the US Census Bureau Censtats database, aggregated to 2013 CBSA definitions.	T2, T4-T6, A1
Murder Rate (2000)	County-level murder statistics from the Federal Bureau of Investigation's (FBI) Uniform Crime Reporting (UCR) database. As certain states do not report to the FBI (i.e. Florida, Illinois, , etc.), these data are obtained from state run databases.	T2, T4,T6, A1
Rent Growth (1980-90)	Constructed using county-level median gross rent data from the U.S. Census. I calculate weighted average median gross rents for each CBSA, where weights are the number of rental-occupied housing units.	T2-T4, T6-A2
% of Housing Stock Built Pre-1939 (1990)	County-level data from the 1994 County and City Data Book	T2-T4, T6-A2
% of Total Earnings from Farms (1990)	County-level data from the 1994 County and City Data Book. The ratio of earnings from farms to the total earnings.	T2-T4, T6-A2
Per Capita Sales (1992)	This is per capita sales in private retail and service establishments. County-level data obtained from the 1992 Economic Census.	T2-T4, T6-A2
Per Capita Property Tax Revenue (1997)	County-level data from the 2000 County and City Data Book. Use the variables total tax revenue and percent of total revenue from property taxes to construct this variable.	T2-T4, T6-A2
Price-to-Rent Ratio	Constructed from county level census data. Calculate weighted average house values and rents, where the weights are owner-occupied units and renter-occupied, respectively	T3
WRLURI	The Wharton Residential Land Use Regulatory Index. This index is given for a Census-defined place. I then construct CBSA-level estimates as population-weighted averages of each place.	T2, T4-T6
Change in Average Construction Wages	Constructed from county-level wage data from the QCEW. All employment in wages in NAICS industry 23.	T2, T4-T6
Predicted Employment Growth	Described below.	T5, A2

Table A2.4: Housing Affordability, Robustness Checks		
	(1)	(2)
	Average Wages Per Job, (BEA)	Average Wages Per Job, (BEA)
VARIABLES	$\left(\frac{Rent}{Avg\ Wage}\right)$	$\left(\frac{Rent}{Avg\ Wage}\right)$
Immigration Impact	-0.709	-0.300
	(0.554)	(0.511)
Unemployment Rate (t-1)	-0.0153	-0.0161
	(0.0336)	(0.0355)
Δ Per Capita Income (t-1)	-0.0687**	-0.0922***
	(0.0303)	(0.0304)
Rent Growth (1980-90)	0.00470	0.0116**
	(0.00562)	(0.00563)
Per Capita Sales (1992)	0.00688***	0.00644***
	(0.00186)	(0.00212)
Per Capita Proper Tax Revenue (1997)	-0.000734	-0.00101
	(0.00157)	(0.00114)
% Housing Stock Built Pre-1939 (1990)	0.0264***	0.0210***
	(0.00769)	(0.00721)
% Total Earnings from Farms (1990)	-0.0105	-0.00440
	(0.0149)	(0.0144)
WRLURI	0.000479	-0.000216
	(0.000786)	(0.000634)
% Pop with a Bachelor's (1990)	-0.0196**	-0.0260***
	(0.00933)	(0.00955)
State-by-year Fixed Effects?	Yes	No
Bartik-style Imputed Employment Growth?	No	Yes
Observations	4,225	4,225
R-squared	0.454	0.306

Calculation of Predicted Employment Growth

Predicted employment growth uses CBSA-specific employment shares and national growth rates to predict future employment growth. Essentially, this is the measure of employment growth assuming the industrial mix of the city is held constant. In using national employment trends, it is reasonable to assume that this measure of employment growth will be uncorrelated with local conditions.

Predicted employment growth ($\hat{E}_{kt}$) is calculated as:

$$\hat{E}_{kt} = \sum_j \left(s_{kjt-1} * \left(e_{jt}^{US} \right) \right);$$

where s_{kjt-1} is the share of employment in industry *j* in city *k* a time *t-1* and e_{jt}^{US} is the growth rate in overall US employment in industry *j* in year *t*.

The data used in the calculations comes from the Quarterly Census of Employment and Wages from the Bureau of Labor Statistics (http://www.bls.gov/cew/datatoc.htm). Both the employment shares and employment growth are calculated using 3-digit NAICS codes.

