THREE PAPERS IN URBAN AND REGIONAL ECONOMIC AND DEVELOPMENT

BY

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Abstract

This dissertation presents three chapters that studies the regional evolution over time and how the local markets adapt to the changing environment.

The first chapter focuses on the regional convergence or divergence debate. Current studies have provided conflicting evidences. The regression analysis study (Barro & Sala-i-Martin, 1992) finds evidence supporting regional convergence theory. While the distributional dynamic study (Quah, 1996) provides evidence to support club convergence theory. In this chapter, the finite mixture model is introduced as a new exploratory method to study the regional growth issue. This study finds the emergence of convergence clubs in the United States since the 1980s. The finite mixture normal model is used to identify the clubs based on the per capita personal income dataset for 700 U.S. labor market areas from 1969 to 2009. The results reveal that the collection of high income areas, termed the "rich places club," was formed in the 1980s, and the share of the rich places club stabilized at around 10-12% of total labor market areas for the 1990s and 2000s. We also find that the gap between the rich places club and the "everywhere else club" has been increasing since the 1990s.

To better understand what is driving the formation of the convergence clubs found in chapter one, chapter two studies how expected labor demand shifter and natural amenities impact the local market. Traditionally, the local labor market literature focuses on price signals (wage and housing rent) and operates under a spatial equilibrium assumption, while the local economic development literature focuses on job creation, migration and operates under a spatial disequilibrium assumption. In this chapter, a united local economy framework is presented that links the local labor market and local economic development literatures and explores four aspects of local economy: wages, housing rent, job growth, and population growth. In the empirical

section of this paper, two key factors, an expected labor demand shifter and appreciation of natural amenity, are investigated to show how they impact the four featured aspects of the local economy.

From a local price perspective, as the expected labor demand increase, both wages and housing rents increase. The natural amenities do not significantly impact inter-regional wage difference, but natural amenities are a significant factor for inter-regional rent levels. From a job growth and a population growth perspective, a one unit job increase in expected labor demand growth will create more than one additional jobs (1.367-1.392). For every one unit increase of expected labor demand shifter, population will increase 0.8. Regions with higher amenities not only attract new population, they are also places where more jobs are created.

This chapter provides evidence that the expected labor demand shifters (*ELDS*) and natural amenities could significantly impact local market outcome. Therefore, public policies can be draw up for different types of regions (type 1 high *ELDS* high amenities, type 2 high ELDS and low amenities, type 3 low ELDS and high amenities, type 4 low ELDS and low amenities). For type 1 regions, special attention should be paid to housing rent affordability, because both high *ELDS* and high natural amenities could drive up the housing rent. For type 2 region, human capital retention could be a challenging issue. For type 3 regions, public policy could focus on how to translate their desirable natural amenities into local, economic and social development. And for type 4 regions, while these regions are likely going to decline, it is very important to evaluate whether public policy should focus on bringing jobs to these regions or help people move out of these regions.

The “rich places club” found in chapter one are usually places with larger population. Therefore, chapter three looks directly into the question: Why do people living in urban areas, especially large urban areas, receive higher wages? Based on the theory on agglomeration economies, labor market matching and knowledge spillover are considered to be two of the primary micro-foundations. Most empirical literature has found sizeable positive effects from labor market matching (Heuermann *et al*., 2010; Melo *et al*., 2009). However, there is far less consensus on the existence of knowledge spillovers. The reason for that is the difficulty in identifying knowledge spillover effects. The identification challenge comes from three directions: direction of causality (Duranton, 2006), the inability to distinguish imperfect substitution from externalities (Moretti, 2004), and sorting (Wheeler, 2001). Corresponding strategies are developed to ease the estimation biases. This study presents three major findings: first, from 2000 to 2011, the contribution of human capital externalities to productivity growth is at least three times the contribution of the labor market matching effect; secondly, this paper finds that higher skill groups experience higher human capital externality effects; third, the human capital externalities observed for the low skill group are more likely to be a migration sorting effect.

This study also finds that younger workers are more likely to benefit from the labor market matching effect while older workers are more likely to benefit from the human capital externalities effect. Among younger workers, the group without a high school degree shows no gain from either human capital externalities or labor market matching effects. This group of low-skilled young adults should be the central focus for human capital policy. Meanwhile, older and highly educated workers seems to gain large benefits from both human capital externalities and labor market matching effects. This group of workers should be encouraged to work longer (Munnell & Sass, 2009).

Further research should further examine the low-skilled young adult group. Is there a strong inflow of immigrants that could be impacting this group? Are white and non-white, low-skilled younger adult labor market performance similar or different? Is there a gender performance difference in the low-skilled young adult group? Looking deeper into these issues can help form better policy to help this segment of the labor market.

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Chapter 1: The Evolution of US Regional Inequality: A Mixture Model Exploratory Approach

Abstract: This paper studies the emergence of convergence clubs in the United States since the 1980s. The finite mixture normal model is used to identify the clubs based on the per capita personal income dataset for 700 U.S. labor market areas from 1969 to 2009. The results reveal that the collection of high income areas, termed the "rich places club," was formed in the 1980s, and the share of the rich places club stabilized at around 10-12% of total labor market areas for the 1990s and 2000s. We also find that the gap between the rich places club and the "everywhere else club" has been increasing since the 1990s.

Key words: finite mixture normal model, convergence clubs, rich places club

1.1 Introduction

Following Solow (1956), neo-classical economic theory predicts that, in the long run, the economic development levels in different regions within a country will tend to converge to a steady state; this is the basis of the economic convergence hypothesis. Many methods have being developed to test this economic convergence hypothesis since the 1980s (Durlauf, *et al.*, 2005). These methods can be divided into two categories: the regression analysis approach (Barro and Sala-i-Martin, 1992) and the distributional dynamics analysis approach (Quah, 1997). Conclusions reached by these two analytical methods differ from each other dramatically: the regression analysis approach usually points to convergence, while the distributional dynamics approach usually points to club convergence or divergence.

Barro and Sala-i-Martin (1992) propose the β-convergence model and find that the per capita personal income data for the 48 contiguous U.S. states provides clear evidence of the convergence hypothesis. However, as Quah (1993) points out, the results from the β-convergence model could be false because it could be a manifestation of a regression toward the mean. Thus Quah (1993a) concludes that the β-convergence model does not provide enough evidence to support the convergence argument.

Quah (1996, 1997) proposed the distributional dynamics approach to study economic growth. The distributional dynamics approach focuses on the evolution of the entire distribution over time. Quah proposes two distributional methods: the Markov chain transaction probability (Quah, 1993b) and the stochastic kernel density plot (Quah, 1997). By using both methods, Quah finds that the income distributions evolve from a unimodal "one peak" distribution toward bimodal "twin peaks" distribution: "Eventually, the middle-income group of economies vanish, and the rich continue to become richer, and the poor, poorer. Clustering occurs at high and low parts of the income distribution." (Quah, 1996)

The conflicting evidence from the regression analysis approach and the distributional dynamic approach led to the search for a new method that could help understand regional economic development patterns. In this paper, the finite mixture model is introduced as a new exploratory method to study the convergence or club convergence debate. The paper is organized as follows: the finite mixture model is introduced in section 2; data and descriptive statistics and the rationale for using the finite mixture model are in section 3; section 4 contains estimation results, section 5 is the robustness check; and section 6 provides some concluding commentary.

1.2 Finite mixture normal model

According to McLachlan and Peel (2000), the mixture model was first introduced to the statistical field by Karl Pearson in 1894 when he and his colleague Raphael Weldon discovered the asymmetry in the histogram of the crabs they sampled from the Bay of Naples. Pearson and Weldon suspected that the asymmetry in the histogram might be a signal that this crab population was evolving towards two new subspecies. Pearson fitted a mixture of two normal distributions with different means μ_1 and μ_2 and variance σ_1^2 and σ_2^2 in proportions π_1 and π_2 to accommodate the apparent skewedness in the crab data. The model used by Pearson and Weldon was a mixture model with two normal distributions, thus it is a finite mixture normal model; in this paper it is also referred to as a mixture normal model. To provide readers an example of the mixture normal distribution, a two components mixture normal model was simulated with the means as 0 and 3, and standard deviations as 1 and 2. The proportion of the first normal distribution was 40%, while the proportion of the second normal distribution was 60%. In figure 1.1, the red line represents the first normal distribution and the green line represents the second normal distribution.

Combining them together provides the overall distribution, shown as the black line in figure 1.1. The overall distribution is skewed toward the right side.

A more general version of the mixture normal model can be presented as follows:

$$y_i \sim \pi_j N(\mu_j, \sigma_j^2), for\ j = 1, \ldots, m$$

$$0 \leq \pi_j \leq 1, for\ j = 1, \ldots, m$$

$$\sum_{j=1}^{m} \pi_j = 1$$

In our case, y_i denotes the per capita income for region i. Here it is assumed that the underlying data generating process is a mixture of *m* normal distributions, where each distribution has mean μ_j and variance σ_j^2. The key parameter, π_j, is the mixing proportion, or weight, of the j^{th} normal distribution. The sum of all the *m* normal distribution proportions $(\pi_1, \pi_2, \ldots, \pi_m)$ is equal to one.

The mixture normal model provides a natural way to deal with the heterogeneity in a dataset that may contain two or more sub-populations. In the field of regional development, there has always been the debate about whether regions grow more like each other or whether they grow apart. In the language of the mixture normal model, the regional development debate can be presented as follows: for all regions, can they be classified into one normal distribution, or are the distinctions between them so great that they have to be treated as if they are drawn from different normal distributions?

To identify the convergence clubs using the mixture normal distribution, the likelihood ratio test is used to choose the number of components. Then, the Expectation-Maximization (EM) algorithm is used to estimate the means, the variances, and the mixing weights for each normal component. In the final step, a parametric bootstrap will be conducted to produce standard errors for all the parameters in the mixture normal model estimated in the second step.

Using the mixture normal approach to identify the convergence club has two significant advantages over the distributional density approach proposed by Quah (1997). First, the mixture normal model approach provides a more powerful test for the convergence club hypothesis (Pittau *et al*. 2010). To detect the convergence club, the distributional density approach relies on the detection of multimodality by observing the kernel density function, while the mixture approach relies on the detection of multiple components within the distribution. In the distributional density approach, a great deal of emphasis is placed on the researcher's personal judgment to detect convergence clubs based on the shape of the kernel density function. Compared to the distributional density approach, the mixture normal approach is a more powerful test for the convergence club hypothesis because the distribution does not have to be as sharply multimodal for this approach to detect the multiple components. Furthermore, it is possible to use the bootstrap technique to produce standard errors for the parameters in the mixture normal model. The convergence club test based on the mixture normal model is supported by statistical evidence.

The second advantage of the mixture normal approach is on the mobility analysis. Mobility is a measurement used to quantify the transitions out of and into distinct clubs. A low mobility implies stable convergence clubs, while a high mobility implies the convergence clubs are not so stable. Quah (1993b) first applied the Markov chain transitional probability approach to study the mobility of convergence clubs. The Markov chain approach has a drawback in this case because it relies on studying the transition matrix with arbitrarily defined cell boundaries—usually the entire group is equally divided into four quarters. In a later paper, Quah (1997) proposed using the stochastic kernel approach to study the mobility between the clubs. The stochastic kernel is an improved version of the Markov chain approach because it is built on a continuum transition matrix. However, the drawback of the stochastic kernel transition matrix is that it is usually represented in 3-D graphs. This approach does not provide a direct measurement for researchers to draw conclusions with respect to whether regions converge or diverge.

The mobility measurement for the mixture normal approach is derived from the conditional probability that can be calculated from the mixture normal model estimation result. The mixing weights, π_j, can be interpreted as the unconditional probability that region *i* comes from the normal component *j*. The conditional probability $\zeta_{j,i}$ for each region *i* is given by:

$$\zeta_{ji} = \frac{\pi_j N(\mu_j, \sigma_j^2)}{\sum_{j=1}^{m} \pi_j N(\mu_j, \sigma_j^2)}, for\ j = 1, \dots, m$$

$$\sum_{j=1}^{m} \zeta_{j,i} = 1$$

For each region *i*, there will be a *j* conditional probability. All the *j* conditional probabilities for region *i* sum up to one. These conditional probabilities can be used to assign region *i* to that component with the largest estimated $\zeta_{j,i}$. In this research, use is made of the regional income data from 1969 to 2009 for all the labor market areas in the continental United States; therefore it will be possible to study mobility by tracing the change of assignment of region *i* over time.

Given the advantages of the mixture normal approach over the distributional dynamics approach, the use of the mixture normal model for detecting convergence clubs is still limited. Paapaa and Van Dijk (1998) and Pittau, *et al*. (2010) used this approach to study the cross-country distribution of per capita income. In the European Union, Pittau (2005) and Pittau and Zelli (2006) used this approach to detect EU convergence clubs. Tsionas (2000) used the finite normal mixture model to study the distribution of per capita gross state product for the U.S. from 1977-1996. Tsionas found that there was a club of rich states and a club of poor states. However, his finding lacks validity, because he did not provide statistical evidence to support the significance of his estimations. Without knowing the statistical significance of these estimations, one cannot draw the conclusion that there is a division between a rich states club and a poor states club. Pittau *et al*. (2010) present the most recent development in utilizing the mixture normal model in identifying the convergence clubs. They find three categories within their data set of 102 countries: rich counties such as the U.S and many EU countries, median countries like China and Peru, and poor countries such as Nepal and Nigeria.

