IMMIGRATION AND ECONOMIC GROWTH IN METROPOLITAN AREAS

By

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DEDICATION

This dissertation is dedicated to my father, Hu Ran.

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ABSTRACT

IMMIGRATION AND ECONOMIC GROWTH IN METROPOLITAN AREAS

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This research answers the question whether immigration contributes to metropolitan areas' productivity and economic growth, and it also quantifies the impacts of immigration on productivity and economic growth. It examines the relationships between metropolitan Gross Domestic Product (GDP) and the measures of immigration in the United States from 2000-2010 and attempts to find evidence in three mechanisms through which immigration can contribute to the economic growth: the overall effects, the skill effects and the complementarity effects. In each effect' analysis, this research uses reduced- and structural-form equations and uses fixed-effects and first-difference models.

First, reduced-form analysis with the specification of GDP per worker as the dependent variable and share of immigrant workers in total workforce as the independent variable revealed that the overall immigration has a small negative impact on metropolitan productivity growth, and this potential negative impact increases with metropolitan population size. Structural-form analysis with the specification of GDP level as the dependent variable and numbers of immigrant worker as the independent variable found that immigration has a significant positive impact on economic growth. However, using instrumental variables cannot enhance this finding with reduced endogeneity. Second, neither reduced- or structural- form analysis found that high-skilled immigrants contribute to the productivity and economic growth. Interestingly, fixed-effects panel regression results pointed out that low-skilled immigrants make a substantial contribution to the productivity and economic growth. Third, this research revealed evidence that immigration contributes to the economic growth through complementing native workers and the complementarity comes from both the immigrant and native workers with the same and with different levels of education.

Immigration's impact on labor market outcomes has been extensively studied. However, previous literature seldom focuses on immigration's effect on the aggregate economic measurement such as GDP. By providing an in-depth analysis of immigrants' impact on metropolitan GDP, this research seeks to fill the gap in the immigration economic impact and regional economic growth literature. This research's findings provide direct guidance in making and implementing metropolitan-specific immigration policy.

Key words: Immigration, economic growth, metropolitan area, GDP

CHAPTER I
INTRODUCTION

Background and Purpose

In 2010, the immigration population in the United States reached 40 million, accounting for about 13 percent of the total population and about 16 percent of the total labor force in the United States[1]. The foreign-born population in the United States has been doubling every 20 years since 1970 (Papademetriou, Sumption, and Terrazas 2011, P29) until the recent recession.

During the slow recovery from the 2007-2009 recession in the United States, immigration has been considered by some a potential driver of economic growth as it boosts labor supply and enlarges the tax payer and consumption base. On the other hand, it is also a popular belief that immigration hinders economic opportunities for natives and depresses native workers' wages. In response to that view, money has been spent to deter unauthorized immigrants from coming to the U.S. and to remove those who are already here. Under the Obama administration, deportation of unauthorized immigration reached almost 2 million by 2013, and for the first time in decades, the estimated outflow of unauthorized immigrants has been greater than the inflow (The Economist 2014).

[1] Author's calculation from the American Community Survey (ACS).

Immigration policy makers seek evidence from cost-benefit analyses by think tanks and economic research on the impact of immigration. However, research about the impact of immigration on natives' labor market outcomes yield mixed results and therefore complicate the debate. One view finds that immigrants are substitutes for native workers in terms of production and replace native workers in jobs, thus depressing wages and reducing employment rates. The other view finds that immigrants complement native workers by increasing the efficiency of the skill-job match and raising productivity.

In the field of academic research on immigration's economic impact, attention primarily focuses on labor market outcomes such as native workers' wage and job opportunities, and very few studies have focused on immigration's impact on the aggregate economy. This research addresses whether immigration is good for metropolitan areas' economic growth, as measured by Gross Domestic Product (GDP). By focusing on metropolitan GDP rather than native workers' wages and job opportunities, this dissertation research reveals a different perspective on immigrants' roles in host economies and provides policy makers evidence about the relationship between immigrants and regional economic growth in the short- to medium-term.

Subject of the Research

In this research, an immigrant is defined as a foreign-born individual with non-U.S. parents[2]. The terms of foreign-born population and immigration are used interchangeably.

Immigrants are a heterogeneous population. An immigrant's legal status can be as a naturalized citizen, a legal permanent resident (LPR), a non-immigrant alien such as a temporary visitor or foreign student, or an unauthorized resident. This research focuses on immigrants who are employed and excludes other immigrants, including temporary visitors, foreign students and refugees (who are not employed). Unauthorized immigrants, as well as the economic activities generated by unauthorized immigrants, are studied in this research to the extent to which they are counted in the data sources.

Research Questions and Hypotheses

The core question this research addresses is whether immigration has positive impacts on metropolitan GDP and what the impacts are. The hypotheses and research questions of this research reflect three mechanisms through which immigration could contribute to the metropolitan economic growth: the overall effect, skills effect, and complementary effect. The hypotheses and research questions of this research are summarized in the remainder of this section.

[2] Immigration is defined using variable "citizen" in the ACS and Census. Immigrants include people who are "naturalized citizens" and "not citizens." Natives include people who were born in the U.S. and who were "born abroad of American parents."

(1) Overall Effect

Do metropolitan areas with larger proportions of immigrant workers relative to native workers have higher GDP per worker? Do metropolitan areas with more immigrant workers have higher GDP?

This research question reflects the hypothesis that immigrants might increase the productivity (captured by GDP per worker) by increasing the local labor pool. To test this relationship, two measures are taken into consideration: immigration intensity and metropolitan size. This is supported by Partridge et al. (2009) who suggest that immigration intensity, in other words, the proportion of the immigrant population relative to the total population, may be an important factor in how immigrants affect a regional economy. Immigration's relationship to economic growth may not be linear: the immigrant intensity of metropolitan areas may affect the local economies' abilities to absorb immigrants. If this is the case, there might be an "optimal" level of immigration intensity in the regional labor force to boost the economy.

Another consideration is that immigration's impacts vary for metropolitan areas with different population sizes. Inspired by Glaeser and Resseger's (2010) finding that human capital's impact on economic growth increases with metro size, this research hypothesizes that immigration's impact on economic growth also depends on metro size. Smaller economies are more likely to have bottlenecks in labor supply where immigrant labor might contribute more effectively, while larger metro areas might not have bottlenecks.

(2) Skills Effect

Do metropolitan areas with larger shares of high-skilled immigrant workers enjoy higher GDP per worker? Do metropolitan areas with more high-skilled immigrant workers have higher GDP?

This research question reflects the hypothesis that high-skilled immigrant workers contribute to the regional economy through innovation stimulation and technological advancement, relative to high-skilled native workers. In other words, high-skilled immigrant workers may bring with them more new ideas, be more likely to stimulate entrepreneurship and generate more international interactions in markets and firms, and therefore boost the economy.

(3) Complement Effect

Do metropolitan areas with greater complementarity between immigrant and native workers enjoy GDP per worker?

This research question reflects the hypothesis that immigrant workers contribute to the receiving economy through their complementarity with the local native workers. In this research, educational attainment is used as proxy of skill level. Complementarity is measured by a congruence index of education distributions similarity between immigrant and native workers. According to the above hypothesis, regions with immigrant workers with who differ more in educational attainment compared to native workers will have faster growth. In addition, this research will also interact different education levels of immigrant and native workers to detect which combinations have more complementarity effect on the metropolitan economic growth.

In answering the first research questions, per worker metropolitan GPD and metropolitan GDP are used as indicators for economic growth in reduced- and structural-form[3] respectively. The reason that both are used is that they are in the specifications using two different independent variables, immigrant worker's share in total workers (M/L), and number of immigrant workers (M). Statistically, both specifications are the same[4]. Each specification allows different results and interpretations for change in immigration share and immigration level. In terms of the third research question, because congruence index is only in one form calculated by share of different educational levels of immigrants, only reduced-form analysis is conducted.

Methods and Data

All three effects research questions are approached in a reduced-form specification identifying relationships between GDP per worker and immigration share using fixed-effects model. The first two research questions are also approached with a structural-form model framed using a production function using immigrant and native workers' levels and capital to explain GDP. The structural-form specification uses both fixed-effects and first-difference models.

[3] It is not a structural model in the 'strict sense' of the word but rather a model where this research assumes output (GDP) is generated according to a Cobb Douglas production function.
[4] Per capita GDP (GDP/L) and immigration share (M/L) are GDP and just immigration number (M) both divided by total workers (L).

This dissertation uses data that primarily comes from the American Community Survey (ACS), U.S. Census[5], and Bureau of Economic Analysis (BEA), and covers a ten-year period (2000-2010[6]) with three periods included in regressions. Instrumental variable strategies rely on historic settlement patterns of previous immigrants of the same ethnicity.

Contributions

This research makes three contributions to the existing literature of immigration and economic growth studies. First, by providing an in-depth analysis of immigrants' impact on metropolitan economic growth, this research seeks to fill the gap of the immigration economic impact literature. Immigration's impact on labor market outcomes, such as wage and employment opportunities, has been extensively studied. However, previous literature seldom focuses on immigration's effect on the aggregate economic measurement such as GDP. To the author's knowledge, this is the first paper using time panel regression to explore immigration's effect on metropolitan GDP.

Second, this research seeks to build on the knowledge in the regional economic growth literature, particularly at the metropolitan level, by focusing on immigration as a key element in metropolitan economic growth. In this research, framed using a production function, the contributions of both foreign-born and native-born labor are considered in accounting for economic growth. Immigration research rarely takes this approach or directly compares foreign-born and native-born workers in analyzing

[5] ACS 2010, 2005 and Census 2000 5% data accessed through IPUMS (Integrated Public Use Microdata Series).
[6] GDP data from BEA are from 2001-2011.

economic growth. Furthermore, the Bureau of Economic Analysis (BEA) only began to release metropolitan GDP data in 2001, so these data are recent and relatively under-utilized, especially in panel analysis.

The third contribution of this research is to employ a panel regression with both area and year fixed effects as an improvement over the traditional methodologies in immigration's economic impact studies: "area-based" and "time-series" methods. The panel regression, with year and area fixed effects, addresses the endogeneity problem with employment of instrumental variables.

Scope of Dissertation

This dissertation contains six chapters. After the introduction, the remaining chapters are organized in the following way. The second chapter surveys the relevant literature on immigration economics and on human capital and migration within the field of regional economic growth and development. The third chapter details the data sources, methodologies, measurements, and models employed in this research to answer each research question. In addition, Chapter III provides an analytical description of the data. The fourth chapter presents the results for the reduced-form exercise, which identifies relationships between GDP per worker and several measures of immigration. The fifth chapter presents the results for the structural-form exercise, which is framed using a production function, and examines immigrant workers' impacts on metropolitan economic growth. The final chapter concludes with research findings and their policy implications. It also suggests future research stemming from this dissertation.

Research Expectations

This research identifies immigration's impact on metropolitan economic growth over the short- to medium- term (2000-2010). It categorizes immigration into different skill levels and examines their complementarity to native workers to determine how immigration affects economic growth. This research also compares immigrant workers' and native workers' contributions to economic growth.

Given that immigration's impact on metropolitan GDP has not been previously studied, the results of this research have timely importance for the current immigration reform policy debate. Because this research considers metropolitan size and other characteristics, the results are relevant both to national and metropolitan-level immigration and economic policies.

However, as a forerunner of research analyzing immigration's relationship with economic growth as measured by GDP, this dissertation is limited in its ability to account for known variations in immigrant characteristics such as race and ethnicity and legal status. Still, this dissertation's conclusions can be extended in future research when these data are available.

CHAPTER II
LITERATURE REVIEW

The purpose of this chapter is to identify and discuss theoretical and empirical literature related to the issue studied in this research. The related literature largely falls into two groups: one is on economic growth with a focus on human capital's role and migration's relationship to economic growth; and the second is on immigration's economic impact on the receiving economy. As both groups include a large body of literature, this chapter also reviews the literature that is intertwined with economic growth, human capital, and immigration.

Theories and Models of Regional Economic Growth

The central question that all economic growth theories and models attempt to address is what determines economic growth. In this section, regional economic growth theories and models that indicate the relevance and importance of human capital, migration and immigration are discussed.

Changes in labor supply, including labor mobility, is considered among the most important elements in explaining why some places stagnate while others expand. Since Adam Smith (1776) demonstrated that increasing productivity from the division of labor was constrained by market size and population in a region, hence having a large population that ensures ample labor supply has long been viewed as contribution to economic growth. Malthus (1798), however, pointed out the downside of an increasing population is reductions in output per person. Marx (1848) pointed out that the movement of agricultural surplus labor to the cities due to the encroachment of agricultural land actually resulted in and accelerated the industrialization process in the Great Britain. The association of rural-urban migration with urbanization through a structural shift of employment has been widely recognized.

Some theorists (Lewis 1954) (Rostow 1960) (Todaro 1969) use urbanization and the population movement from rural, agricultural sectors to urban, industrial sectors as an integral component of economic development. A cluster of large population and migration inflow has been viewed as contributing to a region's economic development because a large supply of population was crucial to maintaining labor supply and thus supported national and regional development (Kuznets 1965).

Examples of regions with large regional population clusters, early civilization and regional prosperity have long stood out in history, such as the wealth in ancient China and India and in contrast, the extinction of isolated island cultures. Kuznets (1965) tested the correlation between population and regional development level using aggregate country data and found that international immigration to the U.S. is positively associated with American's economic development, including GDP, construction activity and employment. Kuznets claimed that this relationship was irrelevant to the capitalism business cycle.

Neoclassical Models (Exogenous Growth Model)

The neoclassical view of long-run economic growth takes population changes and technological progress as given. Represented by the Solow-Swan Model, neoclassical theories of economic growth attribute growth to exogenous factors (Solow 1956) (Swan 1956). The main idea of Solow's growth model is the convergence of growth, stating that more developed regions and less developed regions will eventually have similar growth rates. The growth rate a region experiences declines as it becomes more and more developed. After a temporary rise in productivity growth due to the initial accumulation of physical capital, productivity growth eventually converges to the equilibrium growth rate (steady state). The Solow Model leaves the main determinant of economic growth (the increase in physical capital) mysterious and provides limited policy implications other than general prescriptions, such as more saving. The Solow-Swan growth model is structured in a non-spatial framework which focuses on growth in the aggregate (world or national economy) instead of at the state or local level and thus has limited explanatory power in a regional context.

Borts and Stein (1964) tested and criticized the Solow Growth model within a regional context and derived an economic growth and allocation model by adapting Solow's model. Notably, Borts and Stein introduced labor migration (high rates of both immigration and emigration) and labor market structure (a smaller fraction of labor force in manufacturing) into the model as positively related to growth through capital formation (in housing and services).

Smith (1975) extended the neoclassical model by introducing a spatial context by allowing labor and capital the freedom to migrate between regions. He found that in a model with resource migration across regions, regional incomes will converge.

Labor Mobility and Regional Economic Development

There has been debate whether movements of labor contribute to the agglomeration process and thus lead to more uneven growth, or whether labor movements contribute to the spread of growth and thus lead to more even growth geographically. On one hand, the agglomeration theory predicts that the movement of labor contributes to polarizing growth. Weber developed the theory of agglomeration that illustrates the tendency for industries to cluster through economies of concentration. According to Weber (1909), when two or more economies benefit through pooling production at a common location, more than compensating for the extra transportation costs, they will merge. The consequence of the continuous agglomeration process is the increasing unevenness in regional development. Storper and Walker (1989) reinforced that the geographic and regional development unevenness does not tend to disappear because technological change in industries lead to what they called the "space economy" by creating new growth centers that extend and perpetuate the regional development gap.

On the other hand, the Schumpeterian view (Schumpeter 1934) predicts that there is a tendency for the economic development of regions to converge. This theory rests mainly on three assumptions: first is that technology follows an invention-innovation-adoption path; second; that large companies maintain the leading roles in R & D; and third, industrial maturation, which means any new technology will be gradually exhausted. Piore views long-distance migration as a fourth factor that helps to even out regions by providing labor supply to developing regions (Piore 1979).

In terms of migration's role in the long-run economic development, Storper and Walker (1989) argued that migration cannot eliminate inter-regional differences because labor is always "place-bound", as they do not response to development change by relocating as quickly as they can. They claimed labor has long been underestimated as another "factor of production" in both economic theories and location theories and, by this discussion, both parties pushed labor movement to the forefront in the analysis of regional economic development.

Endogenous Growth Theory

Unlike the neoclassical growth theories that consider economic growth exogenous, endogenous growth theory identifies growth generators as endogenous factors. The endogenous growth model expands the explanation of the largely unexplained factor in Solow Model and states that the concept of human capital (research and knowledge) is the engine of growth (Romer 1994). Because endogenous growth theory views knowledge as "changeable" (endogenous) and "attainable," compared to the "steady state" described in the Solow Model, it provides more insight into the policy implications and institutional arrangements needed to increase knowledge or create new technology, such as tax subsidies for private research, antitrust exemptions for research and innovation, and protection for intellectual property rights.

The endogenous growth theory considers human capital as a primary growth factor that drives economic growth. A large population does not only serve as a source of workers and consumers, it also serves as a source of innovation and technological advancement. As part of the endogenous growth theory, Kremer (1993) suggested that a large population spurs technology and therefore leads to faster economic growth, simply because the more people there are, the more new ideas will be bouncing around, and the more easily knowledge builds upon other knowledge. Under this theory, a large population base, which has a larger absolute number of "talented" and "genius" people, will lead to greater prosperity. On the other hand, if the population falls below a certain level or becomes isolated from other major population centers, that virtuous circle will gradually collapse. The empirical research Kremer conducted supported his theoretical prediction.

An influential, yet academically less-well-regarded author on the subject of human capital and urban growth is Richard Florida. Acknowledging Lucas' growth theory, the main theme of Florida's series of works on class and creativity is that innovation is the single most important growth factor for a region. In his book "Cities and Creativity," Florida points out that talented human capital is the driving force of regional growth. He also points out that diversity, referring to the assortment of firms or regional industrial structures, and tolerance for homosexuals and minorities, both play a central role in attracting more talented people migrating into the region (Florida 2005a). Florida applies his theory first to communities and cities in the United States and then to a global context and extends his theory to include international migration and international development (Florida 2005b). He re-emphasizes that talent drives growth, while tolerance enlarges the talent pool.

One of the major criticisms that Florida's work received is the endogeneity problem existing in the relationship between high human capital (e.g., higher education and diversity) and a region's prosperity, since people can cause a region to prosper or they can migrate to a prosperous region. This is, in fact, a major problem in the whole field of immigration's impact on destination economies. Florida responds that regions of talent *gravitate* themselves, emphasizing the interactions between migration and the regional development.

More Recent Research about Regional Economic Growth / Development, Human Capital and Migration

This section identifies and organizes recent empirical research that examines regional economic growth's relationship with human capital and immigration, including at the metropolitan area, state, and county levels.

In theory, economic growth and development are different concepts. Growth and development often occur simultaneously, however, in the long run, growth and development may indicate different goals: growth emphasis efficiency at the moment, while development emphasizes sustainable and progressive change. Growth means more output (sometimes more input or higher efficiency), while development implies both increase in output and changes in the technical and institutional arrangements by which it is produced (Kindleberger 1958).

As Shaffer et al stated, although the two concepts are very similar, “growth is generally restricted to more of the same (more jobs, more income, more people, or more real estate transactions)” while “development, in its broadest context, simultaneously involves social, environmental, and economic change to enhance quality of life” (Shaffer, Deller, and Marcouiller 2004). In the process of development, there is usually institutional change (changes in cultural / social / legal framework, attitudes and values) or structural change (changes in industry mix, product mix, occupational mix, ownership patterns, and technology). Compared to growth, development is viewed as longer term, purposeful, and permanent. (Shaffer et al, p3-5)

Productivity and output are often used interchangablly with the word growth. There are many observations for measuring economic growth, including labor market outcomes such as employment and income, and capital accumulation. Each measurement has different foucs on different perspectives of growth, and sometimes one measure’s increase will lead to another’s decline. For example, increase in productivity will raise wages, but kill jobs, espeically the blue-collar ones (Moretti 2013).

As economic development is a human/social phenomenon and it is multi-dimension, measurement for development incorporates not only economic but also social and institutional gauges, such as changes in volume and type of economic activity, changes in economic stability, equity or human welfare (Shaffer, Deller, and Marcouiller 2004).

In practice, however, economic growth and development are often used synonymously in empirical research and policy discussions, and they are often measured by the same set of indicators. In the growth/development accounting literature, GDP per worker or per capita are the most commonly used indicators for regional economic growth (Glaeser and Resserger 2010) (Gennaioli et al 2013). Alternative measurements for regional economic growth include per woker total factor productivity (TFP) (Peri 2012a), family income (Glaeser and Resserger 2010), per capita income, wage and expenditures (Gennaioli et al 2013).

The following of the section lists recent growth studies with a focus on human capital. Glaeser, together with many scholars including Gottlieb (Glaeser and Gottlieb 2009) and Resseger (Glaeser and Resserger 2010), conducted research on the agglomeration effects of regional economic growth and human capital. Their research presents empirical evidence that productivity rises with density, measured by population size and population per area. More specifically, Glaeser and Gottlieb (2009) attribute this agglomeration effect to human capital-related factors, such as the acceleration of knowledge flow within a higher density of workers, rather than the traditional agglomeration explanatory factors, such as lower cost of transportation. Glaeser and Resseger's research (2010) includes an examination of the agglomeration effects and human capital at the metropolitan level. They found that economic growth, measured by GDP per worker and real family income, is significantly and positively associated with a metropolitan area's population. The agglomeration effects are especially strong for the more educated metropolitan populations: the authors ranked metropolitan areas by their percentage of college graduates and conducted regressions separately for the 100 "highest-human capital" metro areas and the 100 "least-human capital" areas. The results show that "in the most well-educated places, population can explain 45 percent of the variation in productivity" while in the least-educated places, population-explained productivity almost does not exist. By including the interaction term of population and percentage of college graduates in the metropolitan area into the regression, the authors replicated the evidence that agglomeration effects rise with the metropolitan areas' education level.

Gennaioli et al. (2013) used a cross-country dataset covering 1,500 subnational regions and 97 percent of the world's GDP, to study the relationship between human capital and regional development. Instead of using a Cobb-Douglas production function of growth accounting, they followed the Lucas model of the economy and specifically attributed productivity growth to different measures of human capital, such as education of workers and education of managers. Their findings suggest that human capital is the single most important determinant of regional development.