Appendix 2 (Chapter 3)

A. Creating Manual-to-Communicative Task Index

We use the O*NET database (version 18) to construct the manual-to-communicative task ratio. First, we use select attributes from Ability, Work Activity, Skill, and Knowledge descriptors from the O*NET to create a communicative task-intensity index and a manual task-intensity index. Abilities, Skills, and Knowledge data describe the attributes of workers, while Work Activity describes occupation attributes. For the communicative task-intensity index, we use worker and occupation attributes related to communicating information, social skills, and listening. The manual task-intensity index uses attributes related to basic strength and related characteristics. A full list of attributes for each descriptor used in these calculations (along with their manual/communicative designation) can be found in Table A1 below.

We first compute a measure of overall intensity for each attribute in a given O*NET occupation. The O*NET provides two ratings for the attributes: Importance and Level. The importance rating indicates the importance of a particular attribute to a given occupation, while the level rating indicates the degree to which an attribute is needed to perform a job. We create an overall intensity measure by multiplying Importance (scale 1-5) and Level (scale 1-7). We then normalize each intensity measure to be in the range of 0-1 by dividing by 35.

One limitation of the O*NET is that occupations do not change over time. In order to use these data for my entire sample, we match the occupation groups defined in the ONET (i.e. 11-1011) to the occupation classification (occ1990dd) of Autor and Dorn (2013). The advantage of the occupation classification of Autor and Dorn (2013) is that occupations are a consistent panel from 1960-2010. To do this, we first match O*NET occupations to occupations defined by the U.S. Census (using the standard crosswalk file and OCC codes from the 2000 Census), then we match the Census OCC codes to the occ1990dd codes (using the files provide by the authors on their website). It should be noted that there are significantly more O*NET occupation groups than occ1990dd occupation groups (841 O*NET vs. 330 occ199dd); thus, there are multiple O*NET occupation groups for each occ1990dd code.

As such, the manual (communicative) task-intensity index for each occ1990dd code is simply the weighted average of all manual (communicative) attribute-specific intensity measures within a given occ1990dd code (weighted by total employment). Then, the manual-to-communicative ratio is calculated by dividing the manual task-intensity index by the communicative task-intensity index.

Table A3.1: O*NET Components Used in Communicative-to-Manual Skill Ratio	
Abilities	
Verbal (All)	Communicative
Idea Generation and Reasoning (Fluency of Ideas, Originality, Deductive Reasoning, Inductive Reasoning)	Communicative
Perceptual (Perceptual Speed)	Communicative
Sensory (Speech Recognition, Speech Clarity)	Communicative
Psychomotor (All)	Manual
Physical (All)	Manual
Work Activities	
Interpreting the Meaning of Information for Others	Communicative
Communicating with Supervisors, Peers, or Subordinates	Communicative
Communicating with Persons Outside Organization	Communicative
Establishing and Maintaining Interpersonal Relationships	Communicative
Assisting and Caring for Others	Communicative
Selling or Influencing Others	Communicative
Resolving Conflicts and Negotiating with Others	Communicative
Performing for or Working Directly with the Public	Communicative
Performing General Physical Activities	Manual
Handling and Moving Objects	Manual
Controlling Machines and Processes	Manual
Operating Vehicles, Mechanized Devices, or Equipment	Manual
Skills	
Reading Comprehension	Communicative
Active Listening	Communicative
Writing	Communicative
Speaking	Communicative
Installation	Manual
Operation Monitoring	Manual
Equipment Maintenance	Manual
Knowledge	
English Language	Communicative
Communications	Communicative
Building and Construction	Manual
Mechanical	Manual

1) Abilities, Work Activities, Skills, and Knowledge are the descriptors

2) Within each descriptor, we list all of the “attributes” used in the calculation of the task intensity indices.

B. Sample Description

B.1 Wage Sample

We calculate mean log wages for male workers in each year. Following Borjas (2003), we restrict the sample to include non-self-employed males, aged 18-64, who have positive weeks worked, valid earnings data, and that did not live in group quarters. Mean log wages are represented as constant 2010-dollars and we used hours worked (perwt*weeks*hours/2000) as weights in the calculation. As in Borjas (2003), we use potential experience as a proxy for actual experience. To calculate potential experience, we assume that workers with less than a high school diploma enter the labor force at 17; workers with a high school diploma or GED enter the labor force at 19; workers with some college (less than a bachelor's degree) enter the labor force at age 21; and workers with a college degree enter the labor force at 23. We drop those who report potential experience less than 0 or greater than 40.