This paper uses the same method as Pittau *et al*. (2010); however, this paper is different in two significant ways. First, the focus is on the identification of convergence clubs for the labor markets within a country. The difference between labor markets within a country is likely to be much smaller than the difference between 102 countries. Therefore, if evidence is found to support convergence clubs within a country, the result would provide a very strong counter-argument to the β-convergence notion. Secondly, the paper utilizes spatial visualization methods to provide compelling information for the understanding of spatial development patterns of convergence clubs.

1.3 Data and descriptive analysis

1.3.1 Data

The population and personal income data used in this paper are derived from the Regional Economic Information System (REIS) provided by Bureau of Economic Analysis. The REIS provides state level data starting from the year 1929 and county level data starting from the year 1969. The first issue to address is to decide the appropriate spatial unit to use for the analysis. Most convergence studies have focused on the state level (e.g., Rey and Montouri, 1999; Tsionas 2000). However, the state level may be too large a unit to reflect local labor market dynamics. For example, Upstate New York has a totally different demographic and economic structure when compared with the New York Metropolitan area. The same situation happens in the State of Illinois: the Chicago Metropolitan area is completely different from Downstate Illinois. The second commonly used spatial unit is the county level. The county level analysis may also raise problems because the county boundary is merely an arbitrary political boundary. It does not reflect the economic structure of a region. A county may be only a part of an economic or labor market area. For example, DuPage County, Illinois, is only one part of the Chicago Metropolitan statistical area. In contrast, the third and most widely used spatial unit is the metropolitan statistical area (MSA). It is composed of one or more counties, with a relatively high population density at its core and close economic ties throughout the area. An MSA is a much more complete economic and labor market area. However, it is not defined in the rural parts of the United States.

Therefore, a more appropriate spatial unit for the study would be a system of economic and labor market areas that is defined all across the United States. The commuting zones and labor market areas classification system developed by the U.S. Department of Agriculture (USDA) fits these requirements. The USDA identified 741 commuting zones based on the 2000 census journey-to-work data. Compared with the relatively arbitrary county boundaries, commuting zones are much more useful for analysis because they represent the supply and demand of labor in the local area. This spatial unit has become more popular in recent years because it covers the entire U.S. (Tolbert and Sizer, 1996; Autor and Dorn, 2009; Molloy, *et al.*, 2011; Feser and Sweeney, 2003).

In this paper, use is made of the crosswalk provided by the USDA to link and merge the REIS county level data to commuting zone level data. The per capita personal income data used are calculated simply as each commuting zone's total personal income divided by population. The per capita personal income data are then adjusted to constant 2005 dollars. In the rest of this paper, the commuting zones will be referred to as labor market areas. This study focuses on the continental part of the U.S. that includes 702 labor market areas for the period from 1969 to 2009.

1.3.2 Descriptive analysis

As noted earlier, a great deal of empirical research shows evidence to support the existence of convergence in the U.S. For example, Barro and Sala-i-Martin (1992) find statistically significant β-convergence effects by using U.S. state level data, while Higgins, *et al.* (2006) use U.S. county level data and also find statistically significant β-convergence effects across the U.S. On the other hand, many other studies challenge the notion of convergence. One very good example is provided by Bickenbach and Bode (2003) where the authors used the first order property Markov chains implemented with U.S. state level data. They found two structural breaks: one occurs after World War II and the other in the 1990s. The second structural break in the 1990s indicated that U.S. regional development was switching from convergence to divergence. The U.S. labor market areas data used in the current analysis reveals a similar pattern. In figure 1.2, the measure of σ-convergence, the coefficient of variation (CV), is plotted for the U.S. labor market area from 1969 to 2009. The coefficient of variation is decreasing from 1970 to the 1990s, while it is increasing from the mid-1990s to 2009.

There are many reasons that income divergence could have happened in the late 1990s and 2000s. One of the most important reasons could be technological innovation. The empirical work of Galli (1997), based on a panel data set of labor productivity in 20 industrial sectors of the European Union for the period between 1960 and 1993,suggests that a period of convergence may be followed by a period of divergence as a consequence of radical technological and economic transformations. The new wave of technological innovation was led by the use of computers, semiconductors, data processing, and information and communication technologies. This technological innovation began to be adopted and implemented by the economic system in the 1980s. By the 1990s and 2000s, these new technologies spread quickly and changed not only production methods, but also almost all aspects of doing business and everyday life. Some of these changes include the use of personal computers; the development of the internet, wireless technology, and online commerce; the development of biotechnology; and the use of industrial robots. In the language of Schumpeter's technological innovation theory, this is a new long-run Kondratiev cycle (van Duijn, 1983) led by information technology (IT).

Technological innovations in the IT sector could generate two effects on the economic development levels of regions. First, because of the complementary nature of high-skilled workers and the new technologies (internet and computer), the IT development would bring more benefit to regions with more high-skilled workers (Autor and Dorn, 2009). Secondly, the positive externality from productive high-skilled workers in certain regions could attract more highly motivated workers to these regions. Therefore, a human capital accumulation and polarization process could occur because of the impact of the IT sectors (Berry and Glaeser, 2005; Florida, 2002; Moretti, 2012). The polarization of human capital naturally leads to the polarization of the economic development level.

Figure 1.3 shows the kernel income density functions of the 702 labor markets from 1969 to 2009. All the per capita personal income values are adjusted to the 2005 value. The distributions for the years 1969, 1979, 1989, 1999, and 2009 have been highlighted; it is clear that the income distribution is becoming more dispersed over time and the shape of the density functions are skewed to the right in many cases.

Now the kernel density functions of 1969 and 2009 will be used to further elaborate on the difference between the mixture normal approach and the distributional dynamic approach, and explain how multiple modes in the distribution do not necessarily guarantee multiple components. Using the terminology of the distributional dynamic approach, the income kernel density function of 1969 suggests a "twin-peak" distribution, while the income kernel density function of 2009 suggests a "single-peak" distribution. Therefore, if using the distributional dynamic approach, the year 1969 is more likely to have two convergence clubs than the year 2009. The mixture normal approach shows different results, as presented in the next section. According to the mixture normal approach, the evidence does not suggest that there were two convergence clubs in 1969, but there is statistically significant evidence to conclude that there were two convergence clubs in 2009.

1.4 Results

One of the most efficient ways to estimate the mixture normal model is to use the Expectation-Maximization (EM)[1] algorithm (McLachlan and Peel, 2000). The initial test explored how many components should be included in the mixture model by following the likelihood ratio test procedure used in Pittau *et al*. (2010). Since most papers that utilize the mixture normal model to identify convergence clubs identify 2 or 3 clubs, the likelihood ratio was used to test the two

[1] In this paper, the EM algorithm from the "mixtools" package in R is used (Benaglia, *et al.* 2009)

components mixture normal model against the three components mixture normal model. For some years in the late 1980s, 1990s, and early 2000s, the likelihood ratio tests do not have enough evidence to reject the three components mixture normal model. In the case of a model with three components, in addition to the high income and middle income groups, a low income group is identified. However, this low income group does not persist over time. It appears and disappears in relation to economic conditions. Also the population share of this low income group is much smaller compare to the other two groups. Since this research focuses on identifying the regional inequality that was driven by the disproportional growth of the high income group, it does not change our analysis when we group the middle income group with the low income group. That is why, to facilitate comparisons of the results across years, a two-component model was estimated for all 41 years.

The model estimation results include the mixing proportion/weight for each component, the means for each component, the variance for each component, and also the conditional possibilities for each region. Then, a bootstrap procedure was performed to construct standard errors for the mixing proportions, the means, and the variances. In the case of the two components mixture model, it was only necessary to show one mixing proportion/weight because the two mixing proportions sum to one. The group of labor market areas with significantly higher per capita personal income will be referred to as the “rich places club” (hereafter RPC), and the group of labor market areas with significantly lower per capita personal income as the “everywhere else club” (hereafter EEC).

The present use of the mixture normal model to identify the convergence clubs parallels the practice of biologists when they evaluate the evolution of a species and decide when differences are significant enough to deserve the classification of a new species. In figure 1.4, the mixing proportion/weight for the RPC with the higher per capita personal income from 1969 to 2009 are plotted: the black line with square marks is the proportion for the group of labor market areas with a higher per capita personal income, and the two grey dashed lines are the 90% confident interval for the mixing proportion parameter. The lower bound of the 90% confidence interval is zero or less than zero before the mid-1980s, but in the second half of the 1980s the lower bound increases to above the zero line. The interpretation follows that the RPC began to appear in the 1980s with the proportion of the rich places club increasing in this decade. In the 1990s and 2000s, the RPC accounts for about 10-15% of all the labor market areas. The proportion of RPC has not increased very much in the 1990s and 2000s.

Figure 1.5 shows the plots of the average per capita personal income for the EEC and the RPC from 1985 to 2009. The RPC has a larger variance than the EEC. Figure 1.5 shows that the per capita personal income gaps between the two clubs grew over time. A linear regression model was estimated to see whether the gap between the two clubs was becoming larger over time using the per capita personal income ratio of the RPC to the EEC as a measure of the gap between these two clubs and time as an independent variable. Here, the time is from year 1 to year 25 instead of year 1985 to 2009. The estimated model is as follows:

Ratio = 1.30 + 0.0024 * Time, adjusted R^2=0.1899

(0.0139) (0.0009)

On average, the RPC is 1.30 times richer than the EEC. From 1985 to 2000, the RPC became 0.24% richer each year when compared with the EEC.

In figure 1.6, the spatial distribution of the RPC for 1990-2009 has been plotted. The darkness of grey color represents how many times a labor market area is classified into the RPC between 1990-2009. All the RPC are classified into four quartiles. The top quartile consists of labor market areas that are classified as belonging to the RPC 19-20 times out of 20 time periods; it is the most stable rich club. The quartile consists of the labor market areas that are classified as belonging to the rich places club 9-18 times out of 20 time periods. They are also very stable as members of the rich club. The third quartile collects labor market areas that are classified as belonging to the rich place club 3-8 times out of 20 time periods; essentially, they are the emerging, stable rich club members. The fourth quartile is composed of labor market areas that are classified as belonging to the rich places club only 1-2 times out of 20 time periods; for the most part, these are areas that have not yet qualified as members of rich places club.

For this fourth quartile, labor markets usually move in to the rich places club in one year and move out of the rich places club in the second year. The most active years in which labor markets joined the RPC in the fourth quartile were 1991, 2002, 2005, and 2008, while the most active years of moving down to the EEC for the fourth quartile were 1992, 2003, 2007, and 2009. In the fourth quartile, of the 35 labor market areas, 12 of them are from North and South Dakota. An analogy to the situation of this group of labor market areas would be a "lucky" lower league English football team that finds itself occasionally promoted to the Premier League. However, the performance of this "lucky" football team is never very consistent. That is why, in the next season, the team drops back to its original league. Here, the question is, will this team be again promoted and eventually be able to stay in the higher league? One cannot answer this question without studying the "lucky" factors that allowed this football team to be promoted in the first place. The same thing applies for this current research: there is not enough information to judge whether the labor market areas that made it into the fourth quartile will enter the RPC again in the future. Further research is required.

It is important to distinguish between the third and the fourth quartile. As was just discussed, entering the RPC once or twice could simply be because of idiosyncratic factors. However, for the third quartile, there should be more consistent reasons to explain how these labor market areas were able to enter the RPC for 3-8 times in the last two decades. Therefore, future research should pay special attention to the third quartile and find out the reasons why this group of labor market areas was able to emerge, and establish themselves as stable members of the rich places club.

Figure 1.6 also suggests there is a spatial pattern in terms of distribution of the RPC. Four spatial clusters stand out clearly: the Boston-New York-DC cluster, the southern Florida cluster, the Colorado cluster, and the California cluster. A hot spot analysis using the General *G* statistic (Getis and Ord, 2010) confirmed the existence of these four clusters.

The spatial distribution of the RPC suggests that the rich places are usually places with larger population masses; the average population size for each quartile is presented in table 1.1. The average population size for "always rich (quartile 1) labor market areas" is 2.6 million in 2009, while the average population size for the EEC is only 0.23 million. This pattern seems to amplify the effect of economic agglomeration: a labor market with a larger population mass is more productive than a labor market with smaller population mass (Fujita and Thisse, 2002). The average population size for the second quartile is very close to that of the first quartile, with 2.2 million people in 2009. In contrast with the first two quartiles, the average population sizes for the third and the fourth quartile are only 0.6 and 0.5 million, respectively.

1.5 Robustness Check: Mobility between components

In section 4, the analysis revealed that there is a RPC that emerged in the 1980s and this club accounts for 10-12% of the 702 labor market areas in the Continental U.S. The emergence of the RPC is one necessary requirement for the existence of convergence clubs. The other requirement is low mobility between clubs. Mobility can be equated with transitional probabilities: it refers to the probability transfer into or out of distinct clubs over time. Low mobility will mean that most of the labor market areas that belong to the rich places club in time period *t* will also belong to the rich places club in time period *t+1*. If the low mobility condition holds over time, then it suggests that the classification system and the convergence clubs are stable.