However, growth studies with a focus on human capital rarely shed light on international migration. Furthermore, although there is a large body of literature determining immigration's economic impact on the receiving economy, very few of them have assessed regional macroeconomic performance as the dependent variable. The remainder of this section identifies a few examples of such research.

A Brookings Institution report (Hall et al. 2011) observes human capital and growth at the metropolitan level while focusing on immigration. It introduces a measure that quantifies immigrants' skill levels in metropolitan areas and sheds light on the educational profiles of metropolitan area immigrants. The authors categorize working-age immigrants (age 25 to 64) into low- (less than high school diploma) and high-skilled (college degree and above). They then transpose the skills into a continuous variable by generating the ratio of high- and low- educated immigrants. This measurement skips the medium-skilled immigration because the authors claim that the relative size of this group varies little across the 100 largest metropolitan areas. These metropolitan areas' immigrant skills ratios range from 13.3 (Bakersfield, CA) to 391.3 (Pittsburgh, PA). The report increases our knowledge of recent immigration's educational attainment and the human capital's geographic distribution across U.S. metropolitan areas.

Using data from 68 countries, Osang (2006) provided a cross-country analysis examining international migration and trade's impacts on a country's development level, as measured by per capita GDP. He found positive association between a country's development level and both measures of migration – the remittances' share of GDP and foreign-born population share. In his research, migration was assumed to be exogenous.

Park and Hewings (2009) examined immigration's impact on regional and national GDP using a simulation model. Their results showed that immigration's negative effects on wage and capital/labor ratio and positive effects on national and regional GDP will diminish over time. This study shed light on the time frame of the examination of immigration's economic impact and indicated that immigration's negative and positive impacts may both be limited to a certain period of time and is closely related to the demographic structure of immigration.

Peri (2013) pointed out that immigration's effect on productivity has been overlooked in earlier analyses. Together with many other scholars, Peri conducted a series of studies examining the relationships between immigration and productivity in the United States. Peri suggested that immigration's productivity effects mainly come from stimulation to investment and innovation, as well as from promoting specialization and increasing efficiency. In the medium to long run, this productivity increase drove wage growth. He also admitted the difficulty of identifying the productivity effect of immigration and that is probably the reason why it has largely been neglected.

Peri (2012a) examined immigration's impact on the TFP in the United States at the state level. Peri found that immigrants promote specialization and therefore increase total factor productivity. This impact, however, was offset by immigration's negative impact on the skill-bias of production technologies, leading to a slightly negative effect on average workers' income at the state level.

Peri, Shih and Sparber (2013) examined STEM workers' impact on a series of economic outcomes, including growth of wages and employment, and then implied its impact on the growth of productivity and the skill/occupation shift. Besides the positive impacts on native-born college-educated workers' wages and no effect on their employment, the author also found foreign-born STEM workers were contributing to total productivity growth, measured by TFP.

Some relevant non-U.S. research examined the immigration's impact on productivity. Paserman's (2013) work examined the impact of immigrants on Israeli firm productivity. Paserman framed her research following the Cobb-Douglas production function and found no clear time series evidence that a concentration of immigrant workers in the firm would raise the firm's productivity. The advantage of using firm level data, compared to area level data, is that capital, as one of the two production function factors, is easier to measure. Research by Kangasniemi et al. (2012) on Spain (representing a new immigration destination with a relatively low immigration level) and the UK (representing a traditional immigration destination with a relatively high immigration level) cases found immigration had a negative (or negative but negligible) contribution to labor productivity growth.

Immigration's Impact on the Receiving Economy

This section examines the literature that measures immigration's impact on the receiving labor market's outcomes, such as native workers' wages and job opportunities. This section's scope is limited to those studies that focus on the United States and its regions as receiving economies. The focus of the section is not only on the previous studies' results, but also on the methodologies and data they use, as some of these empirical results and strategies have inspired or are the cornerstones that this dissertation research is built on.

Theories, Hypotheses and Overall Findings

Borjas extrapolated a theoretical model to illustrate what he called the "immigration surplus" - the increase in national income that accrues to natives due to an increased labor supply by immigration inflow (1999). This "immigration surplus," as a fraction of GDP, equals to "- -$\frac{1}{2}$ × labor's share of national income × percent drop in native wage due to immigration × fraction of labor force that is foreign-born" (Borjas 2006). Borjas concluded that the immigration surplus for the United States is about 0.1 percent of GDP, and that the immigration surplus redistributes income from native workers to employers. Smith and Edmonston (1997) also approached this "immigration surplus" model graphically and similarly conclude that "an increase in immigration flows will lead to higher incomes for productive factors that are complementary with immigrants, but lower incomes for factors that compete with immigrants." (Smith and Edmonston 1997) A crucial assumption of the immigration surplus theory is that native and immigrant workers are homogeneous and therefore are perfect substitutes for each other.

The majority of the empirical research on the impact of immigrants' wages finds that immigrants to the United States have caused a small, positive impact on native income and agrees that immigrant inflows increase the overall national output and brings a positive net gain on average (Smith and Edmonston 1997) (Card 2005) (Ottaviano and Peri 2007). However, some economists do find that immigration accounts for a small decline in wages for the native workers and the loss has been borne disproportionally by the lower income and low-skilled native workers (Borjas and Katz 2007). Orrenius and Zavodny (2007) use occupation as a proxy for skill and find that an increase in the fraction of foreign-born workers tends to lower the wages of natives in blue collar occupations—particularly after controlling for endogeneity—but does not have a statistically significant negative effect among natives in skilled occupations.

Empirical studies have primarily focused on whether immigration has caused wage depression for native workers and crowded out native workers from job opportunities, or whether immigrants and their dependents have created a drain on public funds. Consolidating the abundant literature on how immigration affects native workers' wages, Peri (2013) conducted a meta-analysis using a total of 27 original immigration economic impact studies done from 1982 to 2013. The results of these studies centered around 0, meaning that immigration's average effect on natives' wages is zero. The majority of these studies found negligible estimates (within the 0.1 bin, for 1 percent of increase of immigration) and the largest magnitude of the estimates ranges from -0.8 to 0.8.

<u>The Mechanisms</u>

Scholarly studies that found immigration's positive contribution to the receiving economy and labor market suggested that immigration has influenced the U.S. labor market and overall economy in many specific ways. The following section organizes the empirical studies by three specific mechanisms through which immigrants contribute to the host economies.

(1)　Overall effects

Immigration inflows enlarge the receiving regions' labor market, widen the consumption and tax bases and lower the cost of labor which allows firms to grow and to adjust capital invest. Studies show that immigrants are paid less than native workers with similar labor market characteristics and this fact translates to increased profits of the U.S. firms that hire immigrant labors (Ottaviano, Peri, and Wright 2010). A study by Chassamboulli and Palivos (2010) shows that when encouraged by availability of lower cost labor (of immigrants) firms push to create more jobs for both native workers and immigrants and the unemployment rate decreases as a result.

In research about immigration's economic impact, immigration intensity and regional population are suggested as important variables to be considered. Similar to Glaeser's finding of complementarity between population size and skill, research by Partridge et al. (2009) on immigration's economic impact from 2000 to 2005 suggested that "immigration has heterogeneous effects across different-sized metropolitan areas." More specifically, for high-immigration metropolitan areas, the influx of immigration had a significant "crowding-out" effect of native workers but such effect was not significant for low-immigration metropolitan areas. The authors actually identified a "threshold" of immigration intensity beyond which this "crowding-out" effect became significant. Partridge et al.(2009) indicated that the complementarity effects between native- and foreign-born workers also depended on the metro areas' immigration intensity.

(2)　Skill effects

Many scholars view high-skilled immigration as the determinant or driving force for growth and development. Aydemir (2013) noted that "the net effect on growth depends on whether immigrants are more innovative, and the extent of externalities (both positive and negative) created by the influx of high skill immigrants." (Aydemir 2013) Peri (2013) also pointed out that "in the long run, immigrants can increase the overall efficiency of the economy by bringing new skills, stimulating efficient specialization, and encouraging firm creation." (Peri 2013) Ottaniano and Peri's study (2008) showed that immigrant inflows encouraged firms to increase investment and expand their capacity; therefore the inflows resulted in a larger economy and increased productivity for both natives and immigrants.

Hanson (2012) argued that immigration can accelerate the pace of innovation in the U.S. economy. As a matter of fact, from 1960 to the late 2000s, "the share of PhDs awarded to foreign students rose from one-fifth to three-fourths in mathematics, computer science, and engineering; from one-fifth to three-fifths in physical sciences; and from one-fifth to one-half in life sciences." (Hanson 2012: 26) Foreign-born workers who were educated in the United States generated patents and started new firms at a significantly higher rate compared with their native counterparts (Hunt 2011). Innovation and technological advancement promoted by high-skilled immigrant workers contributed to U.S. productivity growth and increased the U.S. international competitiveness.

(3) Complementarity effects

The classical hypothesis of “complements” suggests that immigrants and native workers’ are complements through enhancing the efficiency in job and skill set matching and through entrepreneurial activities. The “complement” notion hypothesizes that immigrants are taking the undesired jobs from natives, in which case “an increase in the number of immigrants raises the productivity of natives” and immigrants may “free the more skilled native work force to perform tasks that make better use of their human capital” (Borjas 1990). A study by Cortes and Tessada (2012) shows that on average, high-educated women in the United States increased their work week by about half an hour thanks to the service help provided by low-skilled immigrants.

Studies suggest that complementarity exists at multiple levels. It exists not only between low-skilled immigrants and high-skilled natives, but also between the two with the same education level. One study by Peri (2012b) pointed out that immigrants play an important role in increasing the effectiveness and efficiency of labor through accelerating the re-organization of production along specialization lines, as immigrant workers are often specialized in manual-intensive occupations. In their research that focuses on a less-educated labor force, Peri and Sparber (2009) find that immigrants tend to concentrate in the manual-physical occupations, while native workers concentrate in the communication-language occupations. In another paper that utilizes O*NET data and focuses on highly educated labor force, Peri and Sparber (2011) use the skills typically required in certain occupations and find that immigrant and native workers of the same education level tend to be specialized in analytical and communicative occupations respectively.

Similarly, Singer's research (2012) suggests that within industries where immigrants are over-represented, immigrants and native workers are concentrated in different occupations. For example, in the accommodation industry, immigrants are clustered in the "back of the house" types of jobs while native workers are more likely to be engaged in the "front of the house" jobs. Ortega and Verdugo's research (2011) finds that immigration's positive impact on natives' wages and employment comes from a reallocation of natives to better-paid occupations within the same education/experience group. They further point out that in occupations where immigrants are over represented; natives tend to perform more "abstract" tasks (in comparison to "routine" tasks).

An issue closely related to complementarity is "superdiversity," which refers to the heterogeneity of ethnicity. Spoonley (2013) points out that there are four ways that high heterogeneity of ethnicity can enhance growth: diversity can provide a dividend of higher productivity; provide cross-fertilization of ideas and contribute to creativity and innovation; boost aggregate demand for goods and services; and reflect new connections locally or internationally. Jacob's (1969) work also stated that social diversity promotes innovation and thus enhances growth. There is negative evidence that such ethnic heterogeneity hampers economic growth, as well. Mauro's study (1995) suggested that ethnic diversity reduces investment and capital formation. Montalvo and Reynal-Querol's study (2005) found that high ethnic diversity reduces trust and impedes market transactions and information spillover. Yamanura and Shin (2013) also found that ethnic heterogeneity reduces labor-productivity growth through impeding information spillover.

However, superdiversity is not necessarily measured the same as complementarity. Ethnic heterogeneity counts the ethnic diversity within a regional population, while complementarity emphasizes how different (therefore how complementary) immigrant and native workers are. In other words, the more different immigrants are from native workers in terms of skills, education levels and demographic distributions, the more immigrants will benefit natives through complementarity.

In sum, the three mechanisms, suggested in the literature, through which immigration contributes to economic growth - overall effects, skill effects and complementarity effects - are the three approaches this dissertation takes in exploring the relationship between immigration and metropolitan areas' economic growth.

The “Area-Based” and “Time Series” Methods

Two primary methodological approaches are used in immigration studies in the economics literature and each of them has advantages and limitations. The first approach is the “area-based” approach, also known as the “local markets” or “spatial correlation” approach. The area-based method uses regional data and was first implemented by Card (1990) in his famous study of the Mariel Boatlift's impact on the Miami, Florida labor market. After this boatlift event when more than one hundred thousand Cubans arrived in Miami in a short period, Card found that these immigrants were absorbed were into the labor market without depressing the wage of the native workers. This approach was criticized for its failure to capture the spatial “spill-over” effects (Borjas 1999). In other words, the fact that Miami's workers did not show an observable wage depression did not guarantee the surrounding regions' workers were not negatively affected by the sudden immigration influx, or that this immigration influx may have kept native workers from other regions from coming to Miami. Card's Mariel Boatlift study used a rare, natural experience event which is hard to repeat. A more "typical" area-based study was Card's research (2005), where he examined the effects of immigrant shares on native workers' wage and job opportunities' in 325 cities.

However, the typical area-based method is still subject to the "spatial correlation" criticism. Borjas (2000) pointed out another shortcoming of the area-based approach – the endogeneity problem. For example, a positive correlation between immigration and natives' wage can indicate that either immigrants improve regional economic outcome or immigrants choose to move to regions where wages are rising natives are doing relatively well.

To overcome the shortcomings of the area-based method, some immigration researchers use the "time series" method (also known as the "national" approach). The "time-series" method uses national data over a period of time rather than regional data in order to avoid the problems of endogenous location choice and spatial spillovers. Using this method, Borjas' study (2003) found that "interstate flows of labor and capital tends to equalize opportunities for workers of given skills across regions" (Borjas 2003). In this research, Borjas identified negative impacts of immigration on the native workers' wages and job opportunities. More specifically, Borjas noted, "the spatial arbitrage effectively cuts the national estimate of the impact of immigration by two-thirds" (-0.40 when workers participate in the national labor market, and -0.13 in states' labor markets). Borjas claimed that the "spatial spill-overs" the area-based method failed to capture, concealed around two-thirds of the true (national) impact of immigration on wages.

Although the "time series" approach uses national data to eliminate the "spill-over" effects, Card (2005) pointed out that the largest limitation of the time series approach is the absence of clear counterfactual; "inferences from the macro time series approach rely on assumptions about the trends in factors like the degree of skill bias in recent technological change." In addition, an "area-based" approach is required when the study's goal is to identify immigration's impact on a regional economy.

<u>Identification Problem and Solutions</u>

A long-standing difficulty in studies of immigration's economic impact is the identification problem imbedded with the usage of natural experiment observation data. Except for rare cases like the Mariel Boatlift, where the immigration inflow was largely "supply-pushed" by an origin country's political change rather than pulled by the economic opportunity, immigration inflow is not usually supply-pushed. Furthermore, immigrants are not distributed randomly; immigrants are attracted to faster growing places. In this dissertation research, because immigration is both a cause and a consequence of regional economic growth, the endogeneity problem makes it difficult to establish the causal relationship between immigration and regional growth. To eliminate or reduce this problem, previous researchers have constructed instrumental variables to include in their regression analyses. An ideal instrumental variable in such studies is one that is “supply-pushed” and correlated with the independent variables (e.g., measures of immigrants), but not correlated with the dependent variable of observation (e.g., economic growth).

The most commonly used instrument idea comes from Altonji and Card (1991), and it was further developed and applied by Card (2001). In their research of immigration’s impact on labor market outcomes of native workers, Altonji and Card (1991) constructed an instrumental variable by using a ratio generated by historical industrial choices of the previous (in a baseline year) cohort of immigrants of the same country of origin and then interacting this ratio with the total number of newly arriving immigrants of that origin country and then summed over all products by countries of origin. Card (2001) followed this idea with one change; he used geographic settlement instead of industrial choice to construct the ratio.

The rationale of the Altonji/Card instrument strategy is that the immigrants of the same ethnicity tend to follow their “networks” (previous cohorts) in terms of industrial and location choices. When there is a nation-wide influx of that ethnicity’s immigrants, they tend to distribute proportionally into industries or locations following the historic pattern. Therefore this predicted immigration pattern in industry or location should be close to the real distribution, but it is unlikely to be correlated with current labor market outcomes, such as native workers’ wage levels or the current growth rate of the region. Ten years are used as an interval due to the frequency of Census data availability.

In his research on the impact of immigration on native youth's employment, Smith (2012) improved Altonji/Card's instrument strategy and designed an alternative instrumental variable. Smith's instrument is based on Card's idea that immigrants of the same origin country tend to have the same geographic settlement pattern. However, there are three differences from Card's instrumental variable composition: first, the ratio is taken using one period ahead, instead of a fixed baseline year; second, the ratio divides ethnic immigrants over all immigrants in that city in one year, rather than over all immigrants of the same ethnicity; third, instead of interacting the ratio with the national change of that ethnic immigrant, Smith chooses to interact it with the national change of the country's immigrants excluding this particular city. These improvements are supposed to reduce possible biases due to the dependence on one year (baseline year) for the immigration's ratio and the dependence on one area for the change of an ethnic group's immigration. Smith's first-stage estimates of the instrumental variables' suitability suggest that this alternative is a better choice than the traditional one.

Other variations of the Card/Altonji instrumental variable include the predicted distribution of immigrants across industry and occupation by Paserman (2013). Paserman's instrument is developed from the rationale that immigrants from a certain country of origin tend to be employed in the same industry and occupation as their previous cohorts. This assumption has been supported by Patel and Vella's (2013) research findings.

Smith also used the product of a city's distance to the Mexican border and the national inflow of Mexican immigrants (excluding inflows into this city) as another alternative instrument. This instrument's assumption is that "a larger national inflow of Mexicans has a larger effect on native employment in areas closer to the border with Mexico only through its effects on the actual change in the number of immigrants in the area." (Smith 2013) This geography-based instrument (together with distances to Los Angeles and New York) was also used by Peri (2012a) in his research of immigration's economic impact in the United States.

In their research on high-skilled immigration's impact on firm structure change, Kerr and Lincoln (2010) and Kerr et al. (Kerr, Kerr, and Lincoln 2013) used the change in the national high-skilled temporary visa (H-1B) program's size across years and the dependency of each firm on H-1B workers to construct a supply-pushed instrumental variable. This instrumental strategy is close in spirit to Altonji/Card's and, by relying on the H-1B program, it is a more suitable instrument for high-skilled immigration. Developing this high-skilled immigration instrument variable, Peri et al. (2013) constructed an instrumental variable for a study of STEM workers' wage impact by using a historical (ten years earlier than that of Kerr et al) H-1B worker dependency and the program's change in size. Most importantly, the calculation is based on 14 major nationalities. Peri et al. claimed "it should be less subject to correlation with recent economic conditions and more accurate." (Peri et al. 2013)

Summary

The theoretical and empirical literature of regional economic growth and immigration has laid the foundation for the hypotheses of this dissertation research. Past empirical research also provides the research methodologies and identifies the variables ideas that this dissertation is built on. However, past empirical research on immigration's economic impact has been primarily focused on immigration's impact on native workers' wages and job opportunities. This dissertation's core research question, immigration's relationship to regional economic growth, has not been directly addressed or researched in either the economic growth or immigration literature. Regions that seek to maximize the contribution of immigration should pay attention to the overall economic measurements such as GDP, as well as labor market outcomes. For this reason, this dissertation is undertaking research to fill in the literature.

CHAPTER III
DATA AND METHODOLOGY

This chapter describes the data sources, presents the variables and their preparation and discusses the data limitations. It illustrates the methodologies and models employed in this research in response to each of the research questions, including the instrumental variable strategies. This chapter also provides a descriptive analysis and summary of the data and variables. It illustrates data variations across years and metropolitan areas that the regression analyses are going to rely on, as well as demonstrates the national and regional trends of immigration and immigrant workers in the Unites States from 2000-2010.

Variable Preparation and Data Sources

Variables and Measurements

This research uses per worker metropolitan GDP and metropolitan GDP as measures for metropolitan areas' economic growth and the dependent variables in the reduced-form and structural-form regression analyses, respectively. Metropolitan GDP captures the metropolitan areas' aggregate economic activities and performance, and is one measure of a metropolitan area's economic prosperity. Changes in metropolitan GDP serve as a proxy of economic growth. Since 2001, BEA started to provide metropolitan GDP as the sub-state counterpart of the national GDP[7].

The key independent variables are metropolitan areas' foreign- and native-born workers and those workers with different educational attainments and immigration's complementarity with native workers, measured by a congruence index constructed using educational attainment. In the reduced-form analysis, the logged share of foreign-born workers among total worker (and shares of different skill levels of foreign-born workers) is used as the key explanatory variable and, in the structural-form analysis, the logged number of foreign-born workers (and shares of different skill levels of foreign-born workers) is used as the key explanatory variable.

(1) Measuring Complementarity

In order to measure the degree of complementarity (or degree of competition) between native and immigrant workers, educational attainment is used as a proxy for skill level. More specifically, this research considers immigrant and native workers' educational attainment distributions based on a five-category scale: "less than high-school," "high-school diploma," "associate degree or some college," "college graduate," and "graduate degrees."

Then a simple congruence index used to measure distribution similarity, as suggested by Vegelius et al (Vegelius, Janson, and Johansson 1986), quantifies how

[7] Data accessed through BEA website Jan 15, 2014
http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=2#reqid=70&step=5&isuri=1&7001=2900&7002=2&7003=900&7090=70&7004=naics

similar the educational attainment distributions are among immigrant and native workers (Equation 3.1):

$$\mathrm{I} = \sum_{i=1}^{c} \min(f_{Um}, f_{Un}) \qquad (3.1)$$

Where Um and Un denote immigrant and native workers' educational attainment distributions respectively. The congruence index I is defined as a summation of the smaller (minimum) percentage in each educational category over all five categories.

The congruence index I ranges from 0 to 1, with 0 meaning two groups' educational distributions are extremely different and 1 indicating two groups having identical distributions.

The independent variables controlling for characteristics of metropolitan areas include the areas' capital stock and demographic characteristics, such as the size of the metropolitan population, and, among workers, percent married, percent workers with the race of African-American, Asian, and Hispanic, average age, education (percentage worker with Bachelor's degree or above), immigration's skill level (ratio of high-skilled immigrant workers to low-skilled), and immigrants' average length of stay in the United States. These control variables are chosen because they potentially affect economic growth, and they are supposed to be fixed at the time when the key variables (immigration variables) are determined. Controlling these variables may strengthen the causality inference of the regression analysis.