B.2 Employment Sample

To calculate labor supply in each occupation-experience cohort, we limit the sample to males aged 18-64 who have positive weeks worked that did not reside in group quarters. Here, self-employed workers are included in the calculations. Labor supply in an occupation-experience cohort is the sum of all hours worked. Potential experience is defined as above.

C. Logit Models

C.1 Labor Supply

The multinomial logit specifications resemble those in Card (2001). However, to remain consistent with the above, we restrict the sample to males only. We pool the data from 1970, 1980, 1990, 2000, and 2010 and estimate flexible specifications for natives and immigrants separately. The native specification includes the following controls: education, a quartic in potential experience, an indicator variable for being married, a set of race dummies (include Black, Asian, and other non-white), an interaction of education and race dummies, an interaction of education with linear potential experience and quadratic potential experience, and state and year fixed effects. The immigrant specification includes the following controls: education, a quartic in potential experience, a quadratic of years in the U.S, an interaction of education and the quadratic of years in the U.S., 17 country of origin dummies, an interaction of education with three main origin groups (Mexico, Canada/Australia/Europe, and Asia), a set of race dummies (Black, Asian, and other non-white), and state and year fixed effects. We estimate the predicted probabilities of working in occupation *j* for each individual. The predicted labor supply for each occupation is simply the sum of these predicted probabilities.

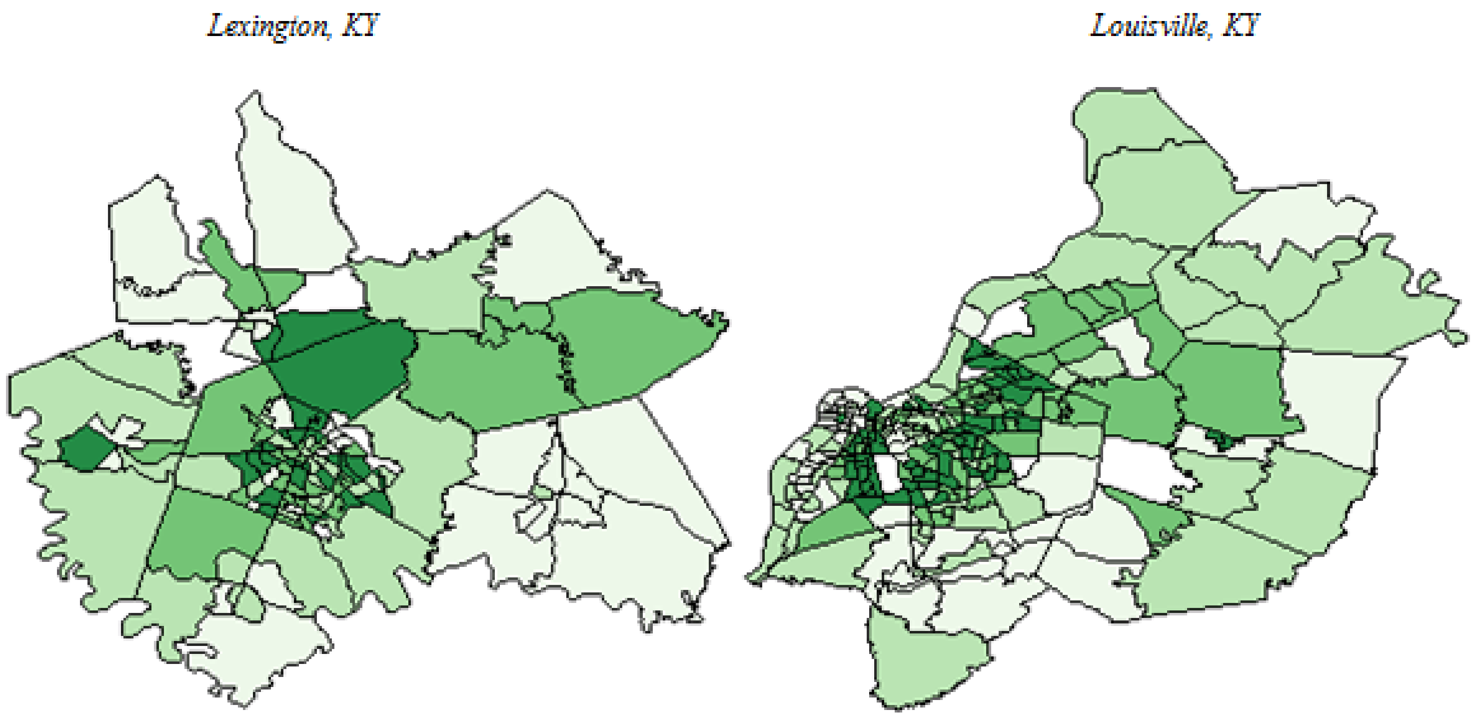


Figure A4.1: Immigrant Clustering Within Metropolitan Areas
Medium-Sized Metropolitan Areas