The conditional probability, ζ_{ji}, is used for the identification of the labor market areas that belong to the RPC and the labor market areas that belong to the EEC; labor market areas are assigned to clubs according to their maximum estimated conditional probability. Since a panel of data for 41 years is available, it is possible to trace the mobility of the change of assignment of labor market areas over time.

We check the transitional probability for three stages (table 1.2): (1) 1970-1979, before the formation of the RPC; (2) 1980-1989, the formation of the RPC; and (3) 1990-2009, when the RPC is stable and the incomes diverge between the RPC and the EEC. Four cells in the transitional probability matrix correspond to four different situations: the diagonal refers to stability; the upper right hand cell indicates downward mobility (rich to non rich) while the lower left cell indicates upward mobility (non rich to rich).

The upward mobility plus downward mobility divided by the share of stable rich places club is used as a measure of stability of the rich places club. For the instability measurement, a smaller number means more stability because there is less upward and downward mobility. The other way to understand this stability measurement is to treat it as a mobility measure: a large number means higher mobility in between clubs. The upward mobility minus downward mobility is used as a measure of the formation of the rich places club. The three key indicators in summarized in table 1.3.

Two indicators confirmed the classification of these three stages. First, the shares of stable RPC members were increasing from 1.51% in the 1970s, to 4.84% in the 1980s, and 7.12% in the 1990s-2000s. Secondly, the rates of formation of the RPC were negative in the 1970s and the 1990s-2000s, with values of -0.13% and -0.15%, respectively, while the rate of formation of the RPC was 0.88% in the 1980s. The positive RPC formation rate in the second stage confirmed the 1980s as the time when the RPC was established. The third indicator, the instability of the RPC measurement, is very important for the convergence club test. In the first stage, the 1970s, the RPC was very unstable; the instability measurement for this stage is 1.01, meaning high mobility between the two clubs. This corroborates the evidence shown in figure 4 from the previous section: the mixing parameter is insignificant in the 1970s. The RPC was relatively stable for the second and third stage, with instability measurements of 0.36 and 0.33, respectively. There is no clear cut point for determining whether a stage is stable or mobile. However, with only 0.33 instability measurement for stage 3 (about 15% inflow and 18% outflow), one might suggest that stage three is relatively stable. Hence, the suggestion can be made that the convergence clubs identified by the mixture normal model for U.S. labor market areas are stable clubs.

What is the difference in between this transitional probability approach and the Markov chain approach? In the Markov chain approach, it is assumed that the regional per capita income follows a first-order Markov Chain with stationary transition probabilities. However, in the research setting of an economic convergence test, the Markov chain might not be stationary over time, as shown in Bickenbach and Bode (2003). The results in this paper also show that the transition probability is not a stationary process.

1.6 Conclusion and future research

In this paper, the objective was to demonstrate that the mixture normal model can be used as a new way to identify convergence clubs, and in a more general way, to identify the heterogeneity in the dataset. Using this method, we are able to identify a group of labor market areas in the United States that have significantly different per capital personal income levels than other labor market areas. These high personal income level areas constitute the RPC that formed in the 1980s, and the size of this club has been stable through the 1990s and 2000s. Within the U.S., regions are becoming even more polarized and this polarization trend that began in the 1980s is also based on personal income levels (Autor and Dorn, 2009).

However, this paper only focuses on the identification of the convergence clubs. It does not provide an explanation for the possible mechanisms that created this divide between the clubs. The results support the recent findings of Moretti (2012) who explored the role of the accumulation of human capital as one mechanism that may have created this regional divide, since it seems that places with higher levels of human capital are more productive. There are two possible ways of enhancing the human capital level of a region: increasing the education level of its people, and attracting high-skilled migrants. Future research might profitably test the contribution of these two human capital enhancing channels to the creation and sustainability of the RPC and EEC.

1.7 Tables and figures

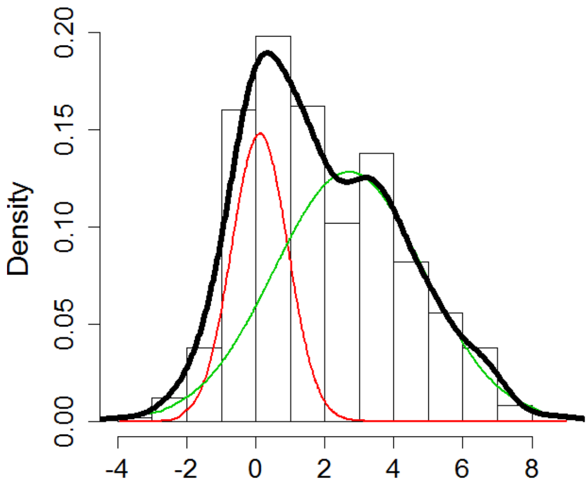

Figure 1.1: A simulated example of the mixture normal distribution with two components