(2) Measuring Metropolitan Capital

The most important control variable is the capital stock of metropolitan areas, as labor and capital are the two basic inputs in a production function. Fixed asset is the measure for capital stock. However, the BEA provides fixed assets only at the national level. Garofalo and Yamarik (2002) developed a method of obtaining state level capital using the national measure of fixed assets multiplied by the ratio of state-level personal income to the national personal income. The state level capital is calculated separately for each industry and then summed over all industries. This method is also used for an immigration study by Peri (2012a) as capital control at the state level. Following this method, this research calculated the metropolitan level capital for each industry, multiplied by the ratio of metropolitan personal income over the national personal income (Equation 3.2), it then summarized through all industries (Equation 3.3).

$$K_{m,i}(t) = \left[\frac{y_{m,i}(t)}{Y_i(t)}\right] K_i(t) \qquad (3.2)$$

$$K_m(t) = \sum_{i=1}^{n} K_{m,i}(t) \qquad (3.3)$$

let m denote metropolitan area, i denote industry, y is the personal income in a metropolitan area, Y is the national personal income and K is the capital measured by fixed assets[8]. n denotes the total number of industries, and the BEA's fixed asset report provides the national values of 19 aggregated industries.

[8] Data for personal income was accessed through BEA (http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=5#reqid=70&step=1&isuri=1) Interactive table: CA05N Personal income by major source and earnings by NAICS industry 1/Metropolitan Statistical Area, accessed Feb 20, 2014;

In order to obtain every year's value in chained 2005 dollars to be consistent with the GDP data, the ratio of 2010 and 2000 to 2005 is calculated using chained-type values, then these ratios are multiplied by current values in 2005. One caveat to implementing this method is that the BEA changed from industry code SIC to NAICS in 2001. To link the time periods, the SIC code can be walked to the NAICS by a crosswalk[9].

Data Sources

Demographic variables are calculated by the author from the ACS[10] (2003, 2005-2009) and U.S. Census 5% sample[11] (for the year 2000). The ACS provides comprehensive annual micro data based on a nationally representative survey conducted by the U.S. Census Bureau, and is a very important data source for immigration research. However, the ACS has only continuously provided annual micro data at the metropolitan level since 2005. Data for calculating the capital control variable are obtained from BEA. Data used to construct instrumental variables come from the ACS (2005 and 2010) and the Census (2000 and 1990).

A panel data set is then constructed. The panel covers a ten-year period in five-year intervals. Under the principles of maximizing the usage of data available and having intervals as even as possible, GDP data are matched with demographic data lagged by one year. Specifically, 2001, 2006 and 2011 GDP data are each matched with 2000,

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Data for fixed assets was accessed through BEA (http://www.bea.gov/iTable/index_FA.cfm) Table 3.1ESI. Current-Cost Net Stock of Private Fixed Assets by Industry, and Table 3.2ESI. Chain-Type Quantity Indexes for Net Stock of Private Fixed Assets by Industry (A), accessed Feb 19, 2014;

[9] Access through http://www.census.gov/epcd/ec97brdg/index.html

[10] Accessed through Integrated Public Used Microdata Series (IPUMS)

[11] Accessed through IPUMS.

2005 and 2010 demographic data. There are three reasons for this matching. First, annual metropolitan GDP data are available starting in 2001, while metropolitan area immigration data are only available in 2000 (from the Census), and on a continuous yearly basis starting in 2005 (from the ACS). The demographic data of 2003, due to a smaller survey sample, only contain 49 metropolitan areas rather than all 328 as for the other years. Therefore, 2003 data are not used. Second, a five-year interval is considered to be a suitable length for any potential impact of immigration to be shown in levels of GDP. Finally, though not perfect, the one-year lag can help reduce the potential endogeneity problem.

The geographic unit of analysis in this research is the Metropolitan Statistical Area (MSA). There are several reasons why the MSA is considered to be a suitable unit of analysis in this research, rather than the city, state or county level. First, the foreign-born population and labor concentrate in metropolitan areas. Immigration is mostly an urban phenomenon and considering only cities is not sufficient because suburban areas are where 51 percent of immigrants currently live (Singer and Wilson 2011). In 2000, for all metropolitan areas, the foreign-born population accounted for 13.6 percent of total population and this share increased to 15.5 percent in 2010.

Second, a metropolitan area, by definition, is a more complete economic entity in terms of studying its economic growth and development. In addition, the primary data source this research uses, the ACS, collects residential, rather than employment-based data. As this research considers both demographic characteristics and labor market performance, it makes sense to study metropolitan areas to encompass both residential and working areas.

The metropolitan areas used by the BEA[12] for the GDP statistics are not entirely comparable with the metropolitan areas used by the IPUMS-ACS. When GDP data and demographic data were matched by name of the MSA, some MSAs were omitted. The analyses without instrumental variables include 247 metropolitan areas each year and 741 observations. Because the 1990 Census contained fewer metropolitan areas, the analyses with instrumental variables (which use the 1990 Census data) include 201 metropolitan areas and a total of 603 observations.

Empirical Strategies

A Hybrid of "Area-Based" and "Time-Series" Methodologies

Instead of using one of the two most commonly used methods in immigration economic studies, "area-based" or "time-series" method, this research uses a hybrid method by implementing a panel data regression with both area and time fixed effects. Compared to the traditional "area-based" method, panel regression has better control for the potential endogeneity problem and, compared to the traditional "time-series" method, it aims to estimate immigration's impact on regions using a clear counterfactual. Also,

[12] MSA used by BEA are "the county-based definitions developed by the Office of Management and Budget (OMB) for federal statistical purposes and last updated in February 2013. OMB's general concept of a metropolitan area is that of a geographic area consisting of a large population nucleus together with adjacent communities having a high degree of economic and social integration with the nucleus." http://www.bea.gov/newsreleases/regional/gdp_metro/gdp_metro_newsrelease.htm
In IPUMS-ACS data, metropolitan area "METRO" "indicates whether the household was located within a metropolitan area. For households within metropolitan areas, METRO also indicates whether the housing unit was within a metropolitan area's central city (or cities), or within the remainder of the metropolitan area."
https://usa.ipums.org/usa-action/variables/METRO/#description_section

this research shifts the dependent variable from the micro labor market outcomes, such as wages and job opportunities, to the macro measurement – metropolitan GDP. The measurement of GDP, compared to native-born workers' wages and employment, has a smaller "spatial arbitrage", as industry clusters and firms are less mobile in short run compared to workers. Therefore the "spatial correlation" associated with the traditional area-based method becomes less of a concern. In addition, instrumental variables in the panel regression further reduce the potential endogeneity problem.

Area- and time- fixed effects absorb the unobserved characteristics across metropolitan areas and those related to time that may influence the area's economic growth. Metropolitan areas' time-invariant unobserved characteristics include geography, geology, history, and initial development level.

Identification Strategy

The three key independent variables that are likely to be endogenous and need to be instrumented are all immigrant workers, and high- and low-skilled immigrant workers. Lags of both five and ten years will be used as simplified instrumental variables. In addition, the research also constructs instrumental variables based on the suggestions from the prior literature.

For analysis of the impact of overall immigration on economic growth, an instrumental variable is created by following the Altonji and Card (1991), Card (2001) and Smith's (2012) instrumental variables strategies. In order to estimate immigration's impact on native worker's wages, Altonji and Card (1991) and Card (2001) designed instrumental variables under the assumption that immigrants tends to follow their previous ethnic cohorts in terms of industrial and location choices. For example, Card (2001) calculated a ratio of immigrants of origin k in a city z over national total of immigrants from country k (as the first term in the summation symbol expressed in Equation 3.4). He then multiplied this ratio by the total change of immigrants from country k between time t and $t-1$. Card then summarized this product through all countries of origins. This instrumental variable composition is expressed in the following equation (3.4):

$$\Delta M_{z,t,t-1} = \sum_{k=0}^{n} \frac{\mathrm{M}_{z,k,t_0}}{\mathrm{M}_{k,t_0}} \Delta \mathrm{M}_{k,t,t-1} \qquad (3.4)$$

where M denotes immigration, k denotes country of origin, z denotes city. t_0 is the base year.

Smith (2012) improved on Altonji/Card's and Card's instrumental variables strategies (expressed in Equation 3.5) in the following three ways: (1) the ratio uses one period behind (t-1), instead of a fixed baseline year (t_0); (2) the ratio divides ethnic immigrants over all ethnicities' immigrants in that city ($\mathrm{M}_{z,t-1}$), rather than over all immigrants of the same ethnicity ($\mathrm{M}_{k,t-1}$); (3) instead of interacting with the national change of that ethnic immigrant group ($\Delta\mathrm{M}_{k,t,t-1}$), Smith chooses to interact with the national change of the country's immigrants subtracting the particular city ($\Delta\mathrm{M}_{-z,k,t,t-1}$).

$$\Delta M_{z,t,t-1} = \sum_{k=0}^{n} \frac{\mathrm{M}_{z,k,t-1}}{\mathrm{M}_{z,t-1}} \Delta \mathrm{M}_{-z,k,t,t-1} \qquad (3.5)$$

where M denotes immigration, k denotes country of origin, z denotes metropolitan area.

Based on his three improvements, Smith formed the instrument expressed in Equation 3.6, which he claimed to be more suitable for the change in logged immigrants:

$$\Delta \ln(M_{z,t}) = \ln \sum_{k=0}^{n} \frac{\mathrm{M}_{z,k,t-1}}{\mathrm{M}_{z,t-1}} \mathrm{M}_{-z,k,t} - \ln \sum_{k=0}^{n} \frac{\mathrm{M}_{z,k,t-2}}{\mathrm{M}_{z,t-2}} \mathrm{M}_{-z,k,t-1} \quad (3.6)$$

This research implements Smith's instrumental variables strategies (Equation 3.5 to construct instrumental variables to match panel data with fixed effects, and it uses Equation 3.6 to construct instrumental variables to match differenced panel data in the first-difference model) with a couple of details that are different from Smith's. First, in additional to ten years, this research also tries five years as an interval. Five years is a reasonable time period for new arrivals to maintain contact with the previous migrants and are likely to follow their networks' paths in choosing their location in the U.S. Because there is no Census or ACS to obtain demographic data for 1995, 2000 and 1990 Census data are averaged[13] for constructing a synthetic 1995 data. To get 1995 data from the CPS is an option. However, the CPS's sample size is not big enough to construct instrumental variables by summarizing immigration by metropolitan areas and by country of origin.

Second, in order to keep the summation of ethnicity groups at a manageable level, Smith (2012) divided all countries of origin for immigration into 16 groups based on geographic and culture similarity, although he did not provide his groupings in detail.

[13] More specifically, 1995 data is calculated by averaging the $(\frac{\mathrm{M}_{z,k,2000}}{\mathrm{M}_{z,2000}})$ and $(\frac{\mathrm{M}_{z,k,1990}}{\mathrm{M}_{z,1990}})$.

Peri (2012a), who also used this IV method, divided countries of origin into a more aggregated 10 regions. This research divides countries of origin into 16 regions of birth based on geographic and culture similarity[14] (k=16). Under the original assumption, where immigrants of the same nationality tend to have the same pattern of settlement, it is reasonable to assume that immigrants from countries geographically and culturally close also tend to follow similar settlement patterns. These regions of birth include "other North America," "Mexico," "Central America," "Caribbean and South America," "Northern Europe," "Western Europe," "Southern Europe," "Central/Eastern Europe," "Russia," "China," "Rest of East Asia," "Southeast Asia," "India," "Rest of Southwest Asia," "Middle East/Asia Minor and rest of Asia," "Africa," and "Oceania". This grouping method follows the Census' geographic region definition plus three major immigration-sending countries, Mexico, China and India, are calculated separately.

<u>Panel Regression I – Reduced-Form Strategies</u>

The reduced-form analysis uses panel regression with area- and time-fixed effects. The GDP per worker is used as the dependent variable. Measures for immigration are the shares of immigrants and different skill levels of immigrants. Panel regression equations for analysis of each hypothesis (each effect) are listed below:

(1) *Overall Effects*

The basic specification for overall effects is to regress metropolitan GDP per worker on the share of immigrant workers in the labor force:

[14] Calculation is done based on variables "bpl" and "citizen".

$$\log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \log\left(\frac{M_{z,t-1}}{L_{z,t-1}}\right) + X_{z,t-1} + \gamma_z + \gamma_t + u_{z,t}$$

(3.7)

where z denotes metropolitan area; L denotes total workers (includes N, native, and M, immigrant workers); and t represents year (2000, 2005 and 2010). $X_{z,t-1}$ presents a series of characteristics of the metropolitan area that the regression controls for.

In order to test the hypothesis that immigration's impact on metropolitan areas' growth depends on immigration intensity, the quadratic (and cubic) form of the immigration share is included into the basic equation to allow for nonlinear relationships:

$$\log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \left(\frac{M_{z,t-1}}{L_{z,t-1}}\right) + \alpha_2 \left(\frac{M_{z,t-1}}{L_{z,t-1}}\right)^2 + \alpha_3 \left(\frac{M_{z,t-1}}{L_{z,t-1}}\right)^3 + \gamma_z + \gamma_t + u_{z,t}$$

(3.8)

Taking metropolitan areas' population sizes into consideration, interaction terms between the share of immigrant workers and metro size are included in the panel regression (in order to more directly interpret the coefficients, terms used to produce the interaction term are both demeaned):

$$\log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \log\left(\frac{M_{z,t-1}}{L_{z,t-1}}\right) + \alpha_2 \log(\mathrm{pop}_{z,t}) + \alpha_3 \log\left(\frac{M_{z,t-1}}{L_{z,t-1}}\right) * \log(\mathrm{pop}_{z,t}) +$$

$$\gamma_z + \gamma_t + u_{z,t} \quad (3.9)$$

where the interaction term is the product of logged metropolian population, $\log(pop)$, and logged share of immigrant workers in labor force (demeaned).

(2) Skill Effects

To test the hypothesis that skilled immigrant labor boosts economic growth, immigrant workers are divided into three categories in terms of their educational levels (as a proxy for skill).

$$\log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \log\left(\frac{M_{1,z,t-1}}{L_{z,t-1}}\right) + \alpha_2 \log\left(\frac{M_{\mathbf{2},z,t-1}}{L_{z,t-1}}\right) + \alpha_3 \log\left(\frac{M_{3,z,t-1}}{L_{z,t-1}}\right) + \gamma_{\boldsymbol{z}} + \gamma_t + u_{\boldsymbol{z},t} \quad (3.10)$$

and $M = M_1 + M_2 + M_3 \qquad (3.11)$

where M_1 denotes immigrant workers with less than high school education (also referred to as "low-skilled immigrant labors"); M_2 denotes immigrant workers with high school or some college education (also referred to as "medium-skilled immigrant labors"); M_3 denotes immigrant workers with college degrees and above education (also referred to as "high-skilled immigrant labors").

(3) Complementarity Effects

To generally test the hypothesis that immigrant labor contributes to economic growth through complementing native-born workers, a congruence index is calculated based on the five-category educational attainment distributions between immigrants and native workers following Equation 3.1. Education is again used as a proxy for skill level. Then the congruence index for each metro area is included in the equation:

$$log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \, log\left(\frac{M_{z,t}}{L_{z,t}}\right) + \alpha_2 I_{z,t} + \gamma_z + \gamma_t + u_{z,t}$$

(3.12)

where I denotes the congruence index capturing the disparity of educational distributions between immigrant and native workers (Equation 3.1).

An alternative approach of testing potential complementarity effects is to examine the interactions between different education levels of immigrant and native workers. Compared to the model using the congruence index (Equation 3.12), these models identify any significant complementarity exists within which specific skill combination(s) of immigrant and native workers (for example, low-skilled immigrants and high-skilled natives).

$$log\left(\frac{GDP_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \frac{M_{1,z,t}}{L_{z,t}} + \alpha_2 \frac{M_{2,z,t}}{L_{z,t}} + \alpha_3 \frac{M_{3,z,t}}{L_{z,t}} + \beta_1 \frac{N_{1,z,t}}{L_{z,t}} + \beta_3 \frac{N_{3,z,t}}{L_{z,t}} +$$

$$\delta_{11}\left(\frac{M_{1,z,t}}{L_{z,t}}\frac{N_{1,z,t}}{L_{z,t}}\right) + \delta_{13}\left(\frac{M_{1,z,t}}{L_{z,t}}\frac{N_{3,z,t}}{L_{z,t}}\right) + \delta_{31}\left(\frac{M_{3,z,t}}{L_{z,t}}\frac{N_{1,z,t}}{L_{z,t}}\right) + \delta_{33}\left(\frac{M_{3,z,t}}{L_{z,t}}\frac{N_{3,z,t}}{L_{z,t}}\right) + \gamma_z + \gamma_t + u_{z,t}$$

(3.13)

where N_1 denotes immigrant workers with less than high school education (also referred to as "low-skilled immigrant labors"); N_3 denotes immigrant workers with college degrees and above education (also referred to as "high-skilled immigrant labors"). This model will skip medium-skilled immigration and native workers. This model detects the existence of potential complementarity between the combination of skills of immigrant and native workers, as well as quantifies less- and high-skilled immigrants' impacts on log GDP per worker.

Similarly, the regressions framed under the following models (Equation 3.14) also quantify a potential complementarity relationship between different skills of immigrant and native workers:

$$\log\left(\frac{\mathrm{GDP}_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \frac{M_{z,t}}{L_{z,t}} + \alpha_2 \frac{M_{1,z,t}}{L_{z,t}} + \alpha_3 \frac{N_{1,z,t}}{N_{z,t}} + \beta_1 \left(\frac{M_{z,t}}{L_{z,t}} \frac{N_{1,z,t}}{N_{z,t}}\right) + \beta_2 \left(\frac{M_{1,z,t}}{L_{z,t}} \frac{N_{1,z,t}}{N_{z,t}}\right) + \gamma_z + \gamma_t + u_{z,t} \qquad (3.14\text{-}11)$$

$$\log\left(\frac{\mathrm{GDP}_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \frac{M_{z,t}}{L_{z,t}} + \alpha_2 \frac{M_{1,z,t}}{L_{z,t}} + \alpha_3 \frac{N_{3,z,t}}{N_{z,t}} + \beta_1 \left(\frac{M_{z,t}}{L_{z,t}} \frac{N_{3,z,t}}{N_{z,t}}\right) + \beta_2 \left(\frac{M_{1,z,t}}{L_{z,t}} \frac{N_{3,z,t}}{N_{z,t}}\right) + \gamma_z + \gamma_t + u_{z,t} \qquad (3.14\text{-}13)$$

$$\log\left(\frac{\mathrm{GDP}_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \frac{M_{z,t}}{L_{z,t}} + \alpha_2 \frac{M_{3,z,t}}{L_{z,t}} + \alpha_3 \frac{N_{1,z,t}}{N_{z,t}} + \beta_1 \left(\frac{M_{z,t}}{L_{z,t}} \frac{N_{1,z,t}}{N_{z,t}}\right) + \beta_2 \left(\frac{M_{3,z,t}}{L_{z,t}} \frac{N_{1,z,t}}{N_{z,t}}\right) + \gamma_z + \gamma_t + u_{z,t} \qquad (3.14\text{-}31)$$

$$\log\left(\frac{\mathrm{GDP}_{z,t}}{L_{z,t}}\right) = \alpha_0 + \alpha_1 \frac{M_{z,t}}{L_{z,t}} + \alpha_2 \frac{M_{3,z,t}}{L_{z,t}} + \alpha_3 \frac{N_{3,z,t}}{N_{z,t}} + \beta_1 \left(\frac{M_{z,t}}{L_{z,t}} \frac{N_{3,z,t}}{N_{z,t}}\right) + \beta_2 \left(\frac{M_{3,z,t}}{L_{z,t}} \frac{N_{3,z,t}}{N_{z,t}}\right) + \gamma_z + \gamma_t + u_{z,t} \qquad (3.14\text{-}33)$$

Model 3.14 models 11-33 identify complementarity between low-skilled immigrants and low-skilled natives, low-skilled immigrants and high-skilled natives, high-skilled immigrants and low-skilled natives, and high-skilled immigrants and high-skilled natives, respectively.

Panel Regression II – Structural-Form Strategies

The structural-form analysis uses panel regression with both fixed-effects and first-difference models. Metropolitan GDP (instead of GDP per worker) is used as the dependent variable and the number of workers (instead of shares) are used as the independent variables. Framed under a Cobb-Douglas production function (Equation 3.15), immigrant and native workers, as two different groups of labor, are both included in the panel regression, as well as capital control variable. The last session includes instrumental variables.

$$GDP = K^{\alpha} M^{\beta} N^{\gamma} \quad (3.15)$$

Panel regression equations for analysis of each hypothesis (each effect) are listed below:

(1) Overall Effects

The basic specification is to regress GDP on immigrant and native workers and capital on GDP with fixed effects (3.16) and in the first-difference model (3.17):

$$\log GDP_{z,t} = \alpha_0 + \alpha \log M_{z,t} + \beta \log N_{z,t} + \gamma \log K_{z,t} + \gamma_z + \gamma_t + u_{z,t} \quad (3.16)$$

$$\Delta \log GDP_{z,t} = \alpha_0 + \alpha\, \Delta \log M_{z,t} + \beta\, \Delta \log N_{z,t} + \gamma\, \Delta \log K_{z,t} + u_{z,t} \quad (3.17)$$

where in addition to the symbols explained previously in the reduced-form equations, K denotes capital stock.

(2) Skill Effects

In order to test the skill-effects hypothesis, immigrant and native workers are further disaggregated into difference education categories:

$$\log GDP_{z,t} = \alpha_1 \log M_{1,z,t} + \alpha_1 \log M_{2,z,t} + \alpha_1 \log M_{3,z,t} + \beta_1 \log N_{1,z,t} + \beta_2 \log N_{2,z,t} + \beta_3 \log N_{3,z,t} + \gamma \log K_{z,t} + \gamma_z + \gamma_t + u_{z,t} \qquad (3.18)$$

$$\Delta \log GDP_{z,t} = \alpha_1 \Delta \log M_{1,z,t} + \alpha_2 \Delta \log M_{2,z,t} + \alpha_3 \Delta \log M_{3,z,t} + \beta_1 \Delta \log N_{1,z,t} + \beta_2 \Delta \log N_{2,z,t} + \beta_3 \Delta \log N_{3,z,t} + \gamma \Delta \log K_{z,t} + \gamma_z + \gamma_t + u_{z,t} \qquad (3.19)$$

and $M = M_1 + M_2 + M_3$ (3.11)

and $N = N_1 + N_2 + N_3$ (3.21)

Descriptive Analysis

Variable Descriptions

Table 3.1 presents the basic statistics for the independent (metropolitan GDP and metropolitan GDP per worker) and key independent variables after outliers have been removed[15]. Key independent variables include levels of foreign- and native-born workers, foreign-born workers as a share of total workers, levels of high- and low-skilled foreign- and native-born workers and their shares among workers, as well as the computed

[15] Outliers existed in share of low-, medium- and high-skilled immigrant workers due to the limited survey sample size – for some metropolitan areas with small immigration population, it is possible that no immigrant worker in one or more skill categories are represented by the sample in a certain year. In those cases, the weight-adjusted estimates will also be 0. These metropolitan areas in excluded in the regression. See Appendix A for metropolitan areas that are treated as outliers.

congruence index and capital stock. For example, the complementarity indices for metropolitan areas range from 0.17 to 0.996 with a mean of 0.84. This means immigrant and native workers' educational distributions are relatively similar (an index of 0 indicates the two distributions are very different and 1 indicates identical distributions) on average but that they can differ greatly across MSAs.