Table A4.1: Estimation Results for Imputed Immigrant Calculations		
VARIABLES	(1) Countries With Complete Data m_{it}	(2) Countries With Incomplete Data m_{it}
Relative Real GDP (t-1)	-0.409***	
	(0.113)	
Poverty Rate (t-1)	-0.0517***	
	(0.0112)	
% Young Population (t-1)	0.606***	
	(0.103)	
Regime Change (t-2)	0.0340**	
	(0.0166)	
Revolutionary War (t-2)	0.0593***	0.0298
	(0.0137)	(0.0811)
Genocide (t-2)	0.0845***	0.0537
	(0.0195)	(0.2301)
Allotted Refugee Visas	0.345*	0.1758*
	(0.194)	(0.0956)
Eligible for Diversity Visas	0.0630***	0.1500***
	(0.0191)	(0.0431)
IRCA	66.64***	63.18***
	(6.818)	(20.258)
Average Migration Rate Last 5 Years	0.818***	0.812***
	(0.0114)	(0.0256)
Observations	4,562	527
Number of Countries	154	18

1. Column (1) reports estimates from the full model described by Eq. (2). Column (2) is a modified model estimated for countries with inconsistent data availability over the time period.
2. Country random effects are included, but these estimated effects are omitted when predicting migration rates from a given source country.

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A4.2: Variable Descriptions, Instrument		
Variable	Source	Definition
Real GDP	Penn World Tables	The log of real GDP in international dollars for source country *i* divided by the real GDP in international dollars for the U.S.
Poverty rate	Penn World Tables	The log of the inverse of per capita income squared.
Young Population	WIDER Institute	The share of the total population aged 15-19.
Regime Change	The Integrated Network for Societal Conflict Research (INSCR) – The Political Instability Task Force (PITF) State Failure Problem Set.	The data set identifies incidences of each type of conflict by country. I only use conflicts that occurred within a countries border.
Revolutionary War		
Genocide		
Refugee Visas[62]	Pre 1992: INS *Statistical Yearbooks.* Post-2002: DHS *Yearbook of Immigrant Statistics*	The refugee visa quota for a given region divided by the country's population.
Diversity Visas		Defined for eligible countries only – all other countries take a value of 0. The variable is calculated as the total number of diversity visas divided by the country's population.
IRCA		The number of illegal immigrants living in the U.S. in 1980 divided by the country's population in 1990.
Average Migration Rate		The 5 year moving average of migration rates.

[62] For detailed explanations of the methodology and theory underlying the visa variables, I direct interested readers to Clark et al. (2007).

References (Chapter 2)

Abraham, J. M., & Hendershott, P. H. (1996). Bubbles in Metropolitan Housing Markets. *Journal of Housing Research*, 191.

Accetturo, A., Manaresi, F., Mocetti, S., & Olivieri, E. (2012). Don't stand so close to me: the urban impact of immigration. *Bank of Italy Temi di Discussione (Working Paper) No*, *866*.

Altonji, J. G., & Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, trade and the labor market*(pp. 201-234). University of Chicago Press.

Bartel, A. P. (1989). Where do the new US immigrants live?. *Journal of Labor Economics*, 371-391.

Bartik, T. J. (1991). Who benefits from state and local economic development policies?. *Books from Upjohn Press*.

Beeson, P., & Montgomery, E. (1993). The Effects of Colleges and Universities on Local Labor Markets. *The Review of Economics and Statistics*, 753-761.

Blanchard, O. J., Katz, L. F., Hall, R. E., & Eichengreen, B. (1992). Regional evolutions. *Brookings papers on economic activity*, 1-75.

Blank, D. M. & Winnick, L. (1953). The Structure of the Housing Market. *The Quarterly Journal of Economics*, 67(2), 181-208.

Borjas, G. J. (2003). The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. *The quarterly journal of economics*, *118*(4), 1335-1374.