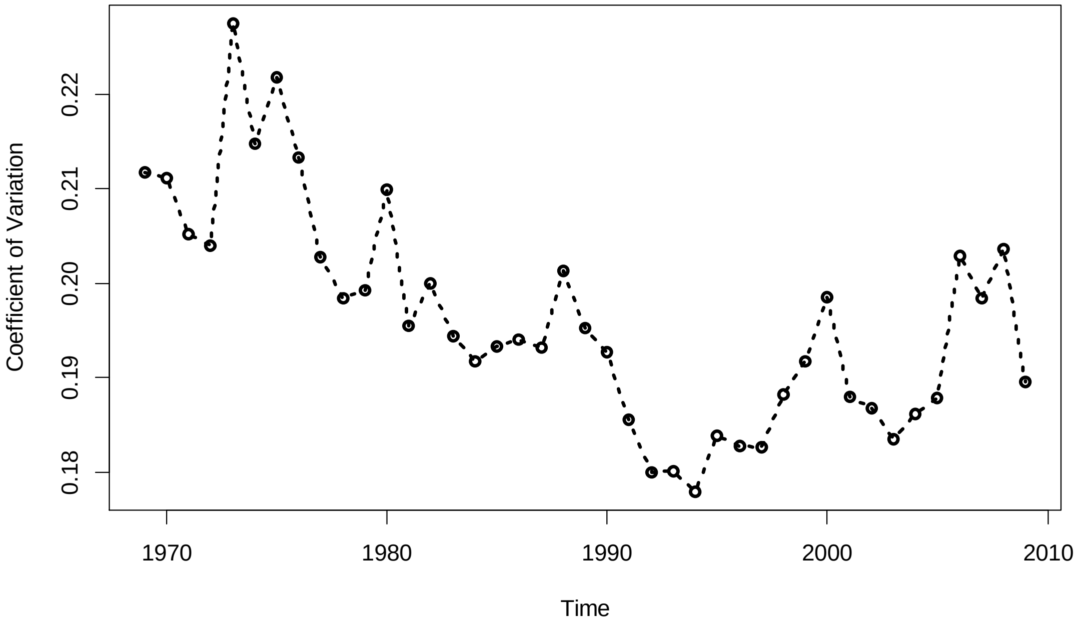

Figure 1.2: Coefficient of variation for labor market areas, 1969-2009

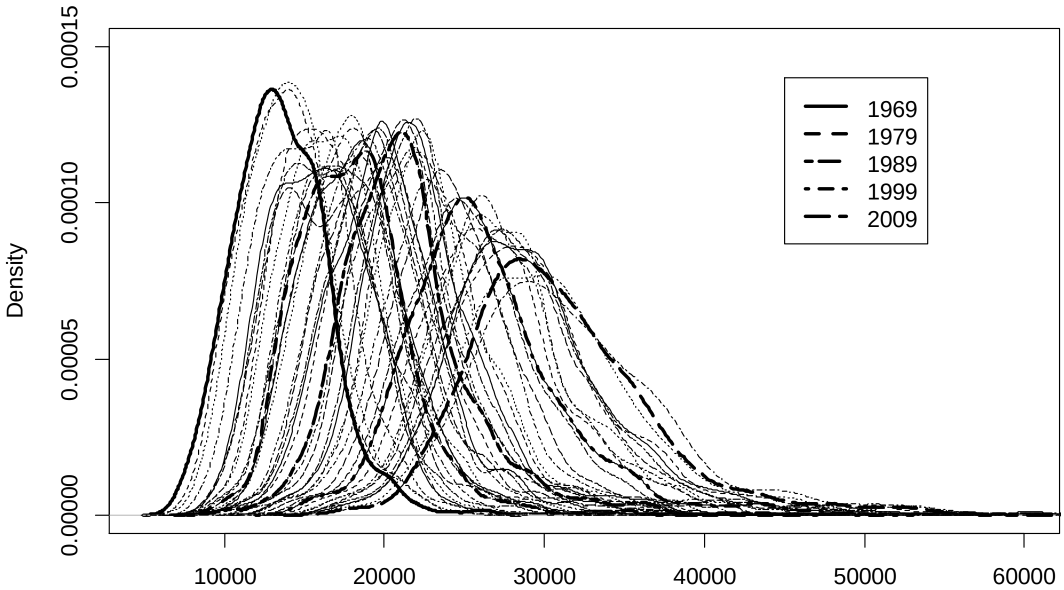

Figure 1.3: Per capita income distributions from 1969-2009

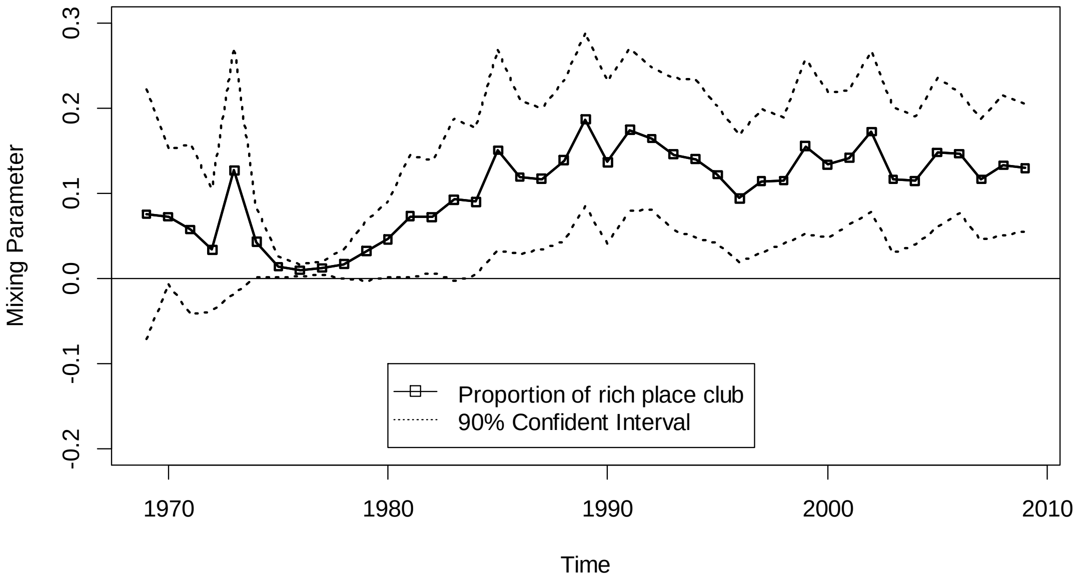

Figure 1.4: Mixing proportion of the rich places club 1969-2009

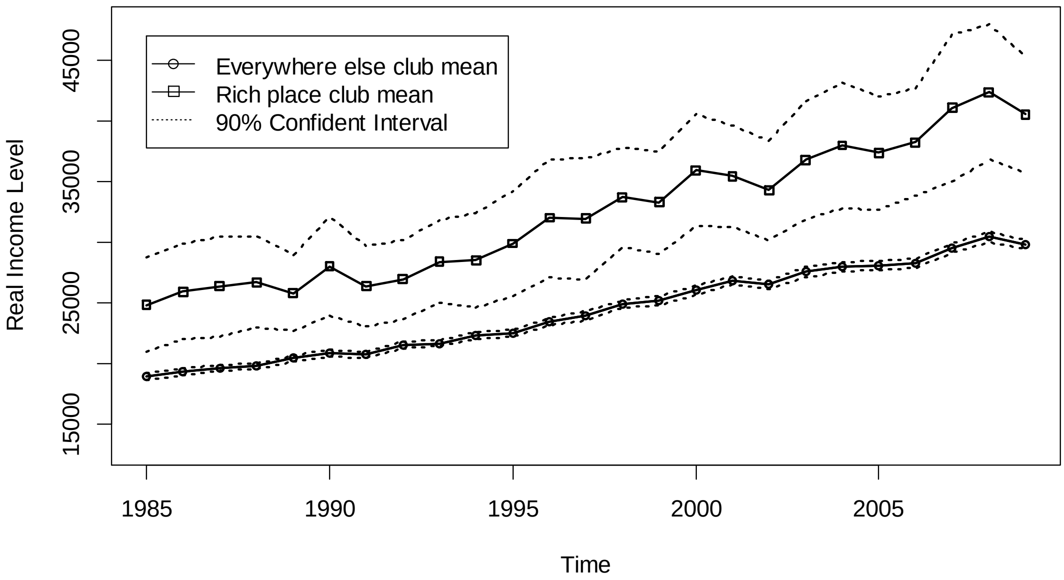

Figure 1.5: Average per capital income for the two clubs from 1985-2009

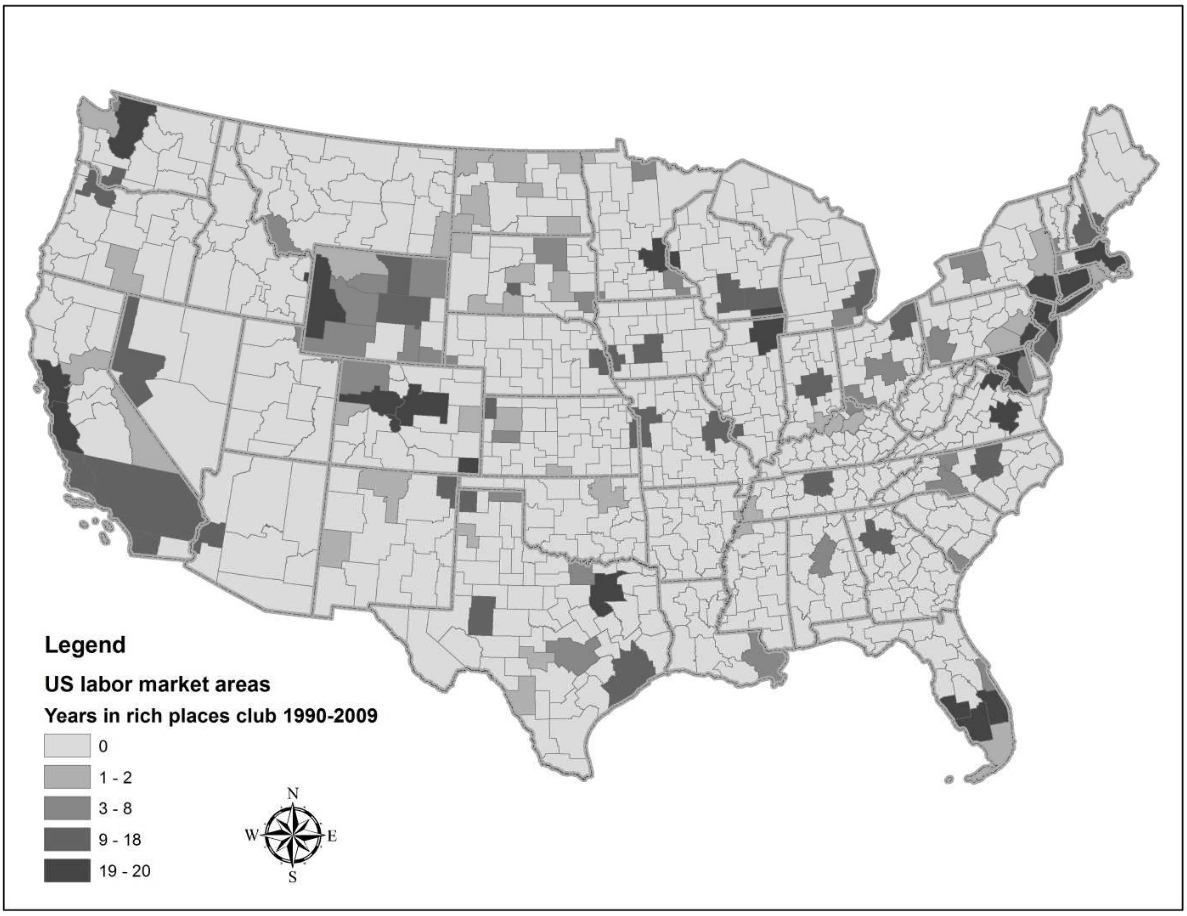

Figure 1.6: the spatial distribution of the rich places club, 1990-2009

Table 1.1: Average population size for four quartile of rich places club and everywhere else club, 2009

	LMA	Total population	Share of U.S. population	Average population size
Quartile 1: 19-20	29	75,820,125	25%	2,614,487
Quartile 2: 9-18	27	60,388,869	20%	2,236,625
Quartile 3: 3-8	31	17,753,180	6%	572,683
Quartile 4: 1-2	35	17,312,969	6%	494,656
Everywhere else club	580	132,209,828	44%	227,948
Total	702	303,484,971	100%	432,315

Table 1.2: transitional probability for three stages

Transitional Probability 1970-1979

		Time *T*	
		Rich place	Everywhere else
Time *T-1*	Rich place	1.51%	0.83%
	Everywhere else	0.70%	96.97%

Transitional Probability 1980-1989

		Time *T*	
		Rich place	Everywhere else
Time *T-1*	Rich place	4.84%	0.44%
	Everywhere else	1.32%	93.39%

Transitional Probability 1990-2009

		Time *T*	
		Rich place	Everywhere else
Time *T-1*	Rich place	7.12%	1.25%
	Everywhere else	1.10%	90.53%

Table 1.3: Measurement of the transitional probability

	Stable rich place club	Rate of forming rich place club	Instability of rich place club
1970-1979	1.51%	-0.13%	1.01
1980-1989	4.84%	0.88%	0.36
1990-2009	7.12%	-0.15%	0.33

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Chapter 2: Demand Change and Labor Market Outcome

***Abstract**:* In this paper, a spatial equilibrium with an embedded dis-equilibrium (spatial heterogeneous) factor model is presented and it is empirically evaluated using U.S. Censes and ACS data on metropolitan areas over 1990-2011. This model focuses on four aspect of local economic system: wage, housing rent, job growth, and population growth. The dis-equilibrium factors empirically evaluated in this study are the expected labor demand shifter and appreciation of natural amenities.

From a local price perspective, as the expected labor demand increase, both wages and housing rents increase. The natural amenities do not significantly impact inter-regional wage difference, but natural amenities are a significant factor for inter-regional rent levels.

From a job growth and a population growth perspective, a one unit job increase in expected labor demand growth will create more than one additional jobs (1.367-1.392). For every one unit increase of expected labor demand shifter, population will increase 0.8. Regions with higher amenities not only attract new population, they are also places where more jobs are created. For the job-people interaction, this study finds that jobs follow people at a 1-to-1 ratio, while people follow jobs at 0.5-to-1 ratio.

***Keywords**: Expected Labor Demand Shifter, Natural Amenity, Wage, Housing Rent, Job Growth, Population Growth*

2.1 Introduction

This paper aims to build a bridge between the local labor market literature and the local economic development literature. Traditionally, the local labor market literature focuses on price signals (wage and housing rent) and operates under a spatial equilibrium assumption, while the local economic development literature focuses on job creation, migration and operates under a spatial disequilibrium assumption. In this paper, a united local economy framework is presented that explores four aspects of local economy: wages, housing rent, job growth, and population growth. In the empirical section of this paper, two key factors, an expected labor demand shifter and appreciation of natural amenity, are investigated to show how they impact the four featured aspects of the local economy.

To build the theoretical framework, an export-based (demand driven) growth model is embedded into a spatial equilibrium model setting so as to provide a way to study the effects of wage, housing rent, employment growth, and population change in a region that is facing a demand change. The demand change could originate from the demand for goods and services a region can offer, or it could be from locally fixed goods a region can offer, such as amenities. Although the natural amenities are not likely to change over time within a region, people's appreciation of these amenities could change over time.

Different metropolitan areas within a country could specialize in the production of different goods and offer different kinds of services (e.g., Detroit has been the center of the auto industry, New York has been the center of the business service industry, and more recently, San Francesco-Silicon Valley has been the center of information and communication technology industry), and this specialization serves as the basis for the "export" of these specialized products or services to other areas (Krugman, 1991). Thus, when a national or global demand shock occurs, such as an internet-based technology innovation, it could be expected to create differential effects on local markets. Meanwhile, labor demand shock to a local areas' export industry will create spillover effects on other industries in local economy (Hewings & Jensen, 1986; Leontief, 1987; Miller & Blair, 2009); for example, the growth of the Silicon Valley tech industry generated a significant impact on local service industries. The direct effects and spillover effects combine to create the overall labor demand effect on the local area. This labor demand effect would induce labor supply changes and also impact local prices (wages and housing rents).

One of the challenges in this type of study is how to identify labor demand shocks. In many cases, employment growth itself is treated as a labor demand shock (Clark & Hunter, 1992; Greenwood, 1975; Muth, 1971). When using employment growth as an indicator of labor demand shock, endogeneity would become a challenge to the validity of the empirical study. In this case, it is not clear if the employment growth is generated by population inflow or if the population inflow is caused by abundant employment opportunities in certain regions (people follow job or jobs follow people debate).

In this study, the labor demand variable, the expected labor demand shifter (ELDS), is defined following Katz and Murphy (1992) to avoid the endogeneity issue. As discussed in detail in this paper, ELDS is defined in a way that captures exogenous shifts in local labor demand that are tied to the city-specific industry mix, while avoiding the endogeneity associated with using the local employment growth rate. This expected labor demand shifter is related to actual labor demand growth, and other regional economic outcomes such as wages, housing rents, employment and population changes.

This framework can also offer a way to study the impact of amenities on the local economy. Amenities provide another critical point of debate in the spatial equilibrium vs. spatial disequilibrium argument. Within the spatial equilibrium theory, local amenities are assumed to be priced into wage and housing rents, therefore, they should not impact the local economy. From a spatial disequilibrium point of view, people are still moving to places with high amenity levels. One of the issues with respect to this debate is that, sometimes it is difficult to differentiate if people are moving for jobs or for amenities. In this paper, a good control over moving for jobs is established through the use of the labor demand shifter variable; therefore, it will be possible to differentiate the effect of amenities over labor market attractors.

To present a comprehensive analysis for the impacts of the labor demand shifter and amenities, four regional economic outcomes are modeled in this paper: regional prices (wages and housing rents), and regional labor demand and supply outcomes (employment growth and population change). The wage and housing rent models are built upon the principles articulated in the Rosen-Roback spatial equilibrium model (Roback, 1982; Rosen, 1979) with the addition of a disequilibrium labor demand factor. The employment growth and population change models are built upon an export base model following Bound and Holzer (2000). Discussions such as "do people follow jobs or do jobs follow people", "do people move for amenities", and "do firms move for amenities" can be inferred after the estimation of employment growth and population change models.

The primary results with respect to expected labor demand shifter are: (1) the labor demand shifter has a positive and significant impact on both wages and rents. When focusing on the sizes of the coefficients, the rent impact is greater than for wages. For a level of expected labor demand shifter, the dollar amount of the increase in wages is larger than for rent. Therefore, a positive labor demand shifter would increase wage income after adjusting for rent expenses (a purchasing power adjustment). From the net benefit point of view for a potential migrant, an increase in the expected labor demand shifter will make a place more attractive and lead to net in-migration. (From the job growth equation) (2) the expected labor demand shifter creates a multiplier effect on job growth. For a 10% increase in the expected labor demand shifter, total labor demand would increase by about 14%. After controlling for the expected labor demand shifter, job growth is driven by population growth at exactly a one to one ratio. From population growth equation (3) For every 10 predicted job increases by expected labor demand shifter, only 2 out of 10 jobs will be taken by locally unemployed or locally not in labor force. After controlling for the expected labor demand shifter, every 10 additional jobs will attract 5 net in-migrants. This set of results provides evidence to support labor demand driven spatial disequilibrium migration theory: for places with higher level of *ELDS*, more jobs are created, the purchasing power is increasing, and people move to these places.

Overall, regions with higher expected labor demand shifter will see favorable growth conditions population, job will grow, and both wage and rent will growth, but the rent growth would not be outpace the wage growth, so rent adjusted wage income would not become a deterrent for a potential migrant.

After controlling for the expected labor demand shifter, the natural amenities impact the local economy in the following ways: (1) natural amenities have a positive effect on rent, but it does not have an effect on wages. This means that, after control for the labor demand shifter and other factors, places with higher amenities have wages similar to places with lower amenities and higher rents than places with lower amenities. (2) Places with high amenities also have higher job and population growth. Places with high amenities would attract more people and more jobs would be created (a positive factor for migration). Overall, places with high amenity attracts both people and businesses, but for people who move to place with high amenity, they have to pay for these amenity in the form of higher housing rent. From a regional growth perspective, places with higher amenities have higher growth potential. Landowners in regions with high amenities will be able to capture higher returns.

This paper is organized as follows: in section 2, a spatial equilibrium model with dis-equilibrium factors is presented. In section 3, data sources and key variable construction is discussed while section 4 presents the empirical estimation results. Section 5 concludes the paper.

2.2 Theoretical Framework

This section sets out to extend a standard spatial equilibrium model to include a spatial heterogeneous demand shifter component. The standard Rosen-Roback spatial equilibrium model is established within a long-run general equilibrium setting, where households and firms are free to move across local labor markets, and where local prices (wages and rents) adjust to maintain the spatial equilibrium of household utility and firm profitability. When regions facing spatial heterogeneous demand shifters—such as demand for products from certain regions, demand for education provided by certain region, and demand for amenities from certain region—local market outcomes such as employment, migration, wages, and rents would react to these demand shifters.