In addition, Appendix A presents all metropolitan areas with the dependent and key independent variables used in the panel regression analysis in 2000, 2005 and 2010, including population, workforce's educational level (BA ratio), number of immigrant workers, intensity, high- and low-skilled immigrant workers and shares, capital stock, computed congruence index.

Figure 3.1 and 3.2 demonstrate the relationships between GDP per worker and immigrant workers share in total metropolitan workers in 2010 (Figure 3.1 uses logged variables and Figure 3.2 uses logged ones). An earlier examination discovered that San Antonio, TX is an outlier. Located near the U.S.-Mexico border, San Antonio is shown to have a higher than average share of immigrant labor with an exceptionally low GDP per worker. It is possible that both unauthorized immigrants are included in the labor data and economic activities that are generated by the unauthorized immigrant workers are largely underestimated by the ACS and BEA. Considering these, the San Antonio metropolitan area was eliminated from the analysis. Overall, the relationship between the immigrant share and GDP per worker is upward sloping.

Table 3.1 Description of Key MSA variables

N=729	Variable	Mean	Min	Max	Std. dev
Growth	GDP (in millions of 2005 dollars)	226,237	2,163	1,157,173	311,006
	GDP per worker (in chained 2005 dollars)	106,472	30,292	478,879	34537
Demographic	Metro population	3,918,602	98,329	17,800,000	4,865,059
	Metro percent worker with college degree (BA/L)	0.32	0.12	0.54	0.08
Overall Effect	Share of FB worker in total employment (M/L)	.16	0.01	0.63	.12
Skill Effects	Share of FB worker with college and above degree (high-skilled) in total employment (M3/L)	0.05	.00	0.24	.038
	Share of FB worker with some college and high school diploma (medium-skilled) in total employment (M2/L)	0.08	0.00	0.36	.06
	Share FB worker without high school diploma (low-skilled) in total employment (M1/L)	0.04	0.00	0.19	.03
Complementarity Effects	Congruence index	.84	.17	1.00	.10
Capital control	Fixed assets (Billions of 2005 dollars)	651	3.06	4,379	1004

Note: author's calculation from the ACS 2005, 2010 and Census 2000. Calculation is based on 248 metropolitan areas after outlier (San Antonio, TX) is eliminated. Wight used for obtaining msa variables is the personal weight provided by ACS and Census. Weight used for obtaining MSA summary statistics is population of each MSA in 2000.

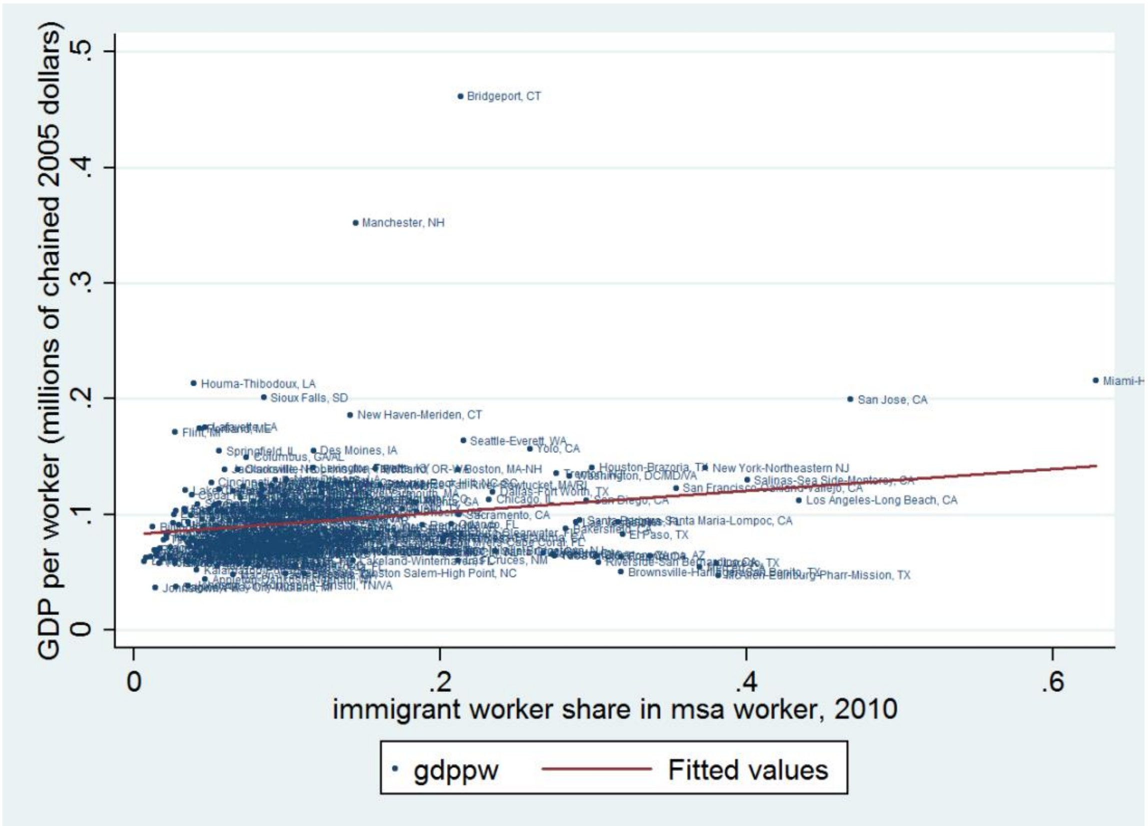

Figure 3. 1 Two-way Scatter Plot of GDP per Worker and Immigrant Worker Share, 2010

Slope = .0980, Standard Error = 0.0286, R-squared = 0.0465, p<0.001. Calculation based on 243 observations.

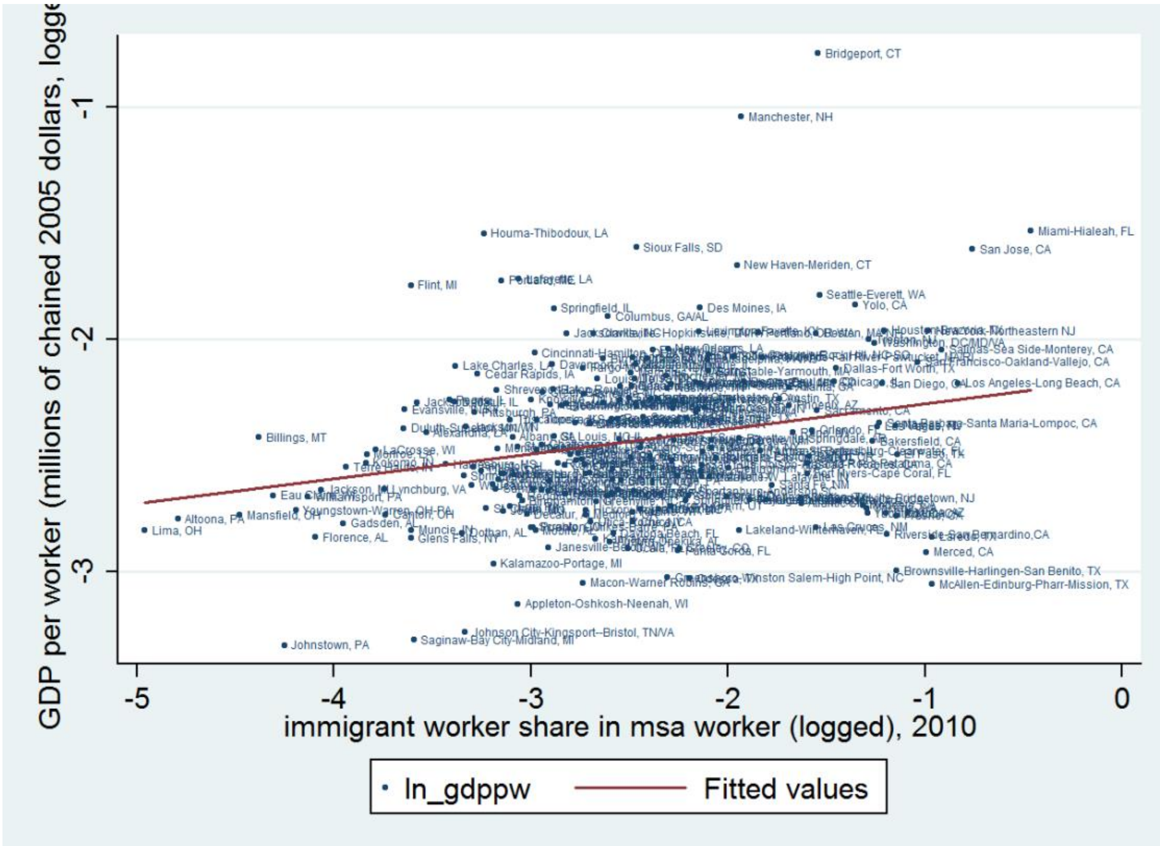

Figure 3. 2 Two-way Scatter Plot of GDP per Worker (logged) and Immigrant Worker Share (logged), 2010

Slope = .1075, Standard Error = 0.0275, R-squared = 0.0599, p<0.001

Calculation based on 243 observations.

Figure 3.3 presents the distribution of immigrant workers' percentage in all three years. Figure 3.4 shows the distributions of the change in the percentage of immigrant workers. The variations are close to normal distributions with the mean larger than 0. This indicates that the majority of the metropolitan areas experienced increases in immigrant worker shares from 2000 to 2005 and from 2005 to 2010. Panel regressions in the next chapter rely on the variations of these changes.

Figure 3. 3 Distribution of Immigrant Worker's Percentage in Workforce, 2000, 2005 and 2010

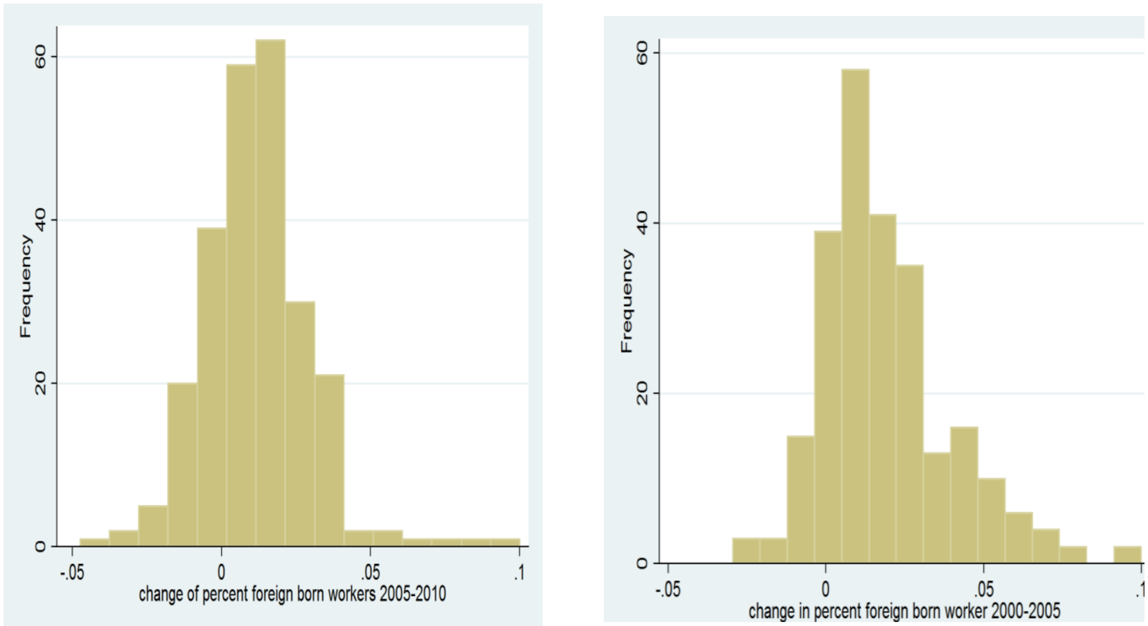

Figure 3. 4 Histograms of Immigrant Workers Percentage Change, 2000-05 and 2005-10

<u>National and Regional Trends of Immigration Population</u>

This section provides a descriptive analysis using the panel data on immigration containing 248 metropolitan areas in 2000, 2005 and 2010 and demonstrates the national and regional trends of immigration stock. Nationally, percent of immigrants in the total population and employment are increasing from 2000 to 2010. The United States is increasingly dependent on immigrant workers in both high-skilled and low-skilled workforce, since the percentages of immigrants in both high- and low-skilled workforce have increased from 14 to 17 percent and from 40 to 58 percent, respectively, over this time period (Table 3.3). The United States has become especially dependent on low-skilled immigrant workers. The educational composition of immigrant workers shifted a small amount towards the higher end. Among all immigrant workers, about 27 percent are high-skilled and 26 percent were low-skilled in 2000, and this changed to 29 percent and 24 percent in 2010.

Table 3.2 Selective Characteristics of Immigrant Workers in the U.S., 2000-2010

	percent foreign-born (FB) population	percent FB worker (M/L)	High-skilled (HS) FB worker share in total HS worker (M3/L3)	HS FB worker share in total FB worker (M3/M)	Low-skilled (LS) FB worker share in total LS worker (N1/L1)	LS FB worker share in total FB worker (N1/N)
2000	13%	15%	14%	27%	40%	26%
2005	15%	18%	17%	28%	51%	24%
2010	16%	20%	17%	29%	58%	24%

Note: author's calculation from ACS 2005, 2010 and Census 2000. Calculation based on 248 metropolitan areas.

Immigrant workers' median length of stay in the United States was 15 years in 2010, one year longer compared to those in 2000 and 2005. The English proficiency score is a metropolitan area's weighted average based on a five-category self-reporting English proficiency of all foreign born workers. It ranges from 0 to 1, with an index of 0 indicating the least English proficiency and 1 indicting the highest. The median English proficiency score for immigrant workers was 0.71 in 2000, 0.68 in both 2005 and 2010. Immigrant workers in 2010 spoke less fluent English compared to a decade prior.

The 20 metropolitan areas with the largest number of immigrant workers account for about 70 percent of the immigrant workers in the United States, while the top 60 account for about 87 percent. As shown in Table 3.4, over ten years, immigrants became slightly less concentrated in the top 20 metropolitan areas and moved gradually to the 21-40 and 41-60 metropolitan areas.

Table 3.3 Top 60 MSAs as Home of Immigration Workers, 2000-2010

percent immigrant workers top 20 metros house	2000	2005	2010
top 20 metros	71.92%	70.39%	68.23%
next 20 metros (21-40)	10.80%	11.79%	12.32%
next 20 metros (41-60)	5.29%	5.34%	5.78%
Total of top 60 metros	88.00%	87.53%	86.34%

Note: author's calculation from the ACS 2005, 2010 and Census 2000. Calculation is based on 248 metropolitan areas.

Table 3.5 presents numbers of immigrant workers and intensity for the largest 20 metropolitan area, ranked by metropolitan population in 2000. For every metropolitan areas except for Los Angeles-Long Beach, CA from 2005 to 2010, the immigration intensity increased both from 2000-05 and from 2005-10. Noticeably, the pace of immigration increasing slowed down in the second half of the decade, likely due to the recession.

Table 3.4 Largest 20 MSAs (Ranked by Population in 2000) Immigrant Workers' Number and Intensity, 2000, 2005 and 2010

		2000		2005		2010	
	MSA (ranked by 2000 population)	FB worker	Percent FB worker	FB worker	Percent FB worker	FB worker	Percent FB worker
1	New York-Northeastern NJ	2,474,970	32.25%	2,893,085	36.21%	3,079,996	37.32%
2	Los Angeles-Long Beach, CA	2,132,167	40.29%	2,591,774	44.61%	2,524,482	43.45%
3	Chicago, IL	793,864	19.30%	976,336	22.93%	982,367	23.19%
4	Philadelphia, PA/NJ	187,330	7.97%	258,139	10.70%	301,058	12.18%
5	Dallas-Fort Worth, TX	426,997	17.10%	621,412	22.50%	700,441	23.43%
6	Washington, DC/MD/VA	501,636	20.42%	647,645	24.71%	824,976	28.43%
7	San Francisco-Oakland-Vallejo, CA	669,700	29.22%	749,367	33.51%	831,905	35.39%
8	Detroit, MI	162,037	7.95%	194,594	9.82%	181,468	10.25%
9	Houston-Brazoria, TX	446,666	22.30%	653,587	28.45%	779,146	29.90%
10	Atlanta, GA	246,337	12.14%	378,258	16.64%	417,998	18.45%
11	Boston, MA-NH	320,342	15.97%	406,168	20.64%	440,085	21.15%
12	Riverside-San Bernardino,CA	292,079	23.11%	475,957	29.18%	496,898	30.33%
13	Phoenix, AZ	212,438	14.84%	347,425	20.32%	309,229	18.45%
14	Minneapolis-St. Paul, MN	108,713	6.99%	162,475	10.05%	187,369	11.50%
15	San Diego, CA	298,547	24.07%	371,542	28.34%	398,005	29.55%
16	St. Louis, MO-IL	44,227	3.53%	65,188	5.04%	71,993	5.60%
17	Baltimore, MD	82,974	6.84%	117,836	9.32%	156,950	12.05%
18	Tampa-St. Petersburg-Clearwater, FL	115,747	10.78%	164,460	13.81%	192,533	15.95%
19	Seattle-Everett, WA	179,138	14.62%	237,242	18.86%	286,421	21.51%
20	Pittsburgh, PA	28,388	2.74%	33,176	3.30%	38,937	3.75%

Note: author's calculation from the ACS 2005, 2010 and Census 2000. Calculation is based on 248 metropolitan areas.

Summary

This chapter described the data sources, clarified the measurements and calculations of all key variables, and illustrated the empirical strategies that will be applied in the regression analysis in the next two chapters. It also discussed the two methods traditionally used in immigration economic impact studies, and emphasized the importance of using a panel approach as one of the contributions this research makes. The analyses in Chapter IV and V will be organized in the same way. The empirical strategies are ordered and listed. In addition, this chapter provided detailed descriptions of the variables that are included in the regression analysis, as well as an analytical description that established a statistical background for further analysis.

CHAPTER IV
REDUCED-FORM ANALYSES

This chapter presents and discusses the results of cross-sectional and panel regressions with area and year fixed-effects using the three-year panel data and the reduced-form model. This chapter is organized following the hypotheses of the three effects: the overall-effects analysis in which immigrant workers are treated as a homogeneous group; the skill-effects analysis, in which immigrant workers are divided into high-, medium- and low-skilled groups and examined separately; and the complementarity-effects analysis, in which both immigrant and native-born workers of different educational levels are examined and interacted. The economic growth of metropolitan areas is measured by GDP per worker and is regressed on various potential immigration-related determinants.

Table 4.1 Univariate Pooled OLS Regressions for Logged GDP per Worker

Independent Vars	Coefficient	Constant	Obs	R-Squared
Log immigrant worker's share in total worker (log M/L)	.108** (.028)	-2.165	747	0.070
Log high-skilled immigrant worker share in total worker (log M1/L)	.143*** (.024)	-1.871	727	0.122
Congruence index for education complemantarity (I)	.474*** (.159)	-2.796	729	0.023

Note: *** significant at the 1% level, ** 5% level, * 10% level. Regression clustered by metro area (fips). Standard errors are in parentheses below the estimated coefficients.

Table 4.1 reports the results of univariate pooled OLS regressions for the logged GDP per worker on the three key independent variables in the overall, skill and complementarity-effects' anlayses – share of immigrants workers (logged), share of high-skilled immigrant worker (logged) and the congruence index. The results show preliminary evidence for the overall and skill-effects hypotheses but the opposite evidence for the complemantarity effects hypothesis (because the larger the index is, the less complementarity there is supposed to be).

The Overall Effects

The overall effects of immigration hypothesize that immigrants may increase the productivity (measured by GDP by worker) by increasing the local labor pool. In this analysis, immigration is measured by the share of immigrant workers to total workers in the metropolitan area. In this analysis, regressions explore the relationships between GDP per worker and the share of immigrant workers in the total workforce, allowing for the non-linear relationship and taking into consideration the metropolitan population size and educational level.

Basics of the Overall-effects Analysis

The relationships demonstrated in Figure 3.1 and 3.2, the OLS regressions for 2000, 2005, 2010 and the pooled OLS regression, as shown in Table 4.2, show that the immigrant share in the workforce is statistically significant and positively associated with GDP per worker. OLS results using single-year data are presented becauuse it is instereting to observe the trend of this relashipship and detect any difference likely due to the recession. In general, OLS regression results of both pooled and single-year specifications suggest that immigration's share and metropolitan GDP's elascitity is 0.10 to 0.11 (a one percent increase in the immigrant workers share is associated with about 0.1 percent increase in metropolitan GDP per worker). This association remains significant and roughly around the same level over the years. The year effects for both 2005 and 2010 are significantly positive. Also, the fitness of these cross-sectional models are not good with a R-squared varying from six to seven percent.

Table 4.2 Results of Pooled OLS and Single-year Cross-sectional Regressions for Overall-effects determinate

Dependent variable: log GDP per worker				
Explanatory variables				
	(1) pooled OLS	(2) 2000	(3) 2005	(4) 2010
Log M/L	0.105*** (0.029)	.108*** (0.030)	.100*** (0.028)	.108*** (0.031)
Dummy 2005	.062*** (0.008)	--	--	--
Dummy 2010	0.027** (0.012)	--	--	--
Constant	-2.203*** (0.091)	-2.195*** (0.093)	-2.154*** (0.082)	-2.169***
R-Squared	0.075	0.071	0.063	0.060
N	729	243	243	243

Note: *** significant at the 1% level, ** 5% level, * 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

Column (1) in Table 4.3 presents the panel regression results only with the basic area- and year-fixed effects, and it shows that the basic year fixed effects are significantly positive. Compared to the OLS results, the panel regression's year effects (coefficents) are larger. Column (2) report regression results based on Equation 3.7 described in the last chapter. Compared to the OLS regressions results, where the coefficient of immigrant share (M/L) is significantly positive, M/L's coefficient in the fixed-effects regression become insignificant and negative. The dramatic change of the relationship's nature may indicate that immigrants are attracted to the metropolitan areas that experience faster growth (endogeneity problem). Also, the changes imply that most of the variations in the key variable is explained by the cross areas effect (between effect), but not much by the time effect (within effect). In fact, ten years may not be long enough for any "within effect" of the key variable to show.