Borjas, G. J., & Trejo, S. J. (1991). Immigrant participation in the welfare system. *Industrial & labor relations review*, *44*(2), 195-211.

Brueckner, J. K. (1982). Building ages and urban growth. *Regional Science and Urban Economics*, *12*(2), 197-210.Card (2005)

Capozza, D. R., Hendershott, P. H., Mack, C., & Mayer, C. J. (2002).*Determinants of real house price dynamics* (No. w9262). National Bureau of Economic Research.

Capozza, D. R., & Seguin, P. J. (1996). Expectations, efficiency, and euphoria in the housing market. *Regional Science and Urban Economics*, *26*(3), 369-386.

Chiswick, B.R., & Miller, P.W. (2004). Where Immigrants Settle in the United States, *IZA Discussion Paper Series*, No. 1231.

Clark, T. E. (1995). Rents and prices of housing across areas of the United States. A cross-section examination of the present value model. *Regional Science and Urban Economics*, *25*(2), 237-247.

Cortes, P. (2008). The effect of low-skilled immigration on US prices: evidence from CPI data. *Journal of political Economy*, *116*(3), 381-422.

Degen, K., & Fischer, A. (2009). Immigration and Swiss house prices. *Unpublished Working Paper*

Drennan, M. P., Tobier, E., & Lewis, J. (1996). The interruption of income convergence and income growth in large cities in the 1980s. *Urban Studies*,*33*(1), 63-82.

Engberg, J., & Greenbaum, R. (1999). State enterprise zones and local housing markets. *Journal of Housing Research*, *10*(2), 163-187.

Eubanks Jr., A. A. & Sirmans, C. R. (1979). The Price Adjustment Mechanism for Rental Housing in the United States. *The Quarterly Journal of Economics*, 93(1), 163-168.

Gallin, J. (2008). The Long-Run Relationship Between House Prices and Rents.*Real Estate Economics*, *36*(4), 635-658.

Glaeser, E. L., & Saiz, A. (2004). The rise of the skilled city. *Brookings-Wharton Papers on Urban Affairs*, *2004*(1), 47-105.

Glaeser, E. L., Scheinkman, J., & Shleifer, A. (1995). Economic growth in a cross-section of cities. *Journal of monetary economics*, *36*(1), 117-143.

Gonzalez, L., & Ortega, F. (2013). Immigration and housing booms: Evidence from Spain. *Journal of Regional Science*, *53*(1), 37-59.
Greulich, E., Quigley, J. M., Raphael, S., Tracy, J., & Jasso, G. (2004). The Anatomy of Rent Burdens: Immigration, Growth, and Rental Housing [with Comments]. *Brookings-Wharton Papers on Urban Affairs*, 149-205.
Gustman, A. L., & Steinmeier, T. L. (2000). Social Security Benefits of Immigrants and US Born. In *Issues in the Economics of Immigration* (pp. 309-350). University of Chicago Press.
Gyourko, J. & Mayer, C. & Sinai, T. (2013). Superstar Cities. *American Economic Journal: Economic Policy*, 5(4), 167-199(33).
Gyourko, J. & Saiz, A. & Summers, A. (2008). A New Measure of the Local Regulatory Environment for Housing Markets: The Wharton Residential Land Use Regulatory Index. *Urban Studies*, 45(3), 693-729.
Hacker, J. S., Huber, G. A., Nichols, A., Rehm, P., Schlesinger, M., Valletta, R., & Craig, S. (2014). The Economic Security Index: a new measure for research and policy analysis. *Review of Income and Wealth*, *60*(S1), S5-S32.
Ihlanfeldt, K. R. (2007). The Effect of Land Use Regulations on Housing and Land Prices. *Journal of Urban Economics,* 61(3), 420-435.
Kutty, N. K. (2005). A new measure of housing affordability: Estimates and analytical results. *Housing policy debate*, *16*(1), 113-142.
Mankiw, N. G., & Weil, D. N. (1989). The baby boom, the baby bust, and the housing market. *Regional science and urban economics*, *19*(2), 235-258.
Maplpezzi, S. (1996). Housing Prices, Externalities, and Regulation in U.S. Metropolitan Areas. *Journal of Housing Research*, 7(2), 209-241.
Malpezzi, S., Chun, G. H., & Green, R. K. (1998). New Place-to-Place Housing Price Indexes for US Metropolitan Areas, and Their Determinants. *Real Estate Economics*, *26*(2), 235-274.
Ottaviano, G. I., & Peri, G. (2012). *The effects of immigration on US wages and rents: A general equilibrium approach* (pp. 107-146). Edward Elgar Publishing Limited.
Passel, J.S., Capps, R., & Fix, M. (2004). Undocumented Immigrants: Facts and Figures. *Urban Institute Immigrations Studies Program.*
Passel, J. S., Cohn, D., & Gonzalez-Barrera, A. (2013). Population decline of unauthorized immigrants stalls, may have reversed. *Washington, DC: Pew Hispanic Center. http://www. pewhispanic. org/files/2013/09/Unauthorized-Sept-2013-FINAL. pdf*.
Pollakowski, O. & Wachter, S. M. (1990). The Effects of Land-Use Constraints on Housing Prices. *Land Economics*, 66(3), 315-324.
Potepan, M. J. (1996). Explaining Intermetropolitan Variation in Housing Prices, Rents, and Land Prices. *Real Estate Economics*, 24(2), 219-245.
Poterba, J. M. (1991). House Price Dynamics: The Role of Tax Policy and Demography. *Brookings Papers on Economic Activity*, 143-203.
Quigley, J. M., & Raphael, S. (2005). Regulation and the high cost of housing in California. *American Economic Review*, 323-328.
Rappaport, J. (2004). Why are population flows so persistent?. *Journal of Urban Economics*, *56*(3), 554-580.
Roback, J. (1982). Wages, rents, and the quality of life. *The Journal of Political Economy*, 1257-1278.
Rosen, K. T. & Smith, L. B. (1983). The Price-Adjustment Process for Rental Housing and the Natural Vacancy Rate. *The American Economic Review*, 73(4), 779-786.
Saiz, A. (2003). Room in the kitchen for the melting pot: Immigration and rental prices. *Review of Economics and Statistics*, *85*(3), 502-521.
Saiz, A. (2007). Immigration and housing rents in American cities. *Journal of Urban Economics*, *61*(2), 345-371.