The theoretical framework in this paper is similar to Bound and Holzer (2000), where they explore the effects of labor demand shifts and population adjustment across metropolitan area on the employment and earning of various demographic groups during the 1980s. One of the advantages of the Bound and Holzer (2000) theoretical framework is that they built upon the spatial equilibrium structure and then incorporated disequilibrium factors. Moretti's (2011) paper on local labor market also provides an extension to the Rosen-Roback spatial equilibrium framework to consider spatial heterogeneous labor demand shocks would impact labor market outcome for varies skill groups.

There are many sub-components of population in a local market area: (1) those who do not derive their income from the local labor market (such as retirees), so that the change in local wages does not impact them directly. (2) There is segment of the population who own their residence (home owners), so the change in housing rent does not impact them directly, and potentially they could gain from an increase in housing rent when they sell their properties. (3) There is a segment of the population who derive their income from local labor market and who have to rent their residence (local-price-takers), so this group's spatial allocation decision is most affected by changes in local conditions.

The local conditions will impact each group differently. This main focus of discussion in this paper is on the third group, because this group has potentially high mobility and they are local price (wage and housing rent) takers. However, when relevant, the local conditions impact the other two groups will also be discussed.

2.2.1 Equilibrium in local labor markets: Rosen-Roback framework

Following Roback (1982), the model assumes an open city with identical mobile workers and firms. The long run spatial equilibrium conditions for workers and firms assume that worker utility (u) and firm profit (π) are equal across regions ($j = 1, \ldots, \mathrm{J}$).

$$\bar{u} = u(w_j, r_j | A_j) \quad (1)$$

$$\bar{\pi} = \pi(w_j, r_j | A_j) \quad (2)$$

w_j is the wage in region j, r_j is the land rent in region j , and A_j is the local conditions of region j. Local conditions includ natural amenities, local labor market characteristics, local housing market characteristics, and local firm productivity.

Equation (1) and (2) perfectly determine wages and housing rents as a function of local conditions, given a level of household utility and firm profit. Local wages and rents can be solved as a function of local conditions:

$$w_j = f(A_j) \quad (3)$$

$$r_j = f(A_j) \quad (4)$$

The basic wage and rent functions can be adapted to evaluate the impact of demand shifter DS_j as shown in equations (5) and (6). One way to justify this adaptation is to treat the demand shifter as one of the local condition variables.

$$w_j = f(A_j, DS_j) \quad \text{(5) Wage equation}$$

$$r_j = f(A_j, DS_j) \quad \text{(6) Housing rent equation}$$

The expected labor demand shifter is one kind of demand shifter that was defined in section 2.3. It is used as an example for discussing the impact of demand shifter on other local conditions. First, it is expected that the expected labor demand shifter would create a positive impact on wages. This positive impact on wages is justified by the labor price adjustment mechanism: when demand for local labor increases, wage increases. Next, when wage increases, housing rents should also increase. This result is derived from the properties of the spatial equilibrium model that assumes household utility equalization. The logic is as follows: first, when wages in a location increase because of a positive expected labor demand shifter, household utility also increases. Then, household utility increases in a region would lead to in-migration to take advantage of the higher utility levels. With more people moving to a region, there would be an increased demand for housing thus increasing housing rent. Finally, the housing rent increase would reduce the household utility level in a region. In the end, household utility in the region that received a positive labor demand shock would fall back to a level that is similar to other regions, thereby providing no further incentive for people to move. However, the new utility level will be higher than old utility level (see Moretti (2011) for detailed discussion).

2.2.2 Framework for modeling labor demand and supply growth

The tradition of spatial equilibrium model focuses on wage and rent adjustment mechanisms. Since it is assumed that the system is in equilibrium, there is no further movement of workers or firms to take advantage of differences in local attributes, since all the local attributes are captured into local prices. Therefore, the worker adjustment and firm adjustment components are usually omitted from study.

As discussed in the previous section, a positive labor demand shifter would increase wages, and this wage increase would lead to an increase in population and an increase in housing rents. There is another non-price channel where the labor demand shifter would impact the local labor market: labor demand and supply effects. When there is a positive labor demand shifter, more jobs will be created in that region; when more jobs are created, more people will move in. When more people move into a region, more jobs will be created for that region. It is expected that both labor supply (population growth) and labor demand (job growth) would increase when a region faces a positive labor demand shifter.

Job growth (Δjob_j) can be written as a function of demand shifter DS_j and the difference between local firm profit level and long-run equilibrium firm profit level ($\pi_j - \bar{\pi}$). Population growth (Δpop_j) can be written as a function of the difference between local household utility level and long-run equilibrium household utility level ($u_j - \bar{u}$). Since both wages and rents are a function of the demand shifter and local conditions according to equation (5) and (6), a reduced form equation of job growth and population growth can also be expressed as a function of local demand shifter and local attributes.

$$\Delta job_j = f(DS_j, A_j) \quad \text{(7) Job growth equation}$$

$$\Delta pop_j = f(DS_j, A_j) \quad \text{(8) Population growth equation}$$

2.2.3 Two cases of demand shifters

The demand shifter presented above is one of the key factors that changes local condition. In this paper, two cases of demand shifters will be discussed. One is the expected labor demand shifter, and the other is change in the evaluation of natural amenities. These two cases are chosen because they are exogenous to current local conditions.

Expected labor demand shifter

There are many mechanisms that would create labor demand changes, such as technology innovation, energy price changes, government economic development policies, etc. The expected labor demand shifter studied here is a special case of labor demand change. It is chosen to be (1) exogenous to current local economic condition; (2) driven by national growth trends; (3) used for local level economic development scenario analysis.

Following Katz and Murphy (1992), the expected labor demand shift ($ELDS_j$) is defined as follows:

$$ELDS_j = \sum_{s} \eta_{s,j} \Delta E_s \quad (9)$$

Here $\eta_{s,j}$ is the employment share of industry *s* in region *j* in the base year, and ΔE_s is the national growth rate for industry *s* from base year to reference year. $ELDS_j$ is the expected labor demand growth for region *j*, if all the industries in region *j* grow at the same rate as the national growth rates.

As discussed above, the *ELDS* is expected to be positively related to all four outcome variables (wage, rent, job growth, and population growth). However, not only the sign of the *ELDS* coefficient matter, the magnitude of the coefficient also matters. Consider the case in which the ELDS positively impacts both wages and rents, in the short and median run, how would a local resident (such as retirees, home owners, and local-price-takers) benefit from this expected labor demand increase? It depends on if the size of the housing rent increase compared with wage increase due to this *ELDS*. In a case where housing supply is relative tight,[2] housing rent increases could come close to or even exceed wage increases, then local price takers would have less disposable income after paying rent.

This kind of information could help local-price-takers decide which makes more financial sense: stay in his/her current region or move to another region with a different level of expected labor demand increase. In addition, the information would help determine whether to stay as a

[2] However, it is not the goal of this research to discuss housing supply elasticity, see Quigley & Raphael(2005) and Saks(2008) for discussion on this topic

renter or purchase a house; the purchase of a house can help the local-price-taker to capture some financial benefit due to labor demand increase, and thus become the land-owner group, although the benefits may not be realized immediately. In the case of a local-price-taker in the region with positive *ELDS*, part of the financial benefit due to ELDS increase will be captured by landlords.

The coefficients also have public policy implications. It can help local government understand, given their local industry structure and a simulated scenario for national growth, how many jobs they could expect to be created in their community related to expected labor demand shifter and indirectly by spillover effects. Local authorities would also be interested, given an expected labor demand shifter, in how many of those expected jobs would be taken by people from outside the region, and how many of those expected jobs could directly benefiting people in the region. The expected labor demand shifter for a region relies on the assumptions about the national growth path. The local authority can take government projections of economic and employment growth (such as the one provide by Bureau of Labor Statistics), or they can purchase it from some commercial source (such as the Moody's analytics), or they can develop their own scenarios of the national growth path and evaluate how that scenario will impact their local economy.

Appreciation of amenity

Natural amenities for certain region are usually considered fixed. However, consumers' appreciation of amenities could change over time. The classical migration literature, such as Harris and Todaro (1970), has ignored the impact of amenity. More recent migration literature, after observing large population moves from the US rust-belt to the sun-belt, raised the question: "Do people move for jobs or for amenities?" This type of question could be difficult to answer when places with high amenities have both large inflow of population and large job growth. In this research design, the expected labor demand shifter is controlled, so it can provide an opportunity to look at the separate impact of amenities.

According to Rosen-Roback's spatial equilibrium theory, amenities valued by producers would have a positive relationship with wages, while amenities valued by consumer would have a positive relationship with housing rent. The natural amenity index used in this study was constructed to reflect the taste of the consumer, not producer. Hence, according to spatial equilibrium theory, this set of natural amenities is expected to have a positive relationship with housing rent (Graves, 1983) and wages should be lower in places with rich natural amenities, because people live in those places are compensated for rich amenities (C Reichert, G Rudzitis 1994). Also noted by Reichert and Rudzitis (1994), the impact of amenities are different for people who are in labor force and people who are not in labor force. This paper only focus on people who are in labor force.

Usually, under the spatial equilibrium model assumption, the effect of natural amenities would be captured in local prices and natural amenities would not be considered as factors inducing population migration. However, consumers' appreciation of amenities could change over time. For example, after the wide availability of indoor air conditioning, the amenities of the sun-belt (sunny, hot, and in some cases humid) were more highly valued by consumers.

In this case, the natural amenity for a certain region being valued is similar to having a positive change in local demand: the demand for local amenities increases, thus leading to population and job growth.

2.3 Data and Variables

The data used in this analysis come from the U.S. decennial Censuses 1990 and 2000, American Community Survey (ACS) 2005-2011 by IPUMS (Sobek *et al*., 2010), the Regional Economic database from Bureau of Economic Analysis, and USDA Economic Research Service Natural Amenities index (McGranahan, 1999). The research design can be more flexible by using both micro (IPUMS) and macro (BEA) datasets. The IPUMS micro level datasets contains detailed demographic, social-economic, housing, geographic, and other information at **individual level** for sampled US population (5% sample for 1990, 2000 census, and 1% sample for 2005-2011 American Community Survey). The detailed work/income, housing and geographic information are obtained from IPUMS datasets. The IPUMS datasets provide the geographic location for each surveyed individual, making it possible to aggregate individual level data to the desirable geographic level to match other regional macro datasets.

This research focuses on the earned income for people who hold full time jobs, and the housing rent they pay if they rent their place of living. Labor demand in certain labor market is measured in terms of hours worked instead of numbers of jobs. This type of tailored information would be hard to obtain from standard macro database. In this study, the unit of analysis is the metropolitan statistical areas (MSA). Regional Economic data from Bureau of Economic Analysis is obtained at the MSA level. USDA amenity data is at the county level and it is aggregated to the MSA level by using county population as weights.

After aggregating the datasets to the MSA level, they are merged to form an MSA level panel data set for over 8 years (2000, 2005, 2006, 2007, 2008, 2009, 2010, and 2011) for 214 MSAs. The summary statistics are presented in table 2.1, and correlations among variables are presented in table 2.2.

Wage and Housing Rent Variables

Median wages for each MSA are obtained from Census 2000 and ACS 2005-2011 based on individuals with full time employment. Full time employment is defined as working at least 35 hours per week. Wages used here are based on individual self-reported total salaries for the 12 months prior to the survey. Median housing rent is also calculated based on individuals with full time employment who are renters. Housing rent is the monthly gross rent multiplied by 12 to obtain annual rent. Log transformations are applied to wages and rent data.

The way local prices are constructed reflected the research design methodology. The income data constructed for this research reflects its spatial tie to a local labor market. The housing cost data constructed for this research reflects its impact to a potential mobile labor. So both local prices are chosen to reflect this spatially attached (from income perspective) and potential mobile (from renter vs. homeowner perspective) worker (local-price-taker).

From an income perspective, households' total income can be derived from salary income, investment income, retirement income, and welfare income, etc. This research focuses on the salary income that can be derived from local labor market, and can be used as a productivity indicator of local labor market. Other components of household income may not provide this strong spatial tie to local labor market. The case retirement community could demonstrate this point; for a wealthy retirement community, retirees earned their income in other places and move to this community in large part for its high of amenities and lower cost of living. However, for households whose household income depends locally earned salary in this type retirement community, their income could be lower than the retiree's household income.

From a housing perspective, households' housing cost could be derived from housing rent cost or from the cost of home ownership (PITI, mortgage principle, mortgage insurance, property tax, and insurance). The reason for using housing rent data instead of the cost of home ownership cost to indicate local land price is that cost of home ownership strongly ties with when the house was purchased and owning a house is not only a reflection of the price of consumption housing goods, but also a reflection of investment value associated with housing ownership. Therefore, using cost of home ownership could generate measurement error in a local housing cost model. The other reason for using housing rent for this group of people who have full time employment and who are also renters is that their attachment to a local labor market are more flexible than homeowners. So if they find better opportunity in another region, they can move without facing the challenge of selling a house. Therefore, housing rent is likely to more accurately reflect local labor market conditions and housing rent can play a direct role in decision making for potentially mobile labor.