Column (3) shows the results of the fixed-effects panel regression with all demographic control variables. Compared to the basic specification, although R-square is increased by about five percentage points, controling for these variables dooes not increase the significance level of the key indepenent variable. It is expected that metropolitan population is significiantly negatively associated with GDP per worker, as population largely captures the denominator of the dependent varaible. Except for immigrants' educational level (measured by raito of high-skilled immigrant workers to low-skilled ones) that is significantly negatively associated with productivity, all other demographic control variables are not statistically significant. Immigrants' education will be further analyzed in this research (in skill-effects analysis).

Table 4.3 Results of Fixed-effects Panel Regressions for Overall Effects

(N= 672**)**	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log M/L		-.009 (.015)	-.014 (0.019)	-.141** (.057)	-.417*** (.128)	-.020 (.015)	-.009 (0.015)
Log M/L - quadratic				-.019* (.008)	-.114*** (.040)		
Log M/L - cubic					-.010** (.004)		
log of metro population (pop)			-.220*** (0.062)			-.241*** (0.066)	
Log M/L (demeaned) * log pop (demeaned)						-.020** (.010)	
Percent with BA (log)			.028 (0.047)				.012 (0.047)
M/L*Percent BA							-.014 (0.031)
Percent Black (log)			-.007 (0.011)				
Percent Asian (log)			-.002 (0.012)				
Percent Hisp (log)			.015 (0.014)				
Immigration Edu (log)			-.011** (0.005)				
Percent married (log)			.087 (0.104)				
Dummy 2005	.085*** (0.005)	.086*** (.006)	.089*** (0.008)	.093*** (.007)	.092*** (.007)	.094*** (.006)	.085*** (0.007)
Dummy 2010	0.068*** (0.006)	.072*** (.009)	0.094*** (0.015)	.082*** (.010)	.081*** (.010)	.102 *** (0.010)	.070*** (0.011)
Constant	- 2.509*** (0.003)	- 2.534*** (.044)	.395 (0.816)	- 2.746*** (.096)	- 2.990*** (.136)	.536*** (.859)	- 2.519*** (0.081)
Within R-Squared	0.365	0.366	0.412	0.374	0.383	0.402	0.366

Note: M is the log of share of immigrant labor in total workers. *** significant at the 1% level, ** 5% level, * 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

This relationship, of course, can be interpreted by the unobserved area or year variables. However, controlling for other metropolitan characteristics, such as log percent Asian, log percentage married, and metropolitan education, does little to change the fixed effect panel regression results. Except for metro population and immigration educational level, both of which will be discussed later, none of the other characteristics is statistically significant. Some of these demographic control variables are highly correlated with each other and including them appear to cause a multi-collinearity problem. In addition, demographic controls may not be exogenous. Therefore, the reduced-form analysis will examine a cleaner model with only key independent variable and dependent variable, excluding other metropolitan demographic controls.

Allowing for the non-linear relationship

Columns (4) and (5) in Table 4.3 present the panel regression results allowing for the non-linear relationship based on Equation 3.8. Column (4) adds the quadratic form of the immigrant share and Column (5) adds both quadratic and cubic forms. Results show that the linear, quadratic and cubic forms of the immigrant share are all statistically significant and negatively associated with the log GDP per worker. This suggests that the more immigration-intensive areas tend to have low average productivity, and this negative impact of immigration becomes larger for more immigrant-intensive metropolitan areas.

A potential concern with this analysis is that when allowing for a nonlinear relationship, the estimated coefficients may merely reflect an aberration of the functional form. The results should not be given too much attention except for the insight of how immigration intensity (measured by the immigrant share) may influence the impact of immigration on the region's economic growth. These results may indicate that the ability of a metropolitan area to absorb immigrant workers declines in general as more immigrants enter the labor market for most metropolitan areas. Metropolitan areas with high immigration intensity, therefore, should be more cautious with immigration influx.

Accounting for Metropolitan Size

Regression (6) in Table 4.3 follows Equation 3.9 and addresses the question how metropolitan size influences the relationship between immigration and growth. The regression includes the immigration share, metropolitan population, as well as an interaction term, a product of the two (demeaned for easier coefficient interpretation). Results show that the interaction term has statistical significance. This suggests that immigration's impact on growth and metro size is not independent. The fact that the interaction term is negatively associated with economic growth means that for smaller sized metroplitan area, an additional percentage of the share of immigrant worker in total work force has a larger impact on the growth. Quantitatively, when the metropolitan population is at its minimum observed value of 98,329 (St. Joseph, MO, which would be –695,624 relative to the population mean of 793,953), the estimated coefficient of the share of immigrant worker in the total labor force is 0.00725[16] (a very small positve impact); whereas for the maximum observed population of 17,800,000 (New York), the

[16] St. Joseph has a log population of 11.49607, which is – 1.36639 from the mean log population. The coefficient is thus calculated as: $(\frac{\partial \ln_{GDPpw}}{\partial \ln_m})\ln\_pop = min$= (-0.0198)+ (-0.0196)*(– 1.36639) = 0.00725

estimated effect of the immigrant share is almost –0.09487. For the mean populated metropolitan area, the estimated coefficient of the immigrant share is the raw coefficient -0.0198, indicating a mild negative effect. More specifically, this means a hundred percent increase in the immigrant share for the average sized metropolitan area is associated with a 2 percent decrease in the GDP per worker.

In sum, the impact of immigration on economic growth depends on the size of the metropolitan population. Immigration has a slightly positive impact on smaller metro areas than larger areas. However, the coefficient of this analysis should not be overly emphasized since the main independent variable, the immigrant share, is not statistically significant.

Accounting for the Metropolitan Education Level

Model (7) in Table 4.3 reflects a regression that allows the immigration share to interact with the metroplitan area’s skill level (measured by the percentage of workers with at least college degrees within the metropolitan area). The interaction term is a product of the demeaned log immigrant worker share and the demeaned log percentage of workers with at least college degrees in a metropolitan area. The purpose of running such a regression is to see if immigrants are more helpful for more educated metropolitan areas. However, the regression results show that either the main effects or the interaction term is not statistically significantly.

Skill Effects

In order to test the skill-effects hypothesis, immigrant workers are divided by their educational attainment into three categories: low-skilled (with less than high-school diploma), medium-skilled (with high-school diploma or with some college education), and high-skilled (college degree and above). All three types of immigrant workers' shares of the total workforce are then included in the regression as independent variables (based on Equation 3.10).

First, the single-year OLS regressions and pooled OLS results are reported in Table 4.4. Results show that high-skilled immigrants, in all models, are significantly and positively associated with growth. High-skilled immigrants (M3/L) are significantly and positively associated with log GDP per worker throughout the regression models. Medium-skilled immigrants (M2/L)'s association with log GDP per worker is significant and positive in the unlogged form but the significance disappears when the logged forms are used. What is interesting is that the low-skilled immigrants' (M1/L) coefficients are all negative, which suggests that metropolitan areas with larger shares of low-skilled immigrants tend to experience lower levels of average productivity. In terms of the magnitude of these associations, the associations of the high-skilled immigrants are generally the largest compared to medium- and low-skilled immigrants, especially in the log forms.

In the panel regression with fixed effects, the results are presented in Table 4.5, the M3/L associations' significance disappears. Medium-skilled immigration's associations remain significant but the coefficients become negative. Only the low-skilled immigration share, in logged form, has a positive impact on log GDP per worker. There is no evidence that high-skilled immigrants contribute to the higher productivity.

Table 4.4 Results of Pooled OLS and Single-year Cross-sectional Regressions for Skill Effects

N=708				
Dependent variable: log of metro GDP per worker				
Explanatory variables (logged)				
	(1) Pooled OLS	(1) 2000	(2) 2005	(3) 2010
M1/L	-.022 (0.024)	-.047 (0.047)	.000 (.028)	-.042* (.029)
M2/L	.037 (.042)	.091 (0.091)	-.006 (.054)	.063 (.045)
M3/L	.203***	.122*** (0.050)	.156*** (.03)	.120*** (.033)
Dummy 2005	.135*** (0.029)		--	--
Dummy 2010	.040*** (0.011)		--	--
Cons.	-.891*** (0.120)	-1.862*** (.134)	-1.819 *** (.121)	-1.938 *** (.116)
R-Sq	0.131	0.133	0.127	0.110

Note: M1/L is share of low-skilled immigrant workers in the total workforce; M2/L is medium-skilled immigrant workers in the total workforce; and M3/L is share of high-skilled immigrant workers in the total workforce. *** Significant at the 1% level, ** 5% level, * 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

This is a surprising finding because in the cross-sectional regression, the high-skilled immigrants have the most significant and strongly positive association with productivity. In fact, this change may indicate that high-skilled immigrants, among all skill levels of immigrants, are most likely to be attracted to more prosperous places and have been the most responsive to regional economic growth, compared to medium- and low-skilled immigrants. It may also indicate that high-skilled immigrants in a certain metropolitan area do not vary as much as other types of immigrants from year to year.

Table 4.5 Results of Panel Regressions with Fixed Effects for Skill Effects

Explanatory variables N=741	
logged M1/L	.016*** (0.006)
logged M2/L	-.032** (0.015)
logged M3/L	-.005 (0.010)
Dummy 2005	.089 *** (0.006)
Dummy 2010	.075 *** (0.009)
Constant	-2.575*** (0.060)
R-Squared	0.390

Note: *** significant at the 1% level, ** 5% level, * 10% level. Regression clustered by metro area (fips). Standard errors are in parentheses below the estimated coefficients. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

Complementarity Effects

There are two statistical models this research conducts in order to test the complementarity hypothesis. First, a congruence index is used to measure how similar immigrant and native workers are distributed educationally based on five categories of educational attainment. The index is included in the fixed effect panel regression to explore the relationship between this similarity in educational distribution (a proxy of complementarity) and GDP per worker. Second, interaction terms among different skill levels of immigrants and native workers are included in the regression. An interaction term is a product of the shares of two types of workers in the total workforce, and it measures the potential complementarity between these two groups. The interaction terms analysis is performed based on three categories of educational attainment (less than high school, high school diploma and some college, and college and above).

Congruence index

In this approach, testing the complementarity hypothesis, an index measuring the difference in the distribution of immigrant and native workers' educational attainment, is calculated for each metropolitan area based on five categories of educational attainment (Equation 3.1). The closer to zero (0) the index is, the greater the difference there is in the immigrants' education distribution from the natives' educational distribution, the more complementarity is supposed to exist between the two groups of workers. The index for all metropolitan areas over three time periods range from .17 to almost 1.00, with a mean of 0.84 (Table 3.1).

Next, the congruence index is included in the panel regression based on equation (3.12). Table 4.7 reports the results, showing that the congruence index is associated in a significantly negatively way with metropolitan economic growth. Because the smaller the index is, the more identical the two distributions are, this result indicates that a larger educational disparity between immigrants and native workers (more complementarity) is associated with higher economic prosperity, holding immigrant workers' share constant.

Table 4.6 Results of Panel Regressions for Complementarity Effects using Congruence Index

N=729		
Dependent variable: log of metro GDP per worker		
Explanatory variables	(1)	(2)
Log M/L (log)		-.006 (.015)
Congruence index	-.082* (.046)	-.081* (.046)
Dummy 2005	.082*** (.005)	.083*** (0.006)
Dummy 2010	.067*** (.006)	.069*** (0.009)
Constant	-2.449*** (.034)	-2.468*** (0.060)
R-Squared	0.372	0.372

Notes: Standard errors are in parentheses below the estimated coefficients. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

One limit of using this index is that it captures potential complementarity only through two types of combinations: high-skilled immigrants versus low-skilled native workers and high-skilled native workers versus low-skilled immigrant workers. In other words, the index can only catch complementarity through the disparity of education of the two groups and fails to reflect any potential complementarity between the same educational levels of immigrants and native workers. For example, native worker may tend to have degrees in law and business, while immigrant workers tend to have degrees in science and physics, and they could well complement each other. In addition, the index does not differentiate between the two combinations (high-skilled immigrants versus low-skilled native workers, high-skilled native workers versus low-skilled immigrant workers). Either combination can result in a high congruence index.

However, these two types of combinations reflect very different immigration policies. In order to identify further which educational combination between immigrant and native workers contribute to complementarity, the following analysis introduces interaction terms between differently educated immigrant and native workers.

Interactions between differently educated immigrant and native workers

The regression following Equation 3.13 uses interaction terms that are products of the share of low-skilled immigrant and native workers (M1/L_N1/L); low-skilled immigrant and high-skilled native workers (M1/L_N3/L); high-skilled immigrant and low-skilled native workers (M3/L_N1/L); and high-skilled immigrant and high-skilled native workers (M3/L_N3/L). Shares are calculated by dividing the number of different types of workers by total workers (L). The purpose of this regression model is to identify and quantify in which combination complementarity exists. N_1 and N_3 are demeaned for an easier interpretation of coefficients. Compared to model 3.12, which only detects any possible complementarity caused by educational differences between immigrant and native workers (low-high and high-low combinations), the model 3.13 also explores possible complementarity between the same educational levels of immigrant and native workers (low-low and high-high combinations).

Table 4.7 Results of Fixed-effects Regressions for Complementarity Effects: Skill interaction (I)[17]

Dependent Variable: Log GPD per worker	
Explanatory variables (unlogged)	
M1/L (α_1)	0.361(0.98)
M2/L (α_2)	-1.039 (2.71) ***
M3/L (α_3)	0.161 (0.21)
N1/L (β_1)	0.605 (1.51)
N3/L (β_3)	-0.449 (1.44)
M1/L _ N1/L (demeaned) (δ_{11})	20.049 (3.94)***
M1/L_ N3/L (demeaned) (δ_{13})	5.716 (1.62)*
M3/L _ N1/L (demeaned) (δ_{31})	-14.149 (0.87)
M3/L _ N3/L (demeaned) (δ_{33})	10.916 (1.67)*
D2005	0.102 (12.15)***
D2010	0.097 (7.13) ***
Constant	-2.418 (28.86) ***
Observations	708
R-squared	0.44

Notes: Standard errors are in parentheses below the estimated coefficients. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars

Regression results, as reported in Table 4.8, show that the low-low combination interaction terms have a highly positive significance, which indicates there is complementarity between these two low-skilled worker groups. The low-high and high-high combinations are also significantly positive, indicating there are complementarity effects in those two combinations, as well. With the highest complementarity coefficient (20.049), the low-skilled immigrants and natives complement each other the most.

[17] Middle-skilled native workers (N2) are not included in the regression because one of the six variables will be omitted, and since N2 is the least of this research's interest, it is chosen to be omitted by not being included.

Quantitatively, the coefficient of the low-skilled immigrants share is 0.361 (although insignificant) and suggests that on an average, one percent increase in low-skilled immigrant worker share increases the log GDP per worker by 0.36 percent[18]. On average, a one percent increase in the high-skilled immigrant worker share increases the log GDP per worker by 0.16 percent[19].

An alternative for Model 3.13, the regressions following Equation 3.14 (models 11, 13, 31, and 33) identify the potential complementarity relationships between (11) the share of low-skilled immigrant and native workers, (13) the shares of low-skilled immigrant and high-skilled native workers, (31) the shares of high-skilled immigrant and low-skilled native workers, and (33) the shares of high-skilled immigrant and high-skilled native workers. Overall the immigrants' share (M/L) is interacted with the less- and high-skilled native workers' shares among the total native workers (namely, N1/N and N3/N). N_1/N and N_3/N are demeaned for an easier interpretation of coefficients.

According to Equation 3.14, whether complementarity exists between two types of workers in each model depends on the significance levels and the signs of the second interaction term coefficient (β_2), and the impact of the magnitude of the observed type among immigrant share on the log GPD per worker equals to α_2 [20].

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[18] Low-skilled immigrant's share's coefficient on log GDP per worker is:

$$\left(\frac{\partial \ln_{GDPpw}}{\partial (\frac{M1}{L})}\right) = \alpha_1 + \delta_{11}\frac{N_{1,z,t}}{L_{z,t}} + \delta_{13}\frac{N_{3,z,t}}{L_{z,t}}$$

And because N1 and N3 are demeaned, the average impact of low-skilled immigrant share impact is α_1.

[19] Similarly, the average impact of high-skilled immigrant share is α_3.

[20] For example, the impact of low-skilled immigrants share on the log GDP per worker is:

The results are reported in Table 4.9. Except for Model (1-3), coefficients for the second interaction term (β_2) are all highly significant and positive, which indicates complementarity between low-low, high-low and high-high combinations of immigrant and native workers. For example, the impact of low-skilled immigrants on productivity is larger for metropolitan areas with a higher low-skilled native worker concentration, and the impact is smaller for areas with a higher high-skilled native worker concentration. Meanwhile, the impact of high-skilled immigrants on growth is larger for metropolitan areas that have a larger concentration of both less- and high-skilled native workers. When the coefficients for the second interaction terms in column (1-1) and (3-3) are above 24, this indicates that the complementarity effects are equally large between low-low and high-high combinations.

Results using Model 3.14 suggested a somewhat different complementarity exists from Model 3.13: both models found complementarity between low-low and high-high combinations, but Model 3.13 also found low-skilled immigrant workers and high-skilled native workers are complementary, while Model 3.14 found high-skilled immigrant workers and low-skilled native workers are complementary. Also, the complementarity within the low-low combination is surprising and counterintuitive to what people normally think, since in this combination, labor market competition is supposed to be the fiercest.

$$((\partial \ln\_GDPpw)/(\partial(M_1/L))) = \alpha_2 + \beta_2 \frac{N_{1,z,t}}{N_{z,t}}$$

Since N_1/N and N_3/N are demeaned, the impact of low-skilled immigrant share on log GPD per worker is $\alpha_2 + \beta_2$.

Table 4. 8 Results of Fixed-effects Regressions for Complementarity Effects: Skill interaction (II)

N=727							
Dependent variable: log of metro GDP per worker							
Explanatory variables (unlogged)							
Low-skilled imm and low-skilled native (1-1)		Low-skilled imm and high-skilled native (1-3)		High-skilled imm and low-skilled native (3-1)		High-skilled imm and high-skilled native (3-3)	
M/L(α_1)	-.705** (.293)		-1.164*** (.260)		-.498** (.204)		-.609*** (.228)
M1/L (α_2)	.717 (.542)	M1/L	1.189** (.526)	M3/L	-.165 (.736)	M3/L	-.874 (.754)
N1/N (α_3)	.482 (.314)	N3/N	-.052 (.223)	N1/N	-.009 (.271)	N3/N	.147 (.203)
M/L* N1/N (demeaned) (β_1)	-6.215 (4.538)	M/L* N3/N (demeaned)	6.431*** (.206)	M/L* N1/N(demeaned)	6.667*** (1.509)	M/L* N3/N (demeaned)	-5.704*** (1.716)
M1/L* N1/N (demeaned) (β_2)	24.195*** (9.248)	M1/L* N3/N (demeaned)	-16.835*** (5.579)	M3/L * N1/N (demeaned)	11.742*** (2.887)	M3/L* N3/N (demeaned)	24.129*** (5.162)
Dummy 2005	.105*** (.008)		.098*** (.012)		.096*** (.008)		.093*** (.008)
Dummy 2010	.100*** (.012)		.087*** (.0117)		.088*** (.012)		.081*** (.012)
Constant	-2.511*** (.030)		-2.436*** (.058)		-2.478*** (.025)		-2.489*** (.054)
R-Squared	0.418		0.415		0.431		0.424
N	710		710		727		727

Notes: Standard errors are in parentheses below the estimated coefficients. *** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Regression clustered by metro area (fips). Robust standard errors are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

In theory, the “likes” are supposed to have the most competition. For example, immigrants are found to be the most harmful for low-skilled natives in terms of lowering low-skilled natives’ wages (Borjas and Katz 2007) (Orrenius and Zavodny 2007). However, since previous studies never focus on aggregate economic measure, this research reveals that this competition may actually be good for overall productivity increase.

These analyses using the congruence index and interaction terms rely on the assumption that educational attainment is a good proxy of skills. Though education is most commonly used as a proxy of skill levels, occupation, fields of degree and English proficiency are all possible alternatives to capture the complementarities between immigrants and native workers for future research.

Summary

Although the raw relationship plotting and the cross-sectional OLS regressions all show that the relationship between the immigration share and the GDP per worker is upward sloping, the panel regression with area- and time fixed- effects do not find that immigration has a positive impact on productivity. The analysis of overall effects and skill effects find that immigrant share is negatively associated with the GDP per worker.

This is not a surprising result and is consistent with some of the previous research finding using non-U.S. cases. Because the majority of immigrant workers are less educated compared to native workers and less productive in the U.S. labor market and, therefore, the larger immigrant share in the metropolitan work force means a disproportionate larger denominator in the dependent variable, the GDP per worker. In other words, unless immigrant workers are contributing to the economic growth disproportionately more than native workers, the regression will not capture this effect as positive impact. This is the reason that the analysis in the next chapter will use a structural-form approach and undertake a panel regression using GDP (instead of GDP per worker) as the measure of metropolitan economic growth and the amount of immigrant and native workers as explanatory variables.

The merit of using GDP per worker lies in the exploration of the interactions between immigration and metropolitan population size, the metro educational level, as well as the identification of possible complementarity between different educational levels of immigrant and native workers. Results show that immigration contributes to the economic growth more when the metropolitan areas' population is smaller and when the areas' workforce is more highly educated.

The skill effect analysis fails to detect that high-skilled immigrants contribute more to the economic growth like the hypothesis suggested. On the other hand, low-skilled immigrants are found to have contributed to more growth. Results show that high-skilled immigrants may have been more likely to be attracted to more prosperous places and therefore there may be a problem of endogeneity. To address this problem, instrumental variables will be introduced into the regression in the next chapter.

The complementarity effect exploration using the congruence index found that there is complementarity effect. However, when further examining this complementarity effect between specific combinations of immigrant and native workers, the complementarity effects are only found within low-low and high-high combinations, but not the most commonly believed "optimal" combination – low-skilled immigrants and high-skilled natives. This is a surprising finding and will be further researched in the next chapter.