Saks, R. E. (2008). Job creation and housing construction: Constraints on metropolitan area employment growth. *Journal of Urban Economics*, *64*(1), 178-195.

Smith, L. B. (1974). A Note on the Price Adjustment Mechanism for Rental Housing. *The American Economic Review*, 64(3), 478-481.

Thalmann, P. (2003). 'House poor'or simply 'poor'?. *Journal of Housing Economics*, *12*(4), 291-317.

van der Vlist, A. J., Czamanski, D., & Folmer, H. (2011). Immigration and urban housing market dynamics: the case of Haifa. *The Annals of Regional Science*,*47*(3), 585-598.

References (Chapter 3)

Altonji, J. G., & Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In *Immigration, trade, and the labor market*(pp. 201-234). University of Chicago Press.

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

Aydemir, A. B., & Borjas, G. J. (2011). Attenuation bias in measuring the wage impact of immigration. *Journal of Labor Economics*, *29*(1), 69-112.

Borjas, G. J. (1994). The economics of immigration. *Journal of economic literature*, *32*(4), 1667-1717.

Borjas, G. J. (2003). The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market. *The quarterly journal of economics*, *118*(4), 1335-1374.

Borjas, G. J., Freeman, R. B., Katz, L. F., DiNardo, J., & Abowd, J. M. (1997). How much do immigration and trade affect labor market outcomes?. *Brookings papers on economic activity*, 1-90.

Borjas, G. J., Grogger, J., & Hanson, G. H. (2010). Immigration and the Economic Status of African-American Men. *Economica*, *77*(306), 255-282.

Bourdieu, P. (1977). Cultural Reproduction and Social Reproduction. In *Power and Ideology in Education*, ed. J. Karabel and A. Halsey, 487-511. New York: Oxford University Press.

Bratsberg, B., & Terrell, D. (2002). School quality and returns to education of US immigrants. *Economic Inquiry*, *40*(2), 177-198.

Bratsberg, B., & Ragan Jr, J. F. (2002). The impact of host-country schooling on earnings: a study of male immigrants in the United States. *Journal of Human resources*, 63-105.

Bucci, G. A., & Tenorio, R. (1997). Immigrant-Native Wage Differentials and Immigration Reform. *Review of Development Economics*, *1*(3), 305-323.