From the summary statistic table: (1) national mean log wage for full time employees increased from 10.15 (equal to $25,600) in 2000 to 10.46 (equal to $34,900) in 2011, it is a 36% increase in real dollar terms. (2) mean log rent level for full time employees increased from 8.87 in 2000 (equal to $7,115) to 9.27 in 2011 (equal to $10,614), a 49% increase in real dollar terms. Overall, the percentage increase in rent is higher than percentage increase in wages, and rent has becoming a larger share of wage. The increasing spending in rent could be driven by higher quality housing and/or pure rent increase. This study does not distinguish these two rent increase factors.

Labor Supply Growth (population growth) Variable

In theory, the labor supply growth should have two components: internal and external labor supply adjustments. The internal labor supply refers to adjustment by people who are already in the region by joining or re-attaching to the labor force or by increasing working hours. The internal adjustment is usually more flexible and less costly, because there is no need for relocation (except in a large MSA, spatial mismatches may exist and require internal relocation). The external labor supply adjustment refers to people relocating to a region through migration. It is a net gain for a region; for this reason, the external labor supply adjustment is the primary focus of this study and thus the labor supply growth in the paper refers only to the external labor supply adjustment.

Population change can be used to approximate external labor supply. It is widely used (Partridge, et al., 2011) and it is a straight forward and reliable variable to construct. Population change has two components: natural growth (birth-death), and migration. The natural growth rate is usually quite stable over time for a specific region, and its effect can be absorbed by using a fixed effect estimation procedure. Using population change to approximate external labor supply adjustment should not bring systematic bias in a panel structure data setting. MSA level mean population growth from 1990 to 2000 was 13.98%, from 1990 to 2011 it was 28.24%.

Labor demand growth (job growth) Variable

Job growth (Δjob_j) is defined at the labor-hour level for each MSA. Using labor-hours instead of number of jobs provides a more accurate measure of labor demand, because the number of jobs does not differentiate between full time jobs or part time jobs, while using a labor-hour metric avoids this problem. The Census survey asked each surveyed individual if they worked, how many hours per week they usually worked and how many weeks they worked last year. Using this information, total annual labor-hours can be calculated for each individual surveyed in the data, then multiple total annual labor-hours by sample weight derived and summed over industry for sample years for each MSA and for US.

Expected Labor Demand Shifter Variable

To construct $ELDS_j$ following equation (9), a base year MSA level employment share and national level employment growth by industry from the base year are needed. In this study, 1990 is used as base year, and 2000, 2005-2011 are used as study years. Expected labor demand growth ($ELDG_j$) is calculated as the growth of labor-hours from study years compared to the 1990 base year.

The expected labor demand shifter ($ELDS_j$) is the predicted/expected labor demand growth, while job growth (Δjob_j) is the realized labor demand growth. Using data from year 2000 as an example, the MSA mean level expected labor demand shifter indicates that the study areas' growth will be 17.50% if all the industries in the study areas grew at the same speed as national growth rate. However, the realized mean level job growth is 30.37%, 1.74 times of the national grow rate. This is an indication that the 214 MSAs in this study are preforming better than the nation as a whole during this period.

Natural Amenity Variable

The amenity variable used in this study was developed by the USDA Economic Research Service. This data set was constructed at the county level by combining six measures: warm winter, winter sun, temperate summer, low summer humidity, topographic variation, and water area. McGranahan (1999) developed this natural amenity index based on the principle that people are drawn to places with varied topography, warm, sunny winters, and temperate low humidity summers. A combined single index instead of a long list of amenity variables is preferred in this study because, first, this single index is based on a group of factors that reflect the general public's taste and secondly, it is not the interest of this paper to discuss explicitly how each amenity variable affects wages or rents. The amenity index is in the range of 1 to 7, with the higher number indicating better amenities.

Other local level variables included in this study are: renter share, college degree holder share, labor force participation rate, population size, unemployment rate, and GDP per job. These groups of variables are included to control other aspects of local labor market conditions that are not captured by the expected labor demand shifter and natural amenities.

In table 2, the correlations among variables are presented. When two dependent variables in the same model with correlation level higher than 0.8, it is likely to create bias in estimation because of the multicollinearity issue. Because all the correlations are less than 0.8, multicollinearity is not a concern here. In addition, variance inflation factors (VIF) are calculated for each independent variables in regression analysis. The VIF provides another way to detect multicollinearity issue.

The expected labor demand shifter, the key dependent variable is modestly correlated with four independent variables. The correlations between expected labor demand shifter, and wage, rent, job growth, population growth, are 0.34, 0.39, 0.22, and 0.28 respectively. Natural amenities, the other variable of interest, shows a strong correlation with housing rent (0.44) and population growth (0.44), modest correlation with job growth (0.22), and almost zero correlation with wages (-0.01).

2.4 Results

The results section is organized as follow: wage and rent section; job growth and population growth section; and summary. Utilizing the panel data structure, both random and fixed effect estimations are presented in the result tables (table 2.3 for wage model, table 2.4 for housing rent model, table 2.5 for job growth model, and table 2.6 for population growth model). A Haussmann test is used to indicator the relative adequacy between the two models. For the job growth model, the random effect model is preferred; for the other three models, the fixed effects models are preferred.

However, it is not wise to discard either random effect result or fixed effect result just based on Haussmann's test. Random effect and fixed effect results offer different lenses through which to inspect the same issue. Using the example of estimating the effect of *ELDS*: random effect estimation result can be interpreted as a comparison of region A to region B to reveal how the difference in *ELDS* between two regions would impact the difference in local market outcomes. The fixed effect estimation result can be interpreted to demonstrate how the change in *ELDS* over time would impact the local market outcomes over time. Both interpretations are useful for understanding the impact of *ELDS* on local market outcomes. If the random effect and fixed effect yield similar coefficients, it indicates that the independent variable is robust. The effect of natural amenity can only be estimated in the random effect models, because natural amenities are fixed for each MSA over time, and when applying fixed effect estimation, natural amenity values are perfectly absorbed by the MSA fixed effects. For both reasons, the fixed effect and random effect results are presented for each model specification.

2.4.1 Wage and housing rent models

The wage model results (table 2.3) and housing rent model results (table 2.4) structures are similar. For both tables, columns 1 and 2 present results for traditional spatial equilibrium wage and housing rent models without the expected labor demand shifter, where wage and housing rent are functions of local amenities and other local attributes. In columns 3 and 4 for wage and housing rent model results tables, the expected labor demand shifter factor is added. Comparing the results in column 1 and 2 to those in column 3 and 4 in both wage and rent models, it can be seen that adding the labor demand shifter does not significantly impact other coefficients. This demonstrates that the labor demand shifter is a good exogenous measurement for labor demand, because it does not create disturbance to other parts of the model.

In columns 5 and 6 for both tables, the other local price factor is added. Therefore, for the wage model, housing rent factor is added; while for the housing rent model, wage factor is added. The last set of results for wage and rent models (in table 2.3 and 2.4, columns 5 and 6) are presented to provide some information for wage and rent inter-active relationships after control for all other local attributes.

Expected labor demand shifter impact on Wage and Rent

The effects of the expected labor demand shifter on median wages are positive and significant for both fixed effect (0.267) and random effect (0.186) models according to result column 3 and 4 in table 2.3. Since the wage is log transferred, the result implies that a 10% increase of expected labor demand shifter, wages would increase in the range of 2.04% to 3.06%.[3] Median wage in

[3](exp(0.267)-1)*10%=3.06% (exp(0.186)-1)*10%=2.04%,

2000 is $25,591. Therefore, a 10% increase in expected labor demand shifter would increase wage in the range of $523 to $783.

The effects of expected labor demand shifter on median housing rents are also positive and significant for both fixed effect and random effect models. According to results column 3 and 4 in table 2.4, the coefficients are 0.419 and 0.368, respectively. Given a 10% increase in the expected labor demand shifter, housing rent would increase in the range of 4.45% to 5.20%, respectively. Median rent in 2000 is $7,115. Therefore, a 10% increase in labor demand shifter would increase rent in the range of $317 to $370 on an annual basis.

How would a local-price-takers' expendable income (wage minus housing rent) be affected by increasing the expected labor demand shifter? In spatial equilibrium theory, household utility is determined by the local amenities and disposable income they can spend on other goods after paying rent. In the case of the expected labor demand shifter increase for a certain region, the dollar amount increase in wages is higher than the dollar increase in housing rents. Therefore, because the household disposable income increases and local amenities remain at the same level, household utility increases when the expected labor demand shifter increases.

When these spatially heterogeneous expected labor demand shifters create spatially different utility increases, then the spatial equilibrium status would be disturbed. Households would move to places with higher utility levels. Therefore the wage and housing rent model empirical results suggest that population will be positively related to the expected labor demand shifter. The empirical result presented here confirms Moretti's (2011) point labor demand shock leads to positive change to wage and housing rent. The direct evidence is presented in table 2.6: the expected labor demand shift is positively and significantly related to population growth.

This result can also help to shed some light on the spatial equilibrium migration and spatial dis-equilibrium migration debate. In this case, the expected labor demand shifter is a dis-equilibrium force. This dis-equilibrium force lead to regions having different utility levels. According to spatial equilibrium theory, different utility level across regions will lead to migration. So spatial equilibrium migration and spatial dis-equilibrium migration theories can work together to explain migration.

Amenity impact on Wage and Rent

The natural amenity index positively and significantly impacts rent (results column 2, 4 and 6 in table 2.4). This is expected, because the natural amenity index is constructed to reflect the consumption amenities (when McGranahan (1999) constructed this amenity index, only consumers' preferences were considered. It includes factors, such as varied topography, warm sunny winters, and temperate low humidity summers, etc.). This amenity index is not constructed to reflect firms' preference, so it is not surprising that the natural amenity index does not significantly impact the wage level (results column 2, 4, and 6 in table 2.3).

The amenity index is in the scale from 1 to 7. Champaign, IL has amenity index of 1, and San Diego, CA has amenity index of 7. Ceteris paribus, comparing a region with amenity index of 1 to a region with amenity index of 7, there would be a difference in housing rent of 45.1%[4] that is driven by amenities. Hence, amenity is a significant factor for regional rent differences.

According to spatial equilibrium theory, consumers can accept lower wages or pay higher housing rents in places with high amenities. After controlling for other factors, this study find that the effect of high amenity is captured in higher housing rent, not lower wage levels. Purely from

[4] (exp(0.0725)-1)*6=45.1%, use the coefficient from result column 4 in table 4.

spatial equilibrium perspective, the choice between high housing rent and high amenity vs. low housing rent and low amenity, depends on consumers' preferences.

Relationship between wage and housing rent

One issue that traditional spatial equilibrium prices models do not address is the relationship between wages and housing rents. Would wage increase directly increase housing rents after controlling for other factors impacting housing rent? Further, would housing rent increases directly increase wages after controlling for other factors impacting wages? It would bias the estimation results if the housing rent variable entered differently into the wage equation because both wage and housing rent are impacted by local conditions.

Therefore, instead of entering the rent variable directly into wage model, the residual from the housing rent model is used in the wage model to estimate the impact from housing rent to wages. The result is presented in columns (5) and (6) in table 2.3. Since both wage and housing rent are log transformed, the coefficient can be considered as a price elasticity. The housing rent to wage elasticities are 0.151 and 0.267, for random effect models and fixed effect model, respectively.

For the housing rent model, the residual from the wage model is used to estimate the effect from wage to rent with the result presented in the result columns (5) and (6) in table 2.4. The wage to housing rent elasticities are 0.357 and 0.419, for the random effect and fixed effect estimations, respectively. The results find that the effect of wage on the determination of housing rent is stronger than the effect of housing rent on the determination of wage. Beaudry *et al*. (2014) also find similar results.

2.4.2 Job growth and population growth model

Empirical estimations of job growth and population growth models follow equations (7) and (8), where both job growth and population growth are functions of the expected labor demand shifter, amenities, and other local attributes. Columns 1 and 2 in table 2.5 and 2.6 show the basic estimation results; columns 3 and 4 show the results accounting for population growth and job growth interaction; and columns 5 and 6 show the results when considering the effects of local prices.

<<Insert table 5, 6 here>>

Expected labor demand shifter impact on job growth and population growth

The first row of table 2.5 shows the impact of the expected labor demand shifter to job growth. All the coefficients are positive, significant and in a narrow range of 1.367 to 1.392. A 10% increase in the expected labor demand shifter would create at least 13.67% in job growth. The result confirms the existence of spillover effects: one unit increase in expected labor demand growth will create more than one unit (1.367-1.392) in actual job growth.

The first row in table 2.6 presents the effect of expected labor demand shifter on population growth; the coefficients are 0.797 and 0.816, according to random and fixed effect models, respectively. This means for every one unit increase of expected labor demand shifter, population will increase about 0.8 unit. If the labor demand shifter to labor demand growth multiplier effect is around 1.38 as shown in the job growth model, then the implied job increase that will be taken by new population would be around 58%[5], very close to what the previous literature has found (Bartik, 1991; Greenwood & Hunt, 1989; Muth, 1971).