CHAPTER V
STRUCTURAL-FORM ANALYSES

This chapter presents and discusses the results of fixed-effects and first-difference panel regressions using the structural-form model. The analyses in this chapter include overall and skill effects, and each hyphothesis will be approached using fixed-effects and first-difference models. In addition, instrumental variables will be included in the analysis to address the potential endogeneity problem. In the structural-form analyses, the economic growth of metropolitan areas that is measured by metropolitan GDP (instead of GDP per worker) and is regressed on various potential immigration-related determinants (in levels instead of shares). Specifications with and without catpial stock are both run, because capital stock is an important control variable, but it also could be endogenous, which means captial could be one of the channels through which immigration influences GDP.

Overall Effects

Pooled OLS and single-year cross-sectional regressions using GPD as the dependent variable and immigrant and native workers as independent variables show that both groups of workers have significantly positive associations with economic growth (Table 5.1 model 1-4). The native worker's coefficient is about four to five times larger than the immigrant worker's coefficient. After controlling for metropolitan capital stock, generally, the native workers' coefficients became smaller, and the immigrant workers' association with GDP loses significance except for in the 2000 regression (Table 5.1 model 5-8). The coefficients on immigrant workers, in the model controlling for capital, are much smaller compared to those in the model without capital control. In other words, the differences in the coefficients' magnitude between immigrant and native workers become systematically larger with capital control. These results suggest that while native workers are substantially positively associated with growth, the immigrants' positive association with growth exists, but may be weaker. Also, in the pooled OLS regression, with a capital control variable year dummies becomes negatively associated with GDP. Finally, all models have high R-squared and suggest that the two types of workers, together with capital, can explain a great amount of the metropolitan GDP growth.

The reason native workers are included in the model is to provide an easy comparison between native and immigrant workers' impacts on metropolitan economic growth. The direct coefficient comparison is based on the assumptions that native workers do not respond to changes in the numbers of immigrant workers and that both native and immigrant workers respond to the economic prosperity of a metropolitan by relocating at the same level. The first assumption will be illustrated more in the First-difference Model analysis which will be conducted later in this section (Table 5.3). In terms of the second assumption, however, there is evidence showing that immigrants are more "footloose" than native workers (Perry and Schachter 2003), especially low-skilled immigrants (Cadena and Kovak 2011). Therefore, in the direct comparison, immigrants' coefficients are likely to be more upward biased than natives' are.

Table 5.1 Structural-Form Results of Pooled OLS and Single-year Cross-sectional Regressions for Overall-effects Determinate

Dependent Variable: log GDP								
	Without Capital				With Capital			
	(1) Pooled OLS	(2) 2000	(3) 2005	(4) 2010	(5) Pooled OLS	(6) 2000	(7) 2005	(8) 2010
Log M	0.179*** (5.44)	0.171*** (5.07)	0.178*** (5.44)	0.19 (5.50)***	0.021 (1.9) *	0.057 (4.78)***	-0.01 (0.69)	0.008 (0.49)
Log N	0.875*** (19.01)	0.89 (19.42)***	0.87 (18.83)***	0.864 (17.77)***	0.276 (7.64)***	0.261 (6.21)***	0.284 (7.60)***	0.269 (6.08)***
D2005	0.063 (6.92)***				-0.026 (2.32)**			
D2010	0.026* (1.81)				-0.079 (7.05)***			
Log K					0.682 (20.73)***	0.635 (17.62)***	0.718 (19.55) ***	0.72 (16.75)***
Cons.	-2.564 (-8.51)***	-2.665 (-9.15)***	-2.426 (-8.04)***	-2.506 (-8.04)***	3.766 (11.17) ***	3.778 (9.93)***	3.815 (10.58)***	3.766 (8.79)***
N	729	243	243	243	729	243	243	243
R-sq	0.92	0.93	0.92	0.92	0.98	0.98	0.98	0.98

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). T statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

There are good reasons both to control and not to control for metropolitan capital stock. To form a production-function-type of model, capital should be included as one of the basic contributors to economic growth. However, this is based on the assumption that capital is exogenous. In fact, capital stock can be one of the channels through which immigrants affect GDP.

Finally, adding other control variables for metropolitan demographic characteristics does little to change the key independent variable’s coefficient or increase the model goodness of fit. It also dilutes the significance of the key variable (immigrant and native workers) because of the multicollinearity between these demographic variables and the key variables. Therefore, the structural-form analysis will continue examining a cleaner model, excluding other metropolitan demographic controls.

<u>Fixed-effects analysis</u>

The first column of Table 5.2 shows a simple panel regression with only the year dummies of 2005 and 2010 and MSA fixed effects. It shows that both year dummies do have a significantly positive impact on GDP. Following the Equation 3.16, Columns (2) and (3) report the results fixed-effects regressions with and with and without capital stock as a control variable. The results show that both immigrant and native workers have a significantly positive impact on economic growth, although with capital as a control variable, immigrant workers' impact becomes less significant. Immigrant worker's coefficients with and without the capital control variable are systematically smaller than native workers' coefficients. This suggests that an increase in immigrant workers is good for growth, but not as much as an increase in native workers. Both models (2) and (3) have high R-Squared (.71 and .74). The results suggest that immigrant workers do have a positive impact on metropolitan GDP, but compared to native workers, the impact's significance and magnitude are both smaller.

Table 5. 2 Structural-Form Results of Panel Regressions with Fixed Effects for Overall-effects Determinate

Dependent Variable: log GDP			
	(1)	(2)	(3)
Log M		0.03 (2.32)**	0.022 (1.76)*
Log N		0.661 (11.96)***	0.512 (8.99)***
Log K			0.115 (6.46)***
D2005	0.125 (23.80)***	0.105 (18.25)***	0.086 (14.18)***
D2010	0.138 (17.93)***	0.102 (12.40)***	0.077 (9.55)***
Constant	9.54 (2415.82)***	1.355 (2.09)**	2.827 (4.39)***
Observations	729	729	729
R-squared	0.54	0.71	0.74

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). T statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

First-Difference Analysis

As an alternative to the fixed-effects model, the first-difference model is used in order to explore the relationship between immigrant worker and GDP growth, controlling for the omitted variables. In this analysis, GDP, capital stock, and numbers of immigrant workers and native workers (all in log form) are transformed to the first-difference form with five-year intervals (2000 to 2005 period, and 2005 to 2010 period). Then these first-difference variables are included in the panel regression. The total number of observations in the first-difference analysis equals two thirds of that in the fixed-effects analysis.

Figure 5.1 shows the relationship between the first-difference log immigrant and native workers. For most metropolitan areas the change of native workers is in the same direction as the change of immigrant workers. No evidence at the aggregated level shows that the immigrants have a “crowding out” effect on the native workers.

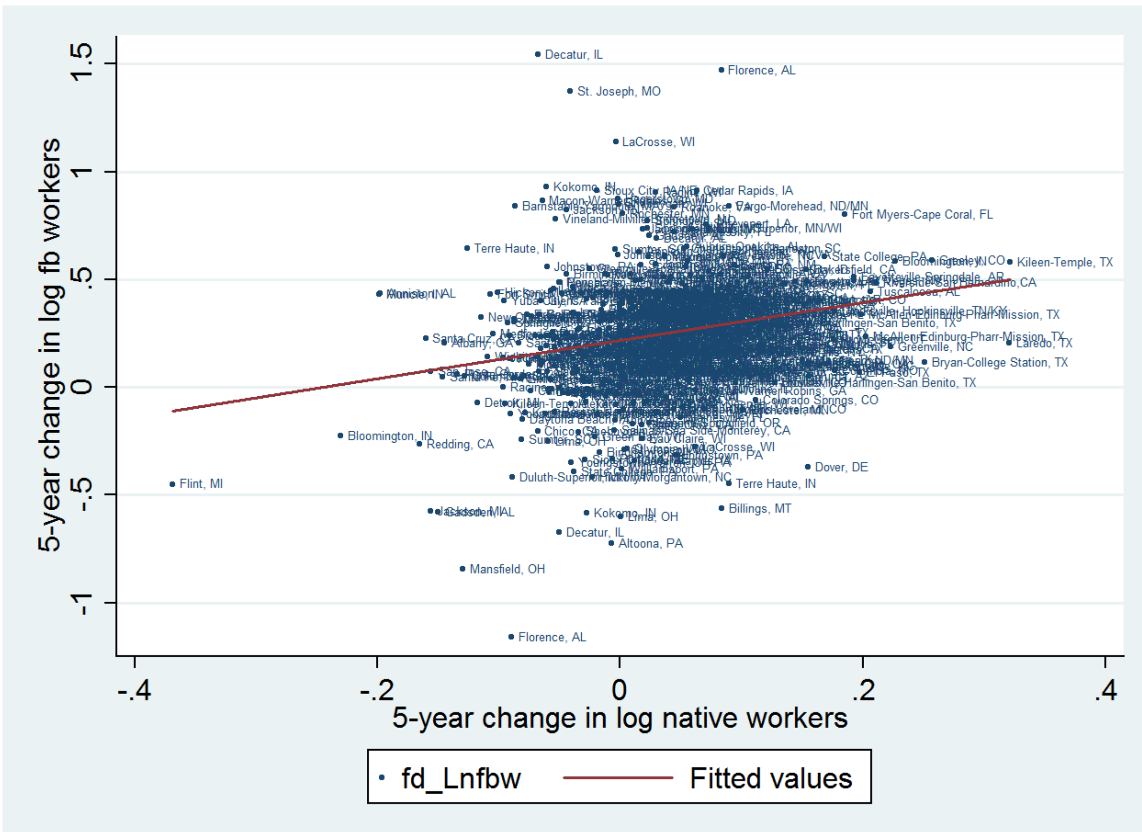

Figure 5. 1 Two-way Scatter Plots of First-difference Log Immigrant Worker and First-difference Log Native Worker, 2000-05 and 2005-10

Slope = 0.883, Standard Error = 0.171, R-squared = 0.0523, p<0.001
Calculation based on 486 observations.

The OLS using single-year first-difference data are reported in Table 5.3, Model (1) and (2). Results show that the five-year change in native numbers are significantly positively associated with the five-year change GDP, either controlling or not controlling for five-year change of capital. However, five-year change of immigrant worker numbers is only significantly associated with GDP in the first half of the decade, not the second. This is likely due to the recession, during which many areas' immigration increase slowed.

Table 5. 3 Structural-Form First-difference Model Single Period OLS Regression and Panel Regressions for Overall-effects Determinate

	(1)OLS 2000-05	(2) OLS 2005-10	(3) FD Panel	(4) FD Panel	(5) FD Panel
M (log)	0.029 (1.82)*	0.006 (0.48)		0.032 (2.60)***	0.022 (1.89)*
N (log)	0.379 (5.69)***	0.427 (7.54)***		0.576 (11.30)***	0.430 (8.85)***
K (log)	0.083 (4.68)***	0.237 (9.25)***			0.129 (6.66)***
Dummy 2005-2010			-0.113 (13.99)***	-0.108 (18.59)***	-0.094 (13.33)***
Constant	0.094 (14.17)***	-0.014 (2.88)***	0.125 (31.20)***	0.106 (18.59)***	0.088 (14.80)***
N	243	243	486	486	486
R-squared	0.31	0.52	0.45	0.56	0.63

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). T statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

The results of the first-difference panel regression (time dummy only, without capital control and with capital control) are reported in the Table 5.3 Columns (3), (4) and (5). Model (4) shows that immigrant workers have a highly significant positive impact on metropolitan GDP, although the magnitudes of the immigrants' coefficients are again smaller than those of native workers. When controlling for capital (Colunm (5)), the significance of the immigrants level decreases but is still significant at the ten percent level. This conclusion is consistent with the findings using the fixed effect model.

Skill Effects

In the skill effect analysis, the logged forms of high-, medium- and low-skilled immigrant and native workers are all included in the fixed-effects panel regression to explain the log GDP. Table 5.4 presents the pooled and single-year OLS results using different skills of immigrant and native workers to explain metropolitan GDP. Only high-skilled native workers are significantly and positively associated with GDP across the models with the largest coefficients compared to all the other skill levels of workers. Low-skilled immigrant workers and medium-skilled native workers are not significantly associated with GDP in any model. In most models, low-skilled immigrants' coefficients are small and negative, indicating an insignificant negative association with GDP.

Table 5. 4 Structural-Form Results Pooled and Single-year OLS Regressions for Skill-effects Determinate

Dependent Variable: log GDP					
	(1) Pooled OLS	(2) Pooled OLS	(3) OLS 2000	(4) 2005 OLS	(5) OLS 2010
Log M1	-.001 (-0.06)	-.020 (-1.33)	-.054 (-1.24)	.016 (.60)	-.0018 (-0.06)
Log M2	.121 (2.96)***	.027 (0.9)	.214 (2.7)***	.077 (1.62)	.144 (2.86)***
Log M3	.059 (1.47)	.029 (1.44)	.005 (0.1)	.103 (2.35)**	.041 (1.00)
Log N1	.119 (2.23)**	.026 (1.03)	.171 (2.79)***	.115 (1.89)*	.088 (1.48)
Log N2	.122 (0.95)	.057 (.99)	.057 (0.47)	.172 (1.5)	.087 (.71)
Log N3	.575 (6.04) ***	.181 (3.94)***	.605 (6.23)***	.516 (5.86)***	.623 (6.87)***
Log K		.659 (21.79)***			

D2005	.037 (2.36)**	-.035 (-2.88) ***			
D2010	.003 (0.10)	-.090 (-2.88) ***			
Constant	-.481 (-1.16)	4.252 (14.24)***	-.509 (-1.42)	-.457 (-1.26)	-.372 (-.96)
N	708	708	234	234	234
R-squared	0.93	0.98	0.93	0.93	0.93

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). T statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

Fixed-effects Analysis

Following Equation 3.18, the logged forms of high-, medium- and low-skilled immigrant and native workers are all included in the fixed-effects panel regression to explain the log GDP. The results are shown in Table 5.5. Results show that low-skilled immigrants, as well as all skill levels of native workers, have a significantly positive impact on GDP. Compared to the OLS regressions, the results for low-skilled immigrants have a dramatic change. This finding is also consistent with the findings using the reduced-form analysis. In addition, compared to the coefficients of the native workers, the coefficients of immigrant workers are smaller. Among all labor coefficients, the coefficients of medium-skilled native workers are systematically the largest. This may be related to the fact that immigrant workers are generally less productive, since they are less skilled. Models controlling for capital or not produce similar results.

Table 5. 5 Structural-Form Results of Panel Regressions with Fixed-effects for Skill-effects Determinate

Dependent Variable: log GDP (N=708)		
	(1)	(2)
Log M1	0.019 (3.00) ***	0.017 (2.66) ***
Log M2	-0.005 (0.35)	-0.007 (0.54)
Log M3	0.008 (0.87)	0.004 (0.41)
Log N1	0.067 (3.55)***	0.044 (2.51)**
Log N2	0.425 (8.12) ***	0.312 (6.13) ***
Log N3	0.152 (3.45) ***	0.131 (3.11) ***
D2005	0.117 (14.16) ***	0.093 (11.45) ***
D2010	0.124 (8.88) ***	0.09 (7.02) ***
Log K		0.115 (6.39) ***
Constant	2.247 (3.41) ***	3.666 (5.54) ***
R-squared	0.70	0.73

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). T statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

The First-difference Analysis

Table 5.6 shows the correlations between the key explanatory first-difference variables. Overall, with a correlation of 0.23, five-year change in numbers of immigrant workers and native workers are not closely correlated with each other. Overall the change in immigrants is highly correlated with the change in high-skilled immigrants (with a correlation of 0.53), and the change in native workers is highly correlated with the change in medium-skilled native workers (with a correlation of 0.90).

Table 5. 6 Correlations between Key Explanatory First Differenced Variables

	ΔM	ΔM1	ΔM2	ΔM3	ΔN	ΔN1	ΔN2	ΔN3
ΔM	1.0000							
ΔM1	0.3295	1.0000						
ΔM2	0.3788	0.8337	1.0000					
ΔM3	0.5298	-0.0002	0.2025	1.0000				
ΔN	0.2288	0.0986	0.1310	0.1414	1.0000			
ΔN1	-0.0095	-0.0318	-0.0563	-0.0807	0.3381	1.0000		
ΔN2	0.2360	0.1366	0.1902	0.1530	0.9039	0.1801	1.0000	
ΔN3	0.1074	-0.0609	-0.0736	0.0925	0.5380	0.0575	0.2320	1.0000

Notes: All variables are logged first, then transformed into first-difference form

Table 5.7 presents the descriptive statistics for the first-difference variables. Low- and middle skilled immigrant workers have an especially large standard deviation. A closer look at the dataset discovered that due to the limited sample sizes of the ACS data, 19 metropolitan areas have missing data for one or more skill categories of immigrant workers in certain years. This missing data problem caused the most extreme log value change between the years. These metropolitan areas are therefore dropped as outliers for the skill effect analysis. The descriptive data after fixing the outlier problem are presented in italics in Table 5.7.

The last column of Table 5.7 shows the number of metropolitan areas that experienced increases in the reference variables. More areas (405) experienced a net increase in immigrant workers than in native workers (278). In terms of skill levels of workers, many more areas (405) experienced a net increase in high-skilled native workers than in low-skilled native workers (73). Only a slightly fewer areas experienced a net increase in low-skilled immigrant workers (317) than medium- and high-skilled immigrant workers (354 and 353 respectively).

Table 5. 7 Descriptive Statistics for Key Explanatory First Differenced Variables

Variable	**Mean**	**Min**	**Max**	**Std. dev**	**Number of MSA that experience increase**
ΔM	.231	-1.162	1.544	.299	405 (N=486)
ΔM1	.154	-6.415	7.184	1.384	333 (N=486)
ΔM2	.098	-7.377	7.996	1.647	369 (N=486)
ΔM3	.211	-6.066	6.102	.701	373 (N=486)
ΔN	.0167	-.369	.321	.078	278 (N=486)
ΔN1	-.223	-1.015	.731	.244	73 (N=486)
ΔN2	.0085	-.384	.367	.090	253 (N=486)
ΔN3	.091	-.385	.508	.117	405 (N=486)
Δ*M1*	*.2281*	*-2.2668*	*3.0173*	*.6068*	*317 (N=448)*
Δ*M2*	*.2314*	*-1.2491*	*1.6785*	*.3795*	*354 (N=448)*
Δ*M3*	*.2340*	*-2.9078*	*1.6562*	*.4709*	*353 (N=448)*

Notes: All variables are all in log form, then transformed into first-difference form. Numbers in italic are after dropping off the outliers. Including both 2000-2005 and 2005-2010 periods.

Table 5. 8 Structural-Form Results of First-difference Panel Regressions for Skill-effects Determinate

Dependent Variable: log GDP		
	(1) without K	(2) with K
M1	.017 (2.58)*	.013 (2.09)**
M2	.001 (0.09)	-.003(-0.18)
M3	.010 (0.91)	.003(0.32)
N1	.055 (3.12)***	.037(2.28)**
N2	.404 (8.05)***	.300 (0.048)***
N3	.099 (2.32)**	.077 (0.041)*
D2005-2010	-.110 (-14.37)***	-.098 (-12.93)***
Log K		.117 (0.018) ***
Constant	.118 (15.01)***	.096 (12.05)***
Observations	448	448
R-squared	0.5746	0.6401

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level Regression clustered by metro area (fips). Z statistics are in parentheses below the estimated coefficients. GDP is in millions of 2005 dollars.

Table 5.8 presents the skill effect analysis using the first-difference panel model. Following the Equation 3.19, both regression models not controlling for capital (1) and controlling for capital (2) yield similar results. Low-skilled immigrants, as well as all skill levels of native workers, have a significant positive impact on growth. Native workers' coefficients are larger than immigrants' coefficients. Among all labor coefficients, those of the medium-skilled native workers are systematically the largest. These results are consistent with the findings using the fixed-effects approach.

Analysis with Instrumental Variables

Whether the key explanatory variable, immigrant workers, is exogenous or endogenous is an important concern. There are many reasons for immigrants to choose their locations, economic reason among the most common. If immigrants choose to locate in the faster growing places, the OLS estimates will be upward biased. Using panel regressions with fixed-effects and first-difference is supposed to reduce this bias. A proper instrument on the key independent variable is another way to control for this problem. A potential candidate for an instrumental variable needs to be correlated with immigrant workers, but not correlated with the dependent variable, GDP.

Overall Fixed-effects Analysis with Instrumental Variable

Using the lagged number of immigrant workers of a previous period in the panel data is an obvious choice of an instrument, as the immigrant level in an area in the past should reasonably predict the current immigrant level, but should be less correlated with the current growth level, since it is difficult for immigrants in the past to predict the destination area's current growth. In fixed-effects panel regression, five and ten years lagged terms of immigrant workers are used as instrumental variables (Lag_5 and Lag_10)[21].

Another instrumental variable is constructed following immigrants' historical settlement of the same origin (Equation 3.5) and used in the fixed-effects regression. Five and ten years intervals are both used. The construction of instrumental variables uses the 1990 Census data, in which metropolitan areas are not coded/named the same as those in the 2000 Census and 2005, 2010 ACS. After merging these with the GDP data from the BEA, the dataset contains 201 metropolitan areas and 603 observations in total.

Table 5. 9 First-Stage Estimates of the Relationship between Immigrant Worker Levels (log) and Predicted Immigrant Worker Levels (log) in Fixed-effects Model

Dependent variable: log immigrant worker level Independent variables: natives, year effects and IV					
	(1) Lag_5	(2) Lag_10	(3) Lag_10 without 2005	(4) Network IV_5	(5) Network IV_10
Predicted number of immigrant workers (IV)	-.178*** (.052)	.076 (0.048)	0.084* (0.048)	.093 (.078)	.261*** (0.072)
R-squared	0.579	0.599	0.758	0.599	0.6088
F-statistics for IV	11.49	2.46	2.99	1.44	13.10
N	688	647	445	603	606
Sample restrictions	2010, 2005, 2000, 1995	2010, 2005, 2000, 1995, 2990	2010, 2000, 1990		

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Standard errors are in parentheses below the estimated coefficients. Each regression includes year fixed effects.

[21] More specifically, 2005, 2000 and 1995 immigrant worker levels are the five-year lagged terms for 2010, 2005 and 2000 immigrant workers. 2000, 1995 and 1990 immigrant worker levels are the ten-year lagged terms for 2010, 2005 and 2000 immigrant workers.