Camarota, S. (2005). Immigrants at Mid-Decade: A Snapshot of America's Foreign-Born Population in 2005. *Center for Immigration Studies Backgrounder*.

Card, D. (2001). Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration. *Journal of Labor Economics*, *19*(1), 22-64.

Card, D. (2009). *Immigration and inequality* (No. w14683). National Bureau of Economic Research.

Card, D., & Lemieux, T. (2001). Going to college to avoid the draft: The unintended legacy of the Vietnam War. *American Economic Review*, 97-102.

Dustmann, C., & Preston, I. (2012). Comment: Estimating the effect of immigration on wages. *Journal of the European Economic Association*, *10*(1), 216-223.

Ferrer, A., & Riddell, W. C. (2008). Education, credentials, and immigrant earnings. *Canadian Journal of Economics/Revue canadienne d'économique*,*41*(1), 186-216.

Friedberg, R. M. (2000). You can't take it with you? Immigrant assimilation and the portability of human capital. *Journal of Labor Economics*, *18*(2), 221-251.

Greulich, E., Quigley, J. M., Raphael, S., Tracy, J., & Jasso, G. (2004). The Anatomy of Rent Burdens: Immigration, Growth, and Rental Housing [with Comments]. *Brookings-Wharton Papers on Urban Affairs*, 149-205.

Ingram, B. F., & Neumann, G. R. (2006). The returns to skill. *Labour Economics*, *13*(1), 35-59.

Kerr, S. P., & Kerr, W. R. (2011). *Economic impacts of immigration: A survey*(No. w16736). National Bureau of Economic Research.

Katz, L. F., & Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. *The Quarterly Journal of Economics*, *107*(1), 35-78.

Levy, F., & Murnane, R. J. (1992). US earnings levels and earnings inequality: A review of recent trends and proposed explanations. *Journal of Economic Literature*, 1333-1381.

Manacorda, M., Manning, A., & Wadsworth, J. (2012). The impact of immigration on the structure of wages: Theory and evidence from Britain.*Journal of the European Economic Association*, *10*(1), 120-151.
Mattoo, A., Neagu, I. C., & Özden, Ç. (2008). Brain waste? Educated immigrants in the US labor market. *Journal of Development Economics*, *87*(2), 255-269.
Murnane, R. J., Willett, J. B., & Levy, F. (1995). *The growing importance of cognitive skills in wage determination* (No. w5076). National Bureau of Economic Research.
Neagu, I. C. (2009). Career Placement of Skilled Migrants in the US Labor Market. *Research Working papers*, *1*(1), 1-50.
Orrenius, P. M., & Zavodny, M. (2007). Does immigration affect wages? A look at occupation-level evidence. *Labour Economics*, *14*(5), 757-773.
Ottaviano, G. I., & Peri, G. (2012). Rethinking the effect of immigration on wages. *Journal of the European Economic Association*, *10*(1), 152-197.
Peri, G., & Sparber, C. (2009). Task specialization, immigration, and wages.*American Economic Journal: Applied Economics*, *1*(3), 135-169.
Reimers, C. W. (1983). Labor market discrimination against Hispanic and black men. *The review of economics and statistics*, 570-579.
Nakhaie, M. R. (2006). A comparison of the earnings of the Canadian native-born and immigrants, 2001. *Canadian Ethnic Studies*, *38*(2), 19.

References (Chapter 4)

Bartel, A. P. (1989). Where do the new US immigrants live?. *Journal of Labor Economics*, 371-391.

Blundell, R., & Powell, J. L. (2003). Endogeneity in nonparametric and semiparametric regression models. *Econometric Society Monographs*, *36*, 312-357.

Boustan, L. P. (2010). Was Postwar Suburbanization 'White Flight'? Evidence from the Black Migration. *Quarterly Journal of Economics*, 125 (1), 417-443.

Bradford, D. F., & Kelejian, H. H. (1973). An econometric model of the flight to the suburbs. *The Journal of Political Economy*, 566-589.

Card, D., Mas, A., & Rothstein, J. (2008). Tipping and the Dynamics of Segregation. *The Quarterly Journal of Economics*, 177-218.

Cascio, E. U., & Lewis, E. G. (2012). Cracks in the melting pot: immigration, school choice, and segregation. *American Economic Journal: Economic Policy*, 91-117.

Clark, W. A., & Blue, S. A. (2004). Race, class, and segregation patterns in US immigrant gateway cities. *Urban Affairs Review*, *39*(6), 667-688.