Amenity impact on job growth and population growth

Amenities also play a positive and significant role in job growth. Compare a region with amenity level 1 to amenity level 7, ceteris paribus, difference in amenities could contribute to a job growth differential of 45.72%[6] from 1990 level. This result seems to infer that job growth follows amenities. However, it is not clear if the job growth follows amenity, or whether people are attracted by higher amenity levels, and, subsequently, jobs follow people. Therefore, population change needs to be modeled within a job growth model. Using the same procedure as in the wage and rent model, the residual term from population change model is used to control for the jobs follow people issue. The coefficient for population change is very consistent around 1 across different specifications (column 3 to 6 in table 2.5). This means, jobs follow people in a perfect one-to-one ratio. This finding confirms the one presented by Greenwood and Hunt (1989). When added population change variable into job growth equation, the effects of amenity are still significant. Therefore, job growth does follow amenities after controlling for population change.

Amenities are a significant factor in determining population growth. Consider two regions, region A has amenity index 1 while the region B has amenity index 7, ceteris paribus, population growth in region B would be 39.72%[7] more than region A (column 2 in table 2.6) from 1990 level. From the prior discussion with respect to amenity impact to job growth, the highest and lowest amenity region could have job growth difference of 45.72% from 1990 level due to amenity

[5] 80%/1.38=58%
[6] 0.0762*6=45.72%
[7] 0.0662*6=39.72%

difference. Regions with higher amenities not only attract new population, they are also regions where more jobs are created. Overall, high amenity levels contribute benefits to the local labor market because the job growth rate associated with amenities is higher than the population growth rate that is attributed to higher amenities.

Job growth and population growth interaction

One issue the traditional regional growth literature focuses on is the interaction between job growth and population growth: do people follow jobs or do jobs follow people? It is a challenge issue to study because job growth and population growth are both driven by the favorable economic conditions. Without an appropriate definition of this "favorable economic conditions", the study of population growth and job growth interaction could face endogeneity issues. Greenwood (1975) addresses this by using a simultaneous-equations approach.

In the present study, expected labor demand shifter and natural amenity index are used to control for "favorable economic conditions." After control for the expected labor demand shifter, natural amenities and other local characteristics: how would population change impact job growth (table 2.5 column 5 and 6); and how would job growth impact population change (table 2.6 column 5 and 6)? It would bias the estimation results if the population change variable entered differently into the job growth equation because both job growth and population growth use the same set of predictor variables. Hence, the same approach used for the analysis of wage and housing rent interaction was employed; the population change residual is entered into the job growth model, and the job growth residual is entered into the population change model.

For each additional unit of population change, one unit of job growth will be created (results column 3 to 6 in table 2.5); and for each additional unit of job growth, about 0.48 to 0.54

unit of population change can be expected (results column 3 to 6 in table 2.6). This set of results indicates that jobs follow people at a 1-to-1 ratio; while people follow jobs at 0.5-to-1 ratio.

Local prices impact on job growth and population growth

In column 5 and 6 of table 2.5, local price residuals are entered into the job growth model. Empirical results show that job growth is positively related with housing rents, but not significantly related with wages. Using the quality of business (rent+wage) and quality of life (rent-wage) indices developed by Gabriel and Rosenthal (2004), these results show that job growth is positively related with both quality of business growth and quality of life growth. Chen & Rosenthal (2008) found similar results in their study.

Local prices residuals are added into population growth model as shown in column 5 and 6 of table 2.6. Housing rent is negatively related with population growth for both fixed effect and random effect estimations. It is expected from spatial equilibrium theory that high rent will lead to negative population change. Wages are positively related with population change in the random effect estimation but the relationship is not significant in the fixed effect estimation. Thus, the relatively high wages for a region (as indicated by the random effect estimation) is a positive factor for population growth, but wage increases for a region (as indicated by fixed effect estimation) are not related to population growth.

Putting these two sets of results together, it is interesting to observe that after controlling for all other factors, job growth is linked with higher rents but not wage increases while population growth is linked with lower rents. Thus, population growth and job growth have different relationship with housing rent.

2.5 Summary and Conclusion

In this paper, a spatial equilibrium with an embedded dis-equilibrium (spatial heterogeneous) factor model is presented and it is empirically evaluated using U.S. Censes and ACS data on metropolitan areas over 1990-2011. This model focuses on four aspect of local economic system: wage, housing rent, job growth, and population growth. The endogeneity concerns with respect to dis-equilibrium factors are adjusted by constructing the variables in a way that is exogenous to current local conditions. The dis-equilibrium factors empirically evaluated in this study are the expected labor demand shifter and appreciation of natural amenities.

From a local price perspective, as the expected labor demand increase, both wages and housing rents increase. The natural amenities do not significantly impact inter-regional wage difference, but natural amenities are a significant factor for inter-regional rent levels. Furthermore, this study finds that the effect of wages on the determination of housing rent is stronger than the effect of housing rent on the determination of wages.

From a job growth and a population growth perspective, a one unit job increase in expected labor demand growth will create more than one additional jobs (1.367-1.392). For every one unit increase of expected labor demand shifter, population will increase 0.8. Regions with higher amenities not only attract new population, they are also places where more jobs are created. For the job-people interaction, this study finds that jobs follow people at a 1-to-1 ratio, while people follow jobs at 0.5-to-1 ratio. Relatively high wages for a region (as indicated by random effect) is a positive factor for population growth, but wage increases for a region (as indicated by fixed effect model) is not related with population growth.

The expected labor demand shifter and consumers appreciation for natural amenities are just two of the dis-equilibrium factors studied in this research. The framework established here can be used to study other dis-equilibrium factors that are potentially impacting local economic outcomes.

Public policies can be draw up for different types of regions (type 1 high *ELDS* high amenities, type 2 high *ELDS* and low amenities, type 3 low *ELDS* and high amenities, type 4 low *ELDS* and low amenities). For type 1 regions, special attention should be paid to housing rent affordability, because both high *ELDS* and high natural amenities could drive up the housing rent. For type 2 region, human capital retention could be a challenging issue. For type 3 regions, public policy could focus on how to translate their desirable natural amenities into local, economic and social development. And for type 4 regions, while these regions are likely going to decline, it is very important to evaluate whether public policy should focus on bringing jobs to these regions or help people move out of these regions.

As a final note, this study assumes symmetric and linear impact which could be further evaluated. From the labor demand side, it means that it is assumed a one unit increase in *ELDS* and a one unit decrease in *ELDS* would bring about impacts of similar magnitude, though in opposite directions. This may not be true. For example, housing rent and population change could react differently while facing positive or negative *ELDS*. For future research, it is recommended to evaluate the possibilities of asymmetric and non-linear impacts.

2.6 Tables

Table 2.1: Summary statistics

	2000	2005	2006	2007	2008	2009	2010	2011
wage (log)	10.15	10.36	10.36	10.41	10.47	10.48	10.48	10.46
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.16)	(0.17)
rent (log)	8.87	9.1	9.14	9.18	9.22	9.25	9.27	9.27
	(0.19)	(0.21)	(0.21)	(0.22)	(0.22)	(0.22)	(0.21)	(0.21)
Job growth	30.37%	34.84%	38.58%	40.29%	45.76%	39.92%	36.97%	37.92%
	(33.47%)	(38.23%)	(40.35%)	(40.72%)	(42.31%)	(41.15%)	(40.51%)	(41.21%)
Population growth	13.98%	20.48%	22.00%	23.45%	24.79%	26.05%	27.24%	28.24%
	(11.68%)	(18.19%)	(20.02%)	(21.44%)	(22.56%)	(23.44%)	(24.36%)	(25.21%)
Labor Demand shifter	17.50%	21.54%	24.81%	26.06%	30.68%	25.77%	22.49%	23.36%
	(3.43%)	(5.51%)	(5.14%)	(5.30%)	(5.29%)	(5.45%)	(5.89%)	(6.01%)
Unemployment rate	5.84%	6.49%	6.04%	5.93%	5.84%	9.13%	10.06%	9.75%
	(1.90%)	(1.67%)	(1.52%)	(1.57%)	(1.66%)	(2.38%)	(2.68%)	(2.64%)
Labor force participation	64.05%	63.99%	63.39%	63.03%	64.24%	63.44%	62.77%	60.40%
	(4.76%)	(4.63%)	(4.39%)	(4.36%)	(4.59%)	(4.56%)	(4.44%)	(4.40%)
college degree share	15.80%	19.70%	19.54%	19.98%	20.31%	20.38%	20.56%	20.08%
	(5.06%)	(5.92%)	(5.87%)	(5.94%)	(6.09%)	(6.07%)	(6.15%)	(6.05%)
GDP per job	10.93	11.1	11.13	11.16	11.18	11.19	11.23	11.25
	(0.21)	(0.21)	(0.21)	(0.21)	(0.21)	(0.20)	(0.21)	(0.21)
renter share	28.29%	23.84%	23.29%	23.27%	24.04%	25.06%	26.37%	26.75%
	(6.26%)	(5.70%)	(5.60%)	(5.70%)	(5.68%)	(5.83%)	(6.01%)	(6.16%)
population (log)	13.3	13.35	13.36	13.37	13.38	13.39	13.4	13.41
	(1.23)	(1.23)	(1.23)	(1.23)	(1.23)	(1.23)	(1.23)	(1.23)

Table 2.2: Correlation coefficients

	wage (log)	Housing rent (log)	Labor Demand (job) growth	Population growth	Labor Demand shifter	Unemployment rate
wage (log)	1.0000					
Housing rent (log)	0.7460	1.0000				
Labor Demand (job) growth	0.1164	0.1671	1.0000			
Population growth	0.0639	0.3264	0.5703	1.0000		
Labor Demand shifter	0.3447	0.3897	0.2204	0.2839	1.0000	
Unemployment rate	0.0061	0.2463	-0.0781	0.1272	-0.1143	1.0000
Labor force participation	0.3469	0.0959	0.0975	0.0307	0.0032	-0.4733
college degree share	0.7009	0.5727	0.1501	0.1737	0.4246	-0.1993
GDP per job	0.7486	0.6443	0.1163	0.1201	0.2157	0.1163
Natural Amenity	-0.0129	0.4442	0.2185	0.4355	0.1603	0.2023
renter share	-0.2142	0.2143	0.0053	0.2157	-0.0586	0.3212
population (log)	0.3785	0.3495	0.1692	0.2581	0.1318	0.0244

	Labor force participation	college degree share	GDP per job	Natural Amenity	renter share	population (log)
Labor force participation	1.0000					
college degree share	0.4280	1.0000				
GDP per job	0.2677	0.4941	1.0000			
Natural Amenity	-0.2480	0.0610	0.0511	1.0000		
renter share	-0.0752	-0.0118	0.0548	0.4914	1.0000	
population (log)	0.2260	0.3545	0.5432	0.1777	0.1464	1.0000

Table 2.3: wage equation results

	wage (log)					
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
Labor Demand shifter			*0.267****	*0.186****	*0.267****	*0.151****
			(0.0550)	*(0.0475)*	*(0.0541)*	*(0.0450)*
Amenity Index		*0.00408*		*0.00216*		*0.00397*
		(0.00435)		*(0.00436)*		*(0.00366)*
Housing rent (log) residual					*0.133****	*0.209****
					(0.0194)	*(0.0178)*
renter share	*-0.245****	*-0.357****	*-0.239****	*-0.356****	*-0.239****	*-0.403****
	(0.0615)	*(0.0548)*	*(0.0611)*	*(0.0545)*	*(0.0601)*	*(0.0513)*
college degree share	*1.001****	*1.154****	*1.027****	*1.140****	*1.027****	*1.122****
	(0.0917)	*(0.0699)*	*(0.0911)*	*(0.0697)*	*(0.0898)*	*(0.0637)*
Labor force participation	*0.286****	*0.332****	*0.239****	*0.313****	*0.239****	*0.328****
	(0.0621)	*(0.0590)*	*(0.0624)*	*(0.0589)*	*(0.0614)*	*(0.0565)*
Unemployment rate	*-0.830****	*-0.694****	*-0.741****	*-0.624****	*-0.741****	*-0.594****
	(0.0701)	*(0.0704)*	*(0.0720)*	*(0.0723)*	*(0.0709)*	*(0.0711)*
GDP per job (log)	*0.132****	*0.218****	*0.105****	*0.207****	*0.105****	*0.229****
	(0.0231)	*(0.0197)*	*(0.0236)*	*(0.0199)*	*(0.0233)*	*(0.0185)*
population (log)	*0.204****	*0.0270****	*0.169****	*0.0268****	*0.169****	*0.0230****
	(0.0262)	*(0.00602)*	*(0.0270)*	*(0.00599)*	*(0.0266)*	*(0.00506)*
RE or FE	*FE*	*RE*	*FE*	*RE*	*FE*	*RE*
N	*1712*	*1712*	*1712*	*1712*	*1712*	*1712*