Table 5.9 presents the results of the first-stage estimates of the relationship between log immigrant workers and these five potential instrumental variables. Each model uses one instrument. Model (1) and (2) uses Lag_5 and Lag_10. Results show that Lag_5 is not a good predict of immigrant workers since the estimate has the unexpected sign. Prediction of Lag_10 has the expected sign but the F-statistics is below the 10, indicating it is not a qualified instrument. Model (3) also uses Lag_10 but skips year 2005 in order to avoid using 1995 data as instrument because it is synthetic. The estimated coefficient is more significant but F-statistics is below the 10. Model (4) and (5) uses the instruments constructed following Equation 3.5 ((4) uses five-year interval and (5) uses ten-year interval). The results show that the estimated coefficients both have the expected signs, and the ten-year instrument has a significant prediction with qualified F-statistics. Therefore, historical settlement-based instrument with ten-year interval is the best qualified instrument among the five candidates.

Table 5.10 presents the fixed-effects panel regression results without[22] and with instrumental variables both with and without capital stock control. Compared to results in Model (1) and (2), the estimated coefficients for the instrumented immigrant workers in Model (3) and (4) become slight negative and statistically insignificant. Therefore, overall immigration's positive impact on metropolitan GDP is not confirmed by such instrumental variable analysis. Since native workers are not necessarily exogenous, and they are not instrumented, the coefficient magnitudes of immigrants and natives should not be compared directly in the models with instrumental variables.

[22] Table 5.2 shows the results of fixed effects regression without IV with a bigger sample size.

Table 5. 10 Second-Stage 2SLS Estimates of the Relationship between log GDP and log Immigrant Workers using IV

Dependent var: Log GDP	(1)	(2)	(3)	(4)
	Without IV		With Historical settlement based IV	
Log M	0.023* (.014)	0.016 (0.013)	-0.014 (0.080)	-.007 (0.074)
Log N	0.698*** (.060)	0.518*** (0.058)	0.734*** (0.092)	0.538*** (0.082)
Log K	___	0.137*** (0.020)	___	.138*** (0.018)
2005	0.105*** (.006)	0.085*** (0.006)	0.113*** (0.019)	0.091*** (0.017)
2010	0.105*** (.009)	0.077*** (0.009)	0.121*** (0.034)	0.087*** (0.030)
Cons	1.036 (0.715)	2.797*** (.676)	0.942 (0.598)	2.771*** (0.571)
N	606	606	606	606
R-square	0.7242	0.7622	0.7196	0.7601

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level. St. Error. in parentheses below the estimated coefficients.

Overall-effects First-difference Analysis with Instrumental Variable

Because first-difference model uses the differenced data of each variable, an instrument constructed following Equation 3.6 is used in the first different model in order to match the other differenced variable. Equation 3.6 is a variation from 3.5 – the latter is the former's differenced logged version constructed in a sophisticated manner. As Smith (2013) points out, it is more suitable to predict the change of immigrants. The first-stage estimates of relationship between log immigrant worker levels and the instrument predicted ones are reported in Table 5.11. Column (1) shows that in the panel regression model, the predicted value does not have the expected sign and therefore. Columns (2) and (3) discover that the instruments for different periods actually have inconsistent signs: the instrument and the immigration level are positively correlated in 2005 but negatively correlated in 2010. This is likely a result of the recession, during which increase in number of immigrants, especially unauthorized immigrants went down (Passel, Cohn, and Gonzalez-Barrera 2013). Therefore, for the first half of the decade, this IV candidate could be a weak (because the F-statistics is smaller than 10 and the significance level is beyond ten percent) instrument for the immigrant workers. Second-stage estimates using this this settlement-based instrumental variable only for period 2000-2005 first different cross-sectional data is presented in Table 5.12. Controlling for it reduces immigrants' coefficients' significance.

Table 5. 11 First-Stage 2SLS Estimates of the Relationship between Immigrant Worker Levels (log) and Predicted Immigrant Worker Levels (log) First-difference Model

Dependent variable: log immigrant worker level Independent variables: natives, year effects and historic settlement based IV			
	(1) FD panel	(2) 2000-05	(3) 2005-10
Predicted change in log immigrant workers (IV)	-.351*** (0.082)	.236 (0.154)	-.452*** (0.094)
Log N	.946*** (0.179)	1.034*** (0.251)	.753*** (0.241)
Year dummy 2010	-.142*** (0.034)		
Const.	.382*** (0.0.040)	.130* (0.068)	.258*** (0.025)
F-statistics for IV (z or t squared)	18.49	3.72	23.14
N	404	202	202

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Standard errors are in parentheses below the estimated coefficients. Each regression includes year fixed effects.

Table 5. 12 Second-Stage 2SLS Estimates of the Relationship between Change of log GDP and Change of log Immigrant Worker using IV, 2000-05 Cross-sectional Data

Dependent variable: change in log immigrant worker level 2000-05 (N=202)				
	without IV		with IV	
	(1)	(2)	(3)	(4)
Log M	.033* (0.019)	.028 (0.018)	.079 (0.175)	.023 (0.168)
Log N	.540*** (0.069)	.384*** (0.072)	.491** (0.202)	.389** (0.181)
Log K		.099*** (0.019)		.099*** (0.022)
cons	.105*** (0.006)	.091*** (0.007)	.094** (0.041)	.092** (0.037)
Adjusted R-Square	0.2803	0.3610	0.2587	0.3607

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Standard errors are in parentheses below the estimated coefficients. Each regression includes year fixed effects.

Skill-effects Analysis with Instrumental Variable

To answer the second research question of whether high-skilled immigration contribute to the economic growth in particular, an instrumental variable for high-skilled immigrant workers is needed. Since it is reasonable to assume that high-skilled immigrants of a certain ethnicity tend to settle in the areas where that ethnicity has a presence, ideally, instruments for high-skilled immigrants can be constructed by historic settlement following the same strategy for instrument for the overall immigration (Equation 3.5 and 3.6). However, due to limited sample size of the ACS data, large numbers of metropolitan areas have zero immigrants from a certain region of origin at higher education level. This will seriously bias the predicted immigrant level and violate the identification assumption.

Lagged terms of are therefore the only instruments this research is able to use. Both high- and low-skilled immigrant worker levels from five- and ten-year ago are used to predict the high- and low-skilled immigrant workers. Table 5.13 reports the first-stage estimates of these instrument candidates. Both lagged terms as instruments predicted high-skilled immigration with the unexpected signs.

Table 5. 13 First-Stage G2SLS Estimates of the Relationship between Immigrant Worker Levels (log) and Predicted Immigrant Worker Levels (log) First-difference Model

Dependent variable: log immigrant worker level Independent variables: natives, year effects and IV		
	Lag_5	Lag_10
Predicted number of immigrant workers (IV)	-.366*** (0.066)	-.134* (0.077)
F-statistics (t squared)	31.025	3.028
N	666	627

Notes: * significant at 10% level; ** significant at 5% level; *** significant at 1% level. Regression clustered by metro area (fips). Standard errors are in parentheses below the estimated coefficients. Each regression includes year fixed effects.

There are many possible reasons why these instrument candidates, some suggested by the literature as suitable instruments, did not work well in this setting. First, under these identification assumptions, there should be at least a certain time periods being included in the regression and a long enough total period of observation. Previous studies used historical settlement-based instruments used Census data, which is available every ten years and their studies covered longer period. This research uses three periods in the panel regression with five-year interval and ten years as the total observed period. The five year interval design requires the instrument construction to use 1995 data, which can only be speculated by averaging the 2000 and 1990 Census data. This synthetic 1995 data may add up the errors. In addition, three time periods in the panel regression may be too few and the total ten-year period may be too short after all. Second, during this research contains the time of the Great Recession, and this may restrict the instrumental variables' predictive power and make the signs of instrument between periods inconsistent. In fact, some of the instruments' predictions have the opposite signs between 2000-2005 and 2005-2010, and this may be caused by the recession. Finally, because of 1990 data contains fewer metropolitan areas, using instruments constructed with 1990 data reduces the sample size from 283 areas to 202, and this will reduce the efficiency both the first- and second-stage regressions.

Kerr at el (2013), in their recent research about high-skilled immigration impact on U.S. firms' structural change, used a high-skilled immigrant instrument constructed based on firms' dependency on H-1B program[23] in the initial time, interacted with the national change of H-1B program's size[24]. There are some obstacles to transfer this identification idea to be used in this research. The most important one is that the equivalent of individual firm's dependency on H-1B, in this research, is metropolitan's dependency on H-1B. A firm is more consistent in foreign-born high-skilled labor demand than a metropolitan's demand on foreign-born high-skilled labor, as the latter is at a much higher aggregated level of the former. The dependency's calculation needs to use the total skilled labor of the firm, and this number is also less stable at the

[23] H-1B dependency was calculated as the ratio of H-1B application of the firm over the firm's total high-skilled employment. Kerr et all also used two other alternatives for the H-1B dependent - share of high-skilled Chinese and Indian workers in a firm, and share of workers in STEM occupations.
[24] Kerr et al used two measurements for H-1B program's size since such record does not exist: Lowell's estimation in 2000, and the summation of the H-1B issuance caps in the previous six years.

metropolitan level. Also, the H-1B visa application number needs to be accessed through Labor Condition Application (LCA) at the micro level, how many metropolitan areas are covered in the integrated data is a concern, since about 91 percent of the H-1B applications are concentrated in the top 108 metropolitan areas based on the an average statistics from 2001-2011 (Ruiz, Wilson, and Choudhury 2012).

Summary

In this chapter, levels of immigrant and native workers and capital stock for metropolitan areas are used to form a production function form and to explain metropolitan GDP. Overall effect analysis, using both fixed-effects and first-difference models, found that immigrants have a significantly positive impact on GDP, though the magnitude of coefficients is systematically smaller than those for native workers. However, the fixed-effects analysis with instrumental variables could not reinforce this finding. The skill-effects analysis, using both fixed-effects and first-difference models, found that low-skilled immigrants have a significantly positive impact on GDP, but found scant evidence that high- and medium-skilled immigrant workers do so.

The overall-effects analysis using the structural form found that overall immigrant workers are good for economic growth, which the reduced-form analysis did not find. The skill-effects results of the structural-form analysis are consistent with those of the reduced-form analysis.

CHAPTER VI
CONCLUSION, POLICY IMPLICATIONS AND DISCUSSIONS

This chapter summarizes the findings of this research in the order of the research questions asked in Chapter I. It also identifies the policy implications based on those findings. Finally, it discusses the limitations of this research and points out the directions for future research.

Summary of Research Findings

Based on the mechanisms of how immigration contributes to regional economic growth as the literature suggests, this research seeks to answer the three questions listed below as to whether immigration is good for economic growth and what the quantitative impacts are.

(1) Do metropolitan areas with larger proportions of immigrant workers relative to native workers have higher GDP per worker? Do metropolitan areas with more immigrant workers have higher GDP?

The analyses undertaken to answer this question are called the overall-effects analyses, in which the employed foreign-born population is treated as a homogenous group. Two approaches, reduced-form and structural-form, are used in the analyses. First, the reduced-form analysis uses GDP per worker and the immigrant workers' share of the total workforce as the dependent variable and the key independent variable. Although the OLS regressions find that the immigration share is strongly associated with GDP per worker, the fixed-effects panel regression does not find that immigration has a statistically significant impact on the economic growth. Further explorations of immigration and metropolitan population size and education found that immigration's impact decreases with metropolitan size and increases with the metropolitan workforce's educational level.

Second, the structural-form analysis used GDP and immigrant workers' levels as the dependent variable and the key independent variable. Using both the fixed-effects model and the first-difference model, the results suggest that immigrant workers have a significantly positive impact on GDP, though these impacts are smaller in magnitude compared to the impacts of native workers. The instrumental variable analysis reinforced the positive impact and increased the magnitude of the impacts.

(2) Do metropolitan areas with larger shares of high-skilled immigrant workers enjoy higher GDP per worker? Do metropolitan areas with more high-skilled immigrant workers have higher GDP?

The analyses undertaken to answer this question are called the skill-effects analyses, in which the employed foreign-born population is divided into high-, medium- and low-skilled groups based on educational attainment. They are included in the regressions allowing each skill level of the immigrant groups to have a separate impact on the economic growth. Again, the reduced-form and structural-form approaches are used to answer this question.

The reduced-form analysis uses GDP per worker and three skill-levels of the shares of immigrant workers in the total workforce as the dependent variable and the key independent variables. The OLS results show strong associations between high-skilled immigration and GDP per worker, but this association disappears in the fixed-effects regression, and only the low-skilled immigrant group has a positive impact on growth.

The structural-form analysis uses GDP and three skill levels of immigrant workers as the dependent variable and the key independent variables. Both the fixed-effects and first-difference models suggest no evidence that high- or medium-skilled immigrants have any statistically significant impact on GDP, while they suggest that low-skilled immigrant workers have a substantially positive impact on metropolitan GDP.

These findings may be restricted by the research setting. Because high-skilled immigration can have growth effects that lag those of low-skilled immigration, the positive effects of high-skilled immigration may be hard to reflect in the current research design. Also, high-skilled and low-skilled immigrant workers tend to have different levels of mobility, which makes them endogenous at different levels. These are all potential difficulties to gauge the effects of different skills of immigrants.

(3) Do metropolitan areas with greater complementarity between immigrant and native workers enjoy more rapid economic growth?

The analyses undertaken to answer this question are called the complementarity-effects analyses, in which the employed foreign- and native-born populations are each divided into high-, medium- and low-skilled groups based on educational attainment. They are interacted and included in the regressions. A congruence index is also used to capture how similar immigrant and native workers' educational distributions are. The reduced-form approach is used, where GDP per worker is used as the dependent variable, and different skill levels of share of immigrant and native workers and their interactions are used as key independent variables.

The analysis using the congruence index found that the congruence index has a significantly negative impact on GDP per worker. Because the smaller the index is, the more identical immigrants and native workers are distributed in terms of educational attainment, this result suggest that the greater the differences are in the two groups, the better it is for economic prosperity. Analysis using interaction terms found that complementarity effects exist in low-low and high-high skills combinations of immigrants and native workers. Complementarity between low-high and high-low skills combinations is not as robustly significant in different models.

Discussions and Limitations

There are many caveats and limitations in this research that researchers and policy makers need to bear in mind. The first one lies in the choice of the dependent variable. For the first time, this research explores the realtionships between immigration and GDP by using U.S. metropolitan data. However, using GDP as the dependent variable has many limitations that yield difficulties in the analyses, as the results using per capita GDP (in reduced-form) and GDP level (in structural-form) specifications are very different.

The reduced-form analysis in this research uses GDP per worker as the dependent variable. As immigrant workers are in general younger, less educated, earn less, speak less English and may be restricted by legal status for work, they do not lead to increase in average productivity. Therefore, it is very hard to detect any positive impact based on the share of immigration and GDP per worker using the reduced form. The results of this analysis is picking up the composition effect. In the structural-form analysis, on the other hand, when the GDP level and immigrant levels are used as the dependent variable and the independent variable, is picking up the growth effect. The results from the strucutral-form analysis are postive, as expected.

Ideally, as Borjas (1999) suggests, an immigration surplus is accrued to output of native-born workers and, therefore, the ideal measurement for the immigration-induced economic well-being should be GDP generated by native and exsiting immigrant workers. However, such data do not exist.

Second, the complementarity-effects analysis using the congruence index points out that immigration with different educational levels from the natives will benefit the economies. However, the analysis using interaction terms does not find that the low-high and high-low combinations of immigrant and native workers are particularly beneficial compared to the low-low and high-high combinations. This may be caused by the difficulties of using area aggregate data. Because this research is at the area level instead of the individual level, it is difficult to identify the objectives of the research using the populations' averages.

Similarly, as immigration is such a highly hetrogenous group of the population, the economic impact of different types of immigrants is likely to be vary considerably. The fact that this research only differentiates immigrants by educational levels is far from satisfying and the effects the analysis found could be muted by many others factors. However, to differentiate immigrants by more characteristics, the area-based research also faces the challenges of using aggregate data (for example, when differentiated in detailed categories, obserations in each cateogry before adjusting the survey weights become dangerously small in ACS data). Individual level studies offer an alternative design that would resolve this problem.

Third, endogeneity problems may remain. Migration has long been the root cause of endogeneity problems in the research of regional development and human capital. In this research, which explores the relationship between migration and growth, the endogeneity problem is especially pertinent. This research uses panel regressions with fixed effects to reduce the potential endogeneity. The GDP data are matched with demographic data with one-year lag so the immigrant workers analyzed in the regression are the ones who entered the metropolitan labor market one year before the GDP data were collected. The instrumental variables constructed by the historical settlement of different ethnic groups and by the distance of the metropolitan areas from the U.S.-Mexico border are used to control for the location response immigrants may have towards multi-year economic booming. A search for more efficient instrumental variables should be continued. In addition, the endogeneity problem may also exist for native workers, as they may also respond to economic growth and to immigration influx.

Fourth, like all area-based research, this research is subject to potential spatial autocorrelation problem and may have biased the panel regression results. Spatial autocorrelation exists when dependent or independent variables are not randomly distributed among regions. In this research, the independent variables, immigration's measurements, are highly likely to be spatially dependent (clustered). For example, the immigration share of the metropolitan area of reference is likely to be similar to its neighboring metropolitan areas. Therefore, spatial panel regression techniques may be implemented to address this problem and make the estimations more precise.

Finally, the time span of this research is limited by the availability of metropolitan GDP. Ten years may not be long enough for any potential impact of immigration to be detected in economic measurements. The complementarity and skill effects are likely to occur in the long run rather than short run, so it is especially important to test these hypotheses with a longer period of data.

Policy Implications

Making immigration policies and laws in the Unisted States is centralized in the federal government, and the states' powers are limited to enforcement. In the discussion of comprehensive immigration reform, the state- or regionally managed immigration program proposals are receiving increased attention (Wainer and Singer 2014). For instance, Michigan Governor Rick Snyder and Snator Rand Paul recently proposed regional visa programs that allow immigrants to stay in the exclusively City of Detroit and other chosen cities (Fuller and Rust 2014). Massachusetts Governor Deval Partick also proposed a Global Entrepreneur in Residence (GER) Porgram, which allows Massachusetts-educated foreign students to stay in the state (Zillman 2014). Whether these regional immigration initiatives are intended to rejuvenate the local population, or to promote entrepreneurship, they give the regions that desire immigration (or want certain types of immigration) the power to authorize immigration with the minimum impact on the states that do not want immigration. This research acknowledges that such state- or regionally managed programs' concerns are valid, since the results show that immigration has very different impacts. Therefore, different metropolitan areas desire different types of immigrants and at different levels.

In addition, this research provides direct guidance in making and implementing metropolitan-specific immigration policy, as it points out how immigration affects metropolitan areas' economic growth differently. For example, the impact of immigration on economic growth decreases with the size of the metropolitan population and increases with the educational level of the regional workforce. So when making immigration policies, the regional population and educational levels need to be considered. The estimated effects of different skill levels of immigrants also shed light on "who" should be given the priority to enter the regional labor market. Because the complementarity among different educaiton levels of native and immigrant workers exists, metropolitan areas will benefit the most by maximizing the regional labor market's educational disparity and by welcoming more immigrant workers with the different skills. For highly educated metropolitan areas, this means to recruit low-skilled immigrant workers. This research provides a start point of accessing a varity of regional immigration policy initiatives.

Second, this research found that low-skilled immigrants substantially contribute to the economy and bring growth. Since low-skilled immigrants are usually viewed the most adversely towards the regional economy, this unexpected result calls for greater attention for policy makers and practioners to consider various channels through which low-skilled immigrants are admitted into the country, settled and integrated into the local comminuty.

Third, although OLS regression found high-skilled immigrant workers are highly associated with high economic growth, the skill-effects analysis using panel regressions did not find that high-skilled immigrants have a positve impact on the economic growth through technology advancement and innovation. This may be caused by how the current U.S. high-skilled immigration policies and laws work. For example, the H-1B visa program, the most important channel the U.S. brings in high-skilled workers, requires that employment positions exist and then the company recruits a foreign-born worker. The nature of the high-skilled temporary worker recruting process dictates that the demand (position) must first exist and then comes supply. H-1B visa is valid for six years. Although many H-1B visa holders will be eventually issued LPRs and have the freedom to move across the U.S, the initial location choice that “nailed them down” to a certain location may have a long impact. The skill-effects results that high-skilled immigrants are “attracted” to areas of high prosperity and growth levels (high endogeneity) are consistant with this policy’s nature.

In the discussion of reforming U.S. high-skilled immigration policy, a proposal of issuing LPRs to all foreign born graduates in STEM fields is hotly debated. It will be interesting to conduct skill-effects analysis after the bill is passed. When such policy is in place, new foreign born graduates in STEM fields will provide a pool of high-skilled labor with freedom to choose location across the United States. However, until this bill is passed, this research cannot offer supporting knowledge of whether high-skilled immgration will lead to economic growth.

Suggestions for Future Research

By exlporing the relationship between immigration and metropolitan GDP, this research is an initial attempt to answer an important, yet long over-looked, question in immigration’s economic impact studies. The results and the limitations of this research point out many directions that future research can take.

First, as the disagregation of immigration that this research uses (edcuational level) is still general; future research should expand studies by differentiating foreign-born population in more dimensions, such as immigrants’ legal status, the motivation for migration (family-base versus work or humanitarian-based), years of migration, age of migration, country of origin, ethnicity, and gender. Analysis focused on more specific groups of immigrants might answer more policy-oriented questions. Of course, more specificity requires more data support.

Second, the search for a better instrumental variable should continue. One idea that has been attempted is to construct an instrumental variable based on the relative GDP between the host country and the immigrants' countries of origin. Assuming that immigrants from a certain country are correlated with the relative GDP of their countries to the GDP in United States, the relative GDP will serve as a supply-pushed instrument for immigrants from that country in the United States.

Third, spatial panel regression techniques need to be introduced to this area-based research to address the potential spatial autocorrelation. Spatial regressions with an instrumental variables technique have recently been sharpened and have received increasing attention by economists.

Fourth, one tentative finding of this research is the search for non-linear relationships between immigration and GDP using a functional form. Although imposing a functional form is convenient, the estimated coefficients may merely reflect an aberration of functional form. The exploration of the non-linear relationship could be strengthened by exploring this in a more non-parametric fashion.

Finally, it would be interesting to see how transferrable the methods and results of this research are to other countries. The immigration density in the United States (13 percent) is low compared to some of the other traditional immigrant-receiving countries like Australia, Canada and New Zealand that have 22-25 percent of their populations born abroad. In those countries, immigrants also come as a result of different policies and their educational levels tend to differ from the ones in the United States. This is due to the

US immigrant admission policy, the point system that tends to admit more immigrants based on human capital instead of family reunification. Conducting similar research using those countries' datasets may result in different conclusions about how immigration contributes to regional economic growth.