Clark, X., Hatton, T. J., & Williamson, J. G. (2007). Explaining US immigration, 1971-1998. *The Review of Economics and Statistics*, *89*(2), 359-373.

Courant, P. N., & Yinger, J. (1977). On models of racial prejudice and urban residential structure. *Journal of Urban Economics*, *4*(3), 272-291.

Crowder, K. (2000). The racial context of white mobility: An individual-level assessment of the white flight hypothesis. *Social Science Research*, *29*(2), 223-257.

Crowder, K., Hall, M., & Tolnay, S. E. (2011). Neighborhood immigration and native out-migration. *American Sociological Review*, *76*(1), 25-47.

Cutler, D. M., Glaeser, E. L., & Vigdor, J. L. (2008). When are ghettos bad? Lessons from immigrant segregation in the United States. *Journal of Urban Economics*, *63*(3), 759-774.

Galster, G. C. (1990). White flight from racially integrated neighbourhoods in the 1970s: the Cleveland experience. *Urban Studies*, *27*(3), 385-399.

Glaeser, E. L., & Saiz, A. (2004). The rise of the skilled city. *Brookings-Wharton Papers on Urban Affairs*, *2004*(1), 47-105.

Goodman, A. C., & Thibodeau, T. G. (1998). Housing market segmentation.*Journal of housing economics*, *7*(2), 121-143.

Goodman, A. C. (1978). Hedonic prices, price indices and housing markets.*Journal of Urban Economics*, *5*(4), 471-484.

Goodman, A. C. (1981). Housing Submarkets Within Urban Areas: Definitions and Evidence. *Journal of Regional Science*, *21*(2), 175-185.

Hannon, L. E. (2005). Extremely Poor Neighborhoods and Homicide*. *Social Science Quarterly*, *86*(s1), 1418-1434.

Kim, T. H., & Muller, C. (2004). Two-stage quantile regression when the first stage is based on quantile regression. *The Econometrics Journal*, *7*(1), 218-231.

King, A. T., & Mieszkowski, P. (1973). Racial discrimination, segregation, and the price of housing. *The journal of political economy*, 590-606.

Lee, S. (2007). Endogeneity in quantile regression models: A control function approach. *Journal of Econometrics*, *141*(2), 1131-1158.

Quigley, J. M., & Weinberg, D. H. (1977). Intra-urban residential mobility: a review and synthesis. *International Regional Science Review*, *2*(1), 41-66.

Rubin, G. M. (1993). Is housing age a commodity? Hedonic price estimates of unit age. *Journal of Housing Research*, *4*(1), 165-184.

Saiz, A. (2003). Room in the kitchen for the melting pot: Immigration and rental prices. *Review of Economics and Statistics*, *85*(3), 502-521.

Saiz, A. (2007). Immigration and housing rents in American cities. *Journal of Urban Economics*, *61*(2), 345-371

Saiz, A., & Wachter, S. (2011). Immigration and the Neighborhood. *American Economic Journal: Economic Policy*, 169-188.

Schelling, T. C. (1972). A process of residential segregation: neighborhood tipping. *Racial discrimination in economic life*, *157*, 174.

Schnare, A. B., & Struyk, R. J. (1976). Segmentation in urban housing markets. *Journal of Urban Economics*, *3*(2), 146-166.

Sheppard, S. (2003). Hedonic Analysis in Real Estate Market. *Handbook of Regional and Urban Economics*, *3*.

Sousa, L. D. (2013). Human capital traps? enclave effects using linked employer-household data. *US Census Bureau Center for Economic Studies Paper No. CES-WP-13-29*.

Weinberg, D. H. (1979). The determinants of intra-urban household mobility.*Regional Science and Urban Economics*, *9*(2), 219-246.

Yinger, J. (1976). Racial prejudice and racial residential segregation in an urban model. *Journal of urban economics*, *3*(4), 383-396.

Vita

James Michael Sharpe

Place of Birth: Saint Simons Island, GA

Education

Masters of Science, Economics, University of Kentucky, May 2012

Bachelor of Arts, Economics, Valdosta State University, December 2009

Bachelor of Arts, Finance, Valdosta State University, December 2009

Professional Experience

Research Assistant, University of Kentucky Center of Business and Economic Research (CBER), August 2013-May 2015

Instructor, University of Kentucky, Summer 2011 – Summer 2013