APPENDIX TABLE
IMPORTANT CHARACTERISTICS OF ALL METROPOLITAN AREAS, 2000

MSA	Population	% FB worker	FB worker	HS FB worker	LS FB worker	Cong Index	GDP (millions)	Capital (billions)
Abilene, TX	126952	5%	2649	539	767	0.82	4242	11.10
Akron, OH	692912	3%	10601	4846	984	0.87	23067	51.00
Albany, GA	120551	2%	1105	230	353	0.69	4625	4.33
Albany-Schenectady-Troy, NY	796100	5%	20815	9196	2394	0.91	31851	70.24
Albuquerque, NM	712937	8%	27126	5293	8944	0.75	27906	44.74
Alexandria, LA	128075	2%	1125	337	274	0.90	3747	6.31
Allentown-Bethlehem-Easton, PA/NJ	641637	6%	17855	5373	3404	0.93	24856	51.02
Altoona, PA*	131023	1%	616	247	99	0.76	3490	6.79
Amarillo, TX	215463	8%	7651	902	3249	0.65	7312	24.10
Ann Arbor, MI	479754	8%	20377	12847	1216	0.77	16028	27.07
Anniston, AL*	110594	2%	1048	186	217	0.92	2718	4.00
Appleton-Oshkosh-Neenah, WI	357928	3%	5393	1502	1131	0.87	8149	17.89
Asheville, NC	225195	5%	5158	1298	1219	0.84	10900	11.59
Athens, GA	153445	8%	5934	2114	1144	0.83	5148	7.03
Atlanta, GA	4.00E+06	12%	246337	72645	54197	0.86	222711	534.36
Atlantic City, NJ	359167	11%	18118	3977	5180	0.88	11904	27.27
Auburn-Opekika, AL	116435	3%	1844	913	132	0.85	2483	3.79
Augusta-Aiken, GA-SC	451061	4%	6906	2601	1160	0.91	16318	14.15
Austin, TX	1.20E+06	14%	86796	24066	25274	0.69	55078	126.65
Bakersfield, CA	650891	20%	45141	3789	23005	0.61	19373	49.07
Baltimore, MD	2.50E+06	7%	82974	37837	9177	0.93	109859	243.22
Barnstable-Yarmouth, MA	144360	6%	3659	846	622	0.93	7775	12.66
Baton Rouge, LA	604708	4%	10207	4761	1515	0.81	27354	40.89
Beaumont-Port Arthur-Orange,TX	381559	5%	7846	1851	2722	0.70	12368	21.72

Bellingham, WA	169001	10%	8162	2026	1445	0.94	5578	9.38
Billings, MT*	128660	1%	804	391	16	0.93	5300	11.94
Binghamton, NY	254116	4%	5067	1946	655	0.90	6234	14.86
Birmingham, AL	803700	3%	10897	4128	1611	0.88	45843	103.00
Bloomington, IN*	122388	4%	2779	2135	60	0.57	4287	7.33
Boise City, ID	430161	6%	12241	1988	4299	0.74	17954	38.89
Boston, MA-NH	4.00E+06	16%	320342	115988	58502	0.92	252182	804.80
Bremerton, WA	234652	7%	6639	1998	904	0.97	7041	7.67
Bridgeport, CT	343379	16%	25499	5903	6232	0.91	70364	269.02
Brownsville-Harlingen-San Benito, TX	336631	30%	32704	3141	17146	0.77	5668	10.37
Buffalo-Niagara Falls, NY	1.20E+06	11%	8334	3129	2568	0.91	36129	91.87
Canton, OH	408072	4%	22210	8491	2765	0.92	12305	25.58
Fort Myers-Cape Coral, FL	440333	2%	3096	1138	390	0.83	16150	29.76
Cedar Rapids, IA	188914	2%	2412	1072	129	0.93	10024	24.60
Champaign-Urbana-Rantoul, IL	181422	9%	8082	4930	706	0.65	6869	11.43
Charleston-N.Charleston,SC	454054	5%	9588	2926	1811	0.88	19646	36.49
Charlotte-Gastonia-Rock Hill, NC-SC	1.50E+06	8%	59926	12408	15768	0.83	89226	244.34
Charlottesville, VA	160421	6%	4403	2194	401	0.87	6854	18.38
Chattanooga, TN/GA	434752	3%	6893	2450	796	0.93	17606	43.17
Chicago, IL	8.80E+06	19%	793864	207581	211092	0.83	447059	1230.90
Chico, CA	202375	7%	5865	1044	2059	0.73	4732	9.99
Cincinnati-Hamilton, OH/KY/IN	1.50E+06	3%	23134	11262	2244	0.84	85746	191.00
Clarksville- Hopkinsville, TN/KY	134209	5%	2488	152	577	0.94	6459	7.15
Cleveland, OH	2.30E+06	5%	55344	20831	7740	0.94	93962	238.90
Bryan-College Station, TX	153194	7%	17295	4608	2651	0.56	4888	9.56
Colorado Springs, CO	515629	5%	3832	2403	243	0.95	19923	45.18
Columbia, MO	136063	4%	11342	4266	1513	0.73	5086	11.21

Columbia, SC	544165	6%	4273	1018	530	0.92	24739	54.67
Columbus, GA/AL	186426	6%	41774	17591	5521	0.98	9640	20.17
Columbus, OH	1.40E+06	6%	6155	1303	1952	0.89	79125	191.26
Corpus Christi, TX	261023	17%	426997	87502	152731	0.88	13169	26.48
Dallas-Fort Worth, TX	5.00E+06	4%	5456	1314	1667	0.65	279067	842.25
Davenport, IA-Rock Island -Moline, IL	268781	3%	11798	5169	1413	0.77	13154	25.31
Dayton-Springfield, OH	954465	7%	12745	2773	2455	0.87	30391	58.05
Decatur, AL	145469	2%	1620	307	500	0.78	3872	4.67
Decatur, IL*	114926	1%	671	195	115	0.94	4560	8.55
Daytona Beach, FL	445477	11%	131006	33125	37046	0.95	11357	17.92
Denver-Boulder, CO	2.20E+06	6%	11472	2809	2836	0.74	122848	380.24
Des Moines, IA	375685	8%	162037	63005	27333	0.84	26920	81.40
Detroit, MI	4.40E+06	2%	1257	325	367	0.89	196741	448.73
Dothan, AL	138133	4%	2441	653	499	0.90	3509	6.58
Dover, DE	125613	2%	1752	400	198	0.94	4658	5.27
Duluth-Superior, MN/WI*	199548	2%	1366	515	110	0.94	8101	22.20
Eau Claire, WI	147758	31%	73809	8432	30846	0.84	4603	9.42
Elkhart-Goshen, IN	182252	10%	8924	978	3480	0.74	7459	15.94
El Paso, TX	676220	3%	4018	1001	770	0.75	20413	40.17
Erie, PA	279521	5%	7829	2310	1414	0.93	8267	18.68
Eugene-Springfield, OR	324317	1%	1791	803	152	0.94	8954	19.37
Evansville, IN/KY*	252410	3%	2235	923	281	0.86	12359	23.52
Fargo-Morehead, ND/MN	121173	6%	6854	1050	862	0.78	7414	15.31
Fayetteville, NC	299932	8%	11724	1883	4398	1.00	11618	11.36
Fayetteville-Springdale, AR	309915	7%	3656	916	919	0.63	12057	20.83
Flagstaff, AZ-UT*	117109	2%	2239	1014	209	0.74	3382	4.90
Flint, MI*	240153	1%	754	232	156	0.78	11868	23.52

Florence, AL	142703	5%	5817	2182	1267	0.80	3076	5.63
Fort Collins-Loveland, CO	235532	11%	19547	2706	5881	0.80	8717	17.14
Fort Smith, AR/OK	169401	7%	5159	294	2683	0.60	7503	12.67
Fort Wayne, IN	460349	4%	8996	2197	2498	0.82	15092	39.88
Fresno, CA	924612	23%	78544	7622	37202	0.60	22307	50.07
Gadsden, AL	102183	1%	644	134	279	0.50	2163	4.22
Gainesville, FL	219795	8%	8388	4471	297	0.87	7420	13.80
Glens Falls, NY	123609	2%	935	236	258	0.88	2969	6.27
Goldsboro, NC	113118	6%	2716	477	1053	0.62	3337	4.62
Grand Junction, CO	111922	3%	1729	391	553	0.71	3322	7.81
Grand Rapids, MI	984107	6%	29739	5405	8853	0.76	36845	86.94
Greeley, CO	178872	9%	7394	455	3651	0.56	5763	14.54
Green Bay, WI	227296	4%	5161	892	2157	0.57	12491	28.65
Greensboro-Winston Salem-HighPoint,NC	1.30E+06	6%	39502	7020	13157	0.74	28413	63.36
Greenville, NC	134932	5%	3086	1223	706	0.76	4523	6.66
Greenville-Spartanburg-Anderson SC	796528	5%	18081	4583	4625	0.86	26435	48.87
Hagerstown, MD	128316	2%	1029	388	70	0.87	6137	10.10
Harrisburg-Lebanon--Carlisle, PA	629304	3%	10679	3561	1541	0.95	23360	58.01
Hattiesburg, MS	111694	3%	1458	314	230	0.94	3456	5.77
Hickory-Morgantown, NC	342072	6%	10226	705	3799	0.81	11352	19.40
Houma-Thibodoux, LA*	103563	2%	841	156	286	0.90	7002	18.60
Houston-Brazoria, TX	4.40E+06	22%	446666	100387	158795	0.72	291132	911.00
Huntsville, AL	344491	4%	6325	2463	744	0.93	12596	21.85
Indianapolis, IN	1.60E+06	4%	31369	11418	6025	0.84	83217	187.77
Iowa City, IA	108518	6%	3483	1978	380	0.76	5563	7.86
Jackson, MI	160391	2%	1553	571	143	0.86	4402	8.19
Jackson, MS	438789	2%	3412	1376	889	0.86	19367	40.88

Jackson, TN	107550	2%	840	431	101	0.79	4121	7.09
Jacksonville, FL	1.10E+06	6%	33666	9937	3894	0.99	44892	139.87
Jacksonville, NC	149091	5%	2508	324	580	0.90	4976	3.06
Janesville-Beloit, WI*	151640	3%	2001	279	643	0.85	4322	8.49
Johnson City-Kingsport--Bristol, TN/VA	314402	1%	2066	634	241	0.97	4307	8.61
Johnstown, PA*	233942	1%	1072	192	134	0.96	3483	8.81
Joplin, MO	155401	3%	1843	302	419	0.85	4544	9.47
Kalamazoo-Portage, MI	451406	3%	7566	3149	1201	0.83	10143	19.98
Kankakee, IL	104042	5%	2230	244	900	0.60	2631	4.97
Kansas City, MO-KS	1.70E+06	5%	46403	12860	10186	0.87	85014	216.22
Kileen-Temple, TX	313151	9%	9526	1685	2329	0.91	9764	10.51
Knoxville, TN	576512	2%	6682	3149	744	0.82	24862	46.56
Kokomo, IN	100506	1%	650	340	63	0.74	3155	7.53
LaCrosse, WI*	105700	1%	574	152	127	0.88	4342	8.46
Lafayette, LA	247230	3%	3323	1376	522	0.88	18776	53.59
Lake Charles, LA	183144	2%	1464	471	269	0.92	9109	12.21
Lakeland-Winterhaven, FL	482562	8%	16413	2577	5826	0.78	12636	30.92
Lancaster, PA	464550	4%	9038	2040	2268	0.93	16438	35.44
Lansing-E. Lansing, MI	445925	4%	9180	3953	723	0.91	16240	36.40
Laredo, TX	190074	36%	22678	2716	10896	0.77	4431	7.70
Las Cruces, NM	173843	19%	12839	951	6716	0.60	3349	4.38
Las Vegas, NV	1.40E+06	20%	126643	16928	42491	0.79	63161	142.81
Lexington-Fayette, KY	258129	6%	7946	3524	1207	0.80	17994	31.37
Lima, OH*	156274	2%	1115	404	173	0.78	4016	6.89
Lincoln, NE	246945	6%	7699	2373	1860	0.85	11170	25.41
Little Rock--North Little Rock, AR	584977	3%	8275	2690	1396	0.92	24513	52.92
Longview-Marshall, TX	170557	5%	3998	549	1748	0.61	6385	18.87

Louisville, KY/IN	921599	3%	15273	5891	2063	0.90	46628	106.58
Lubbock, TX	243899	4%	4337	1494	1040	0.85	7336	18.72
Lynchburg, VA	213723	2%	2278	975	205	0.82	6904	6.51
Macon-Warner Robins, GA	321450	3%	3987	1220	841	0.90	7862	17.42
Madison, WI	429839	6%	14883	6865	1635	0.85	26375	51.81
Manchester, NH	107037	9%	5076	1268	1421	0.82	16148	46.60
Mansfield, OH*	130084	1%	867	296	142	0.86	3574	6.85
McAllen-Edinburg-Pharr-Mission, TX	565800	34%	60933	5967	34665	0.69	9166	17.16
Medford, OR	179811	5%	3901	635	1293	0.81	5196	11.00
Memphis, TN/AR/MS	998698	4%	20098	6944	4072	0.85	52893	120.83
Merced, CA	209707	28%	20852	1292	10739	0.59	4209	6.19
Miami-Hialeah, FL	2.20E+06	60%	541935	115028	132811	0.93	201266	502.49
Milwaukee, WI	1.50E+06	5%	40356	11248	9643	0.85	69302	174.84
Minneapolis-St. Paul, MN	2.90E+06	7%	108713	33581	19305	0.89	160581	430.98
Mobile, AL	540100	3%	6263	2094	1304	0.89	12091	23.20
Modesto, CA	450865	21%	35932	3915	14098	0.73	11718	22.32
Monroe, LA	146975	2%	1035	357	192	0.92	5236	12.45
Montgomery, AL	333479	2%	2987	1100	387	0.96	12019	24.03
Muncie, IN	119028	2%	856	360	45	0.70	3380	6.63
Myrtle Beach, SC	195205	5%	4512	799	1121	0.83	10255	18.99
Naples, FL	249728	23%	24447	2829	9572	0.69	11042	28.09
Nashville, TN	1.20E+06	6%	34908	9556	8306	0.85	61465	142.49
New Haven-Meriden, CT	358125	9%	15305	5547	2134	0.93	32571	70.88
New Orleans, LA	1.20E+06	6%	34383	9666	7359	0.96	65505	127.59
New York-Northeastern NJ	1.70E+07	32%	2.50E+06	720201	538853	0.92	1.00E+06	4379.09
Ocala, FL	259712	5%	5120	929	1286	0.92	5247	11.77
Odessa, TX	238692	10%	9686	693	5218	0.63	3728	10.59
Oklahoma City, OK	892347	7%	30152	7306	8803	0.79	43805	104.03

Olympia, WA	210011	7%	6722	1969	1158	0.93	6735	9.50
Omaha, NE/IA	584099	5%	16063	3391	5022	0.72	35548	75.55
Orlando, FL	1.70E+06	14%	109586	26633	21220	0.95	71971	153.60
Panama City, FL	146122	4%	2621	554	622	0.96	4744	8.16
Pensacola, FL	411270	4%	6904	1746	958	0.99	11200	18.47
Peoria, IL	346102	2%	3784	1740	535	0.77	12637	26.30
Philadelphia, PA/NJ	5.10E+06	8%	187330	73000	28032	0.94	267370	675.53
Phoenix, AZ	3.10E+06	15%	212438	35989	74660	0.66	138302	363.94
Pittsburgh, PA	2.30E+06	3%	28388	14634	2308	0.80	96022	244.29
Portland, ME	241693	4%	5173	2286	744	0.93	20715	39.34
Portland, OR-WA	1.80E+06	12%	109019	27678	25310	0.85	81270	201.37
Providence-Fall River-Pawtucket, MA/RI	1.00E+06	14%	67493	10490	24455	0.79	54170	107.91
Provo-Orem, UT	367035	7%	12249	2885	2360	0.89	9559	16.95
Pueblo, CO	135990	4%	2209	476	689	0.79	3640	7.71
Punta Gorda, FL	141080	8%	4215	875	1114	0.95	2646	5.22
Racine, WI	185041	3%	3006	502	1088	0.73	6001	9.91
Raleigh-Durham, NC	1.20E+06	10%	63832	23764	13583	0.79	38975	73.38
Reading, PA	368284	4%	7938	1485	2035	0.93	11972	28.23
Redding, CA	162160	4%	2783	467	688	0.83	4372	7.21
Reno, NV	339936	15%	25152	4269	8505	0.73	16151	38.69
Richmond-Petersburg, VA	995112	5%	25290	9137	3838	0.94	52134	125.39
Riverside-San Bernardino,CA	3.30E+06	23%	292079	43084	112029	0.74	85496	147.02
Roanoke, VA	236363	3%	3146	914	584	0.94	10935	25.87
Rochester, MN*	122319	6%	3746	1536	611	0.80	6796	12.36
Rochester, NY	1.00E+06	6%	30051	10736	4037	0.95	38225	83.34
Rockford, IL	319846	7%	10384	1803	3794	0.73	10703	24.33
Rocky Mount, NC	143674	2%	1433	163	579	0.68	5364	3.71
Sacramento, CA	1.60E+06	14%	107031	26936	22668	0.90	70874	151.14
Saginaw-Bay City-Midland, MI	400853	2%	4222	2265	724	0.64	6794	14.77

St. Cloud, MN	168856	13%	16616	1417	7076	0.90	5875	9.87
St. Joseph, MO	101442	35%	39573	5570	15901	0.89	3345	6.39
St. Louis, MO-IL	2.60E+06	10%	62083	12453	15261	0.88	110203	284.32
Salem, OR	282595	24%	298547	75131	82380	0.59	9617	19.04
Salinas-Sea Side-Monterey, CA	281166	29%	669700	234525	130877	0.63	14880	36.06
Salt Lake City-Ogden, UT	1.30E+06	39%	329639	139022	57435	0.81	46271	120.39
San Diego, CA	2.80E+06	10%	10403	1824	2873	0.82	126957	274.77
San Francisco-Oakland-Vallejo, CA	4.60E+06	20%	26582	4923	10308	0.91	265166	825.66
San Jose, CA	1.70E+06	9%	6980	2111	2400	0.92	116958	327.99
San Luis Obispo-Atascad-P Robles, CA	246312	15%	34298	6087	11519	0.81	7822	15.50
Santa Cruz, CA	258576	5%	4960	1676	675	0.60	9769	20.65
Santa Fe, NM	148785	2%	5274	2075	720	0.67	5346	9.29
Santa Rosa-Petaluma, CA	459235	15%	179138	66790	23427	0.70	17709	42.66
Savannah, GA	232087	4%	2050	407	605	0.97	10088	16.99
Scranton-Wilkes-Barre, PA	624276	2%	4087	1429	683	0.86	16265	36.48
Seattle-Everett, WA	2.30E+06	8%	4024	390	2091	0.97	173063	380.92
Sheboygan, WI	111021	4%	2694	215	734	0.74	4425	8.67
Shreveport, LA	393700	5%	6408	2340	1230	0.93	17565	30.77
Sioux City, IA/NE	103140	4%	7875	2019	1161	0.49	5899	8.35
Sioux Falls, SD*	124076	2%	1092	627	52	0.79	10749	23.47
South Bend-Mishawaka, IN	266264	2%	2695	846	404	0.87	10085	20.76
Spokane, WA	418375	8%	22446	5326	4106	0.97	15096	33.64
Springfield, IL	112222	3%	2427	509	556	0.70	8249	18.08
Springfield-Holyoke-Chicopee, MA	594643	2%	740	232	69	0.96	18149	41.70
Springfield, MO	327829	4%	44227	18998	6283	0.96	11606	25.64
State College, PA*	134971	7%	4704	3322	87	0.61	4312	6.93
Stockton, CA	562377	23%	49401	6608	17999	0.75	15128	32.63
Sumter, SC	104047	3%	1093	192	283	0.96	2636	4.00

Syracuse, NY	731789	4%	14658	5422	1975	0.93	21943	47.92
Tallahassee, FL	286063	5%	7678	3240	893	0.93	10873	16.69
Tampa-St. Petersburg-Clearwater, FL	2.40E+06	11%	115747	28135	24032	0.95	85589	228.73
Terre Haute, IN*	149397	2%	1052	406	60	0.85	4442	7.77
Toledo, OH/MI	617883	3%	8727	4069	933	0.85	23202	44.26
Topeka, KS	168994	3%	2380	708	738	0.70	8058	19.25
Trenton, NJ	350093	17%	27218	11075	4938	0.91	18941	47.20
Tucson, AZ	843732	13%	48350	10038	13544	0.83	25111	46.99
Tulsa, OK	694760	5%	18408	3889	5249	0.74	36124	106.74
Tuscaloosa, AL	164875	2%	1801	840	236	0.77	6001	13.30
Tyler, TX	174917	8%	6083	629	2802	0.52	6571	22.94
Utica-Rome, NY	300337	4%	5445	1247	1177	0.92	7421	17.14
Vineland-Milville-Bridgetown, NJ	146275	8%	4540	791	1333	0.85	4052	7.97
Waco, TX	212313	7%	6580	633	2628	0.70	6158	16.13
Washington, DC/MD/VA	4.70E+06	20%	501636	192577	89772	0.93	295804	547.84
Waterloo-Cedar Falls, IA	124908	4%	2395	611	590	0.67	5581	10.78
Wausau, WI	127099	3%	1837	259	817	0.67	4843	13.11
Wichita, KS	543518	7%	3727	594	1273	0.74	23492	52.43
Wichita Falls, TX	131595	6%	16611	2793	5709	0.80	5123	12.80
Williamsport, PA	121501	2%	968	444	96	0.83	3237	7.58
Wilmington, NC	233637	4%	4044	710	1162	0.80	7957	13.34
Yakima, WA	223726	18%	15818	804	9103	0.56	5601	8.53
Yolo, CA	170044	21%	15611	4502	4262	0.81	11490	23.85
Youngstown-Warren, OH-PA	593100	2%	5554	1683	972	0.92	16383	34.27
Yuba City, CA	137870	20%	10054	1195	4204	0.69	3393	6.11
Yuma, AZ	160196	29%	14340	762	6977	0.70	3426	5.50

Note: * indicates MSA is an outlier. All numbers estimates from Census 2000. Total of 283 MSAs.

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