Table 2.4: Rent equation results

	rent (log)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Labor Demand shifter			0.419***	0.368***	0.419***	0.357***
			(0.0725)	(0.0627)	(0.0714)	(0.0597)
Amenity Index		0.0763***		0.0725***		0.0723***
		(0.00614)		(0.00618)		(0.00518)
wage (log) residual					0.230***	0.341***
					(0.0337)	(0.0307)
renter share	0.142~	0.174*	0.151~	0.175*	0.151~	0.182**
	(0.0814)	(0.0726)	(0.0805)	(0.0720)	(0.0793)	(0.0684)
college degree share	-0.0712	0.475***	-0.0304	0.447***	-0.0304	0.546***
	(0.121)	(0.0942)	(0.120)	(0.0937)	(0.118)	(0.0861)
Labor force participation	0.435***	0.429***	0.361***	0.387***	0.361***	0.388***
	(0.0821)	(0.0775)	(0.0822)	(0.0771)	(0.0810)	(0.0745)
Unemployment rate	-0.216*	-0.128	-0.0758	0.00687	-0.0758	0.0300
	(0.0928)	(0.0918)	(0.0949)	(0.0938)	(0.0935)	(0.0924)
GDP per job (log)	0.244***	0.302***	0.202***	0.277***	0.202***	0.289***
	(0.0306)	(0.0263)	(0.0311)	(0.0264)	(0.0307)	(0.0248)
population (log)	0.0652~	0.0121	0.0109	0.0117	0.0109	0.00877
	(0.0347)	(0.00845)	(0.0356)	(0.00844)	(0.0350)	(0.00714)
RE or FE	FE	RE	FE	RE	FE	RE
N	1712	1712	1712	1712	1712	1712

Table 2.5: Job growth equation results

	Job Growth					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Labor Demand shifter	1.392***	1.377***	1.369***	1.369***	1.369***	1.367***
	(0.107)	(0.105)	(0.0722)	(0.0711)	(0.0719)	(0.0711)
Amenity Index		0.0762***		0.0772***		0.0770***
		(0.0216)		(0.0185)		(0.0184)
pop chg residual			1.009***	1.011***	1.011***	1.013***
			(0.0238)	(0.0234)	(0.0238)	(0.0235)
wage (log) residual					-0.0193	-0.0120
					(0.0358)	(0.0355)
rent (log) residual					0.0921***	0.0847**
					(0.0271)	(0.0269)
renter share	0.0713	0.0174	0.137~	0.0104	0.138~	0.0133
	(0.123)	(0.120)	(0.0828)	(0.0816)	(0.0826)	(0.0816)
college degree share	0.629***	0.474**	0.445***	0.439***	0.445***	0.471***
	(0.183)	(0.172)	(0.123)	(0.118)	(0.123)	(0.119)
Labor force participation	1.168***	1.169***	1.053***	1.221***	1.053***	1.222***
	(0.126)	(0.124)	(0.0849)	(0.0841)	(0.0846)	(0.0839)
Unemployment rate	-1.540***	-1.549***	-1.675***	-1.560***	-1.676***	-1.555***
	(0.145)	(0.145)	(0.0979)	(0.0975)	(0.0976)	(0.0973)
GDP per job (log)	0.117*	0.0991*	0.0912**	0.0902**	0.0912**	0.0942**
	(0.0477)	(0.0453)	(0.0321)	(0.0311)	(0.0320)	(0.0312)
RE or FE	FE	RE	FE	RE	FE	RE
N	**1712**	**1712**	**1712**	**1712**	**1712**	**1712**

Table 2.6: population growth equation results

	Population Growth					
	(1)	***(2)***	***(3)***	***(4)***	***(5)***	***(6)***
Labor Demand shifter	*0.793**** *(0.0739)*	*0.797**** *(0.0747)*	*0.816**** *(0.0529)*	*0.806**** *(0.0525)*	*0.816**** *(0.0528)*	*0.798**** *(0.0527)*
Amenity Index		*0.0662**** *(0.0107)*		*0.0650**** *(0.00927)*		*0.0654**** *(0.00869)*
Job growth residual			*0.542**** *(0.0128)*	*0.494**** *(0.0120)*	*0.544**** *(0.0128)*	*0.486**** *(0.0120)*
wage (log) residual					*0.0138* *(0.0262)*	*0.0891**** *(0.0265)*
rent (log) residual					*-0.0582*** *(0.0199)*	*-0.0625*** *(0.0202)*
renter share	*0.371**** *(0.0848)*	*0.267*** *(0.0858)*	*0.305**** *(0.0607)*	*0.289**** *(0.0603)*	*0.305**** *(0.0606)*	*0.281**** *(0.0606)*
college degree share	*0.389*** *(0.126)*	*0.439**** *(0.118)*	*0.571**** *(0.0904)*	*0.505**** *(0.0850)*	*0.571**** *(0.0902)*	*0.491**** *(0.0848)*
Labor force participation	*-0.0352* *(0.0855)*	*0.151~* *(0.0896)*	*0.0791* *(0.0622)*	*0.123** *(0.0625)*	*0.0791* *(0.0621)*	*0.133** *(0.0629)*
Unemployment rate	*0.155* *(0.0990)*	*0.269** *(0.105)*	*0.289**** *(0.0717)*	*0.277**** *(0.0730)*	*0.289**** *(0.0716)*	*0.278**** *(0.0736)*
GDP per job (log)	*-0.0204* *(0.0279)*	*-0.0167* *(0.0314)*	*0.00561* *(0.0235)*	*-0.00701* *(0.0225)*	*0.00561* *(0.0235)*	*-0.00452* *(0.0225)*
RE or FE	*FE*	*RE*	*FE*	*RE*	*FE*	*RE*
N	***1712***	***1712***	***1712***	***1712***	***1712***	***1712***

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Chapter 3: Exploring the impacts of productivity (or wage) externalities for the post 2000 US local labor market

Abstract: This chapter explores two potential causes of labor market productivity externalities in the post 2000 US labor market: the human capital externality and labor market matching. Sorting, direction of causality, and imperfect substitutions, are severe identification challenges in this type of research. Corresponding strategies are developed to ease the estimation biases. This study presents three major findings: first, from 2000 to 2011, the contribution of human capital externalities to productivity growth is at least three times the contribution of the labor market matching effect; secondly, this paper finds that higher skill groups experience higher human capital externality effects; third, the human capital externalities observed for the low-skill group are more likely to be a migration sorting effect; finally, younger workers benefit more from labor market matching effect while older workers benefit more from human capital externality effect.

Keywords: human capital externality, labor market matching, post 2000 US labor market

3.1 Introduction

Why do people living in urban areas, especially large urban areas, receive higher wages? Is it because they are closer to people with higher levels of human capital and enjoy the benefit of knowledge spillover? Or is it because they are living in a larger labor market where the chance of finding the job that best matches their ability is higher? Or it is simply because more productive people sort themselves into bigger and more productive cities? More specifically, if there are knowledge spillover and labor market matching effects, are different sub-groups of labor force experience the effects in a similar order of magnitude? These questions are essential for the understanding of interactions between human capital and city.

Based on the theory on agglomeration economies, labor market matching and knowledge spillover are considered to be two of the primary micro-foundations. Most empirical literature has found sizeable positive effects from labor market matching (Heuermann *et al.*, 2010; Melo *et al.*, 2009). However, there is far less consensus on the existence of knowledge spillovers. The reason for that is the difficulty in identifying knowledge spillover effects. The identification challenge comes from three directions: direction of causality (Duranton, 2006), the inability to distinguish imperfect substitution from externalities (Moretti, 2004), and sorting (C. H. Wheeler, 2001).

To control the biases that could be created by these challenges, this chapter proposed a comprehensive set of identification strategies. First, it introduces a new way to measure aggregated human capital based on occupation rather than education. Compared with education-based measurements, the occupation-based measurement could ease the reverse causality concern between human capital and productivity growth. Secondly, to distinguish imperfect substitution from externalities, following Moretti (Moretti, 2004), this chapter investigates the imperfect substitution issue by estimating models for workers across a skill spectrum. Thirdly, two identification strategies are proposed to control for sorting bias: the occupation fixed effect is used to control for skill-based sorting effects (Gibbons & Waldman, 2004) while separate models are estimated for non-migrants and migrants to gauge the migration sorting effects. Finally, regional fixed effects are used to control for time invariant regional characteristics while regional characteristics such as the unemployment rate, rent, and labor demand shock are used to control for time variant regional characteristics.

The goal of this chapter is to explore the relative contributions of human capital externalities and labor market matching effects in enhancing productivity in the post 2000 US labor market. The empirical model is an hedonic wage model with human capital externalities adapted from Rauch (1993), and the data used are from the Census 2000 and the America Community Survey from 2005-2011.

This study presents three major findings: first, from 2000 to 2011, the contribution of human capital externalities to productivity growth is three times the contribution from the labor market matching effect; secondly, this paper finds that higher skill groups experience higher human capital externality effects; thirdly, the human capital externality observed for the low-skill group is more likely to be a migration sorting effect.

This chapter contributes to the local labor market externalities and urban agglomeration literatures in two ways. First, it brings together the human capital externalities literature and urban wage premium literature, and compares the contributions of human capital externalities with the labor market matching effect. Secondly, it investigates different segments of the labor market (by education groups for female, male, manufacturing workers, professional workers, younger workers, older workers, owners, renters, stayers, and movers), and offers a more detailed road map for potential policy discussions.

This chapter is organized as follows. Section 2 discusses the potential micro-foundations of labor market related productivity externalities; section 3 presents the identification strategy, empirical model, and data summary. Section 4 presents the baseline estimation results and section 5 presents the robustness check results. Section 6 concludes the presentation.

3.2 Human capital externality and labor market matching

What are the potential micro-foundations of labor market related productivity externalities? In the *Handbook of Regional and Urban Economics* the chapter for "Micro-foundations of urban agglomeration economies", Duranton and Puga (2004) listed **input sharing**, **labor market matching**, and **learning** as the three micro-foundations of agglomeration economies. Two of the proposed micro-foundations are related to the labor market: labor market matching, and learning. Traditionally, labor economists focus attention on the learning effect, where they usually call it human capital externalities, while urban economists usually focus on the labor market size effect, referred to as the urban wage premium (Heuermann *et al*., 2010).[8]

Learning or knowledge spillover is considered to be the key mechanism behind human capital externalities (Jacobs, 1970). Jacobs (1970) argued that cities are an engine of economic growth because they facilitate the exchange of ideas, especially between highly skilled entrepreneurs and managers. Human capital externality works through the exchange of ideas, imitation, or learning by doing that occurs between workers. Therefore, the presence of high-level

[8] Of cause, in traditional labor market externalities literature labor market size is used as a control variable, and in traditional urban wage premium literature human capital is also used as a control variable. Because of multiple levels of identification challenges, few researches have tried to compare the contributions of these two channels.

human capital in a local labor market is used to identify the human capital externalities (Acemoglu & Angrist, 2001; Moretti, 2004; Rauch, 1993).

Labor market matching is a manifestation of the urban size effect. Larger labor markets are more efficient for employer and employee matching. This is also the “thick labor market” idea of the New Economic Geography (Krugman, 1991). Therefore, it is expected that a larger labor market would bring some wage premium to workers. In much of the literature, the labor market matching effect is measured by using the log of population. According to a meta-analysis by Melo, *et al*. (2009), most research found that the doubling of the size of population usually brings a 3-8% wage premium.

On the other side, there is far less consensus on the existence of human capital externalities. Moretti (2004) and Rauch (1993) find relatively strong evidence for the existence of human capital externalities. Acemoglu & Angrist (2001) find less strong evidence for external returns to human capital. Ciccone & Peri (2006) find no evidence of external returns to human capital after controlling for labor market compositional effects. Besides difference in identification strategies, another key difference among these papers is how to **measure aggregate human capital**. Most of existing literature uses two measurements: average years of schooling(Acemoglu & Angrist, 2001; Rauch, 1993) and the share of college degree holders (Moretti, 2004).

There are limitations in using education attainment to measure aggregated human capital. First of all, education is not a precise measure of skills or abilities. College degree holders in different majors could have very different skill sets. Secondly, when using education attainment, there is reverse causality concern. The reverse causality argument suggest that when productivity rises, income increases, and the demand of education increases because education is a type of normal consumption good (Duranton, 2006).

In this paper, following Autor & Dorn (2009), Bacolod *et al.*, (2009), and Ingram & Neumann (2006), a human capital measurement based on the occupation or cognitive ability is proposed by utilizing the occupation information system (ONET, formally known as the Dictionary of Occupation Classification, DOC). The cognitive ability in ONET is defined as "ability that influences the acquisition and application of knowledge in problem solving." There are 21 measurements of cognitive abilities as listed in table 3.1. There is a very high correlation within the 21 descriptors of cognitive abilities. Principal component analysis (PCA) is used to extract the most important variations from this set of variables. The first principal component is selected from the PCA analysis of cognitive abilities. It accounts for 62.2% of the overall variations. Occupations that require the highest level of the first principal component factor included scientists, doctors, and lawyers, etc. From here on, this first component is referred as "cognitive ability." In figure 3.1a, occupational average wage level adjusted for worker characteristics[9] is plotted against the occupation's cognitive ability. At the occupation level, cognitive ability is a very good predictor of wage levels.

The regional aggregated human capital measure in this paper is built using a share of workers in the top occupations ranked by the corresponding occupation cognitive ability level. The advantage of building a measurement in this way is that researchers can define what "top occupations" are by their own research objectives. Following Jacobs (1970), it is likely that only

[9] The occupation average wage adjusted for workers' characteristics is done by running a hedonic wage equation with occupation dummy variables. Other control variables are: years of education, age, race, sex, marital status, observation year dummies, and metropolitan area dummies.

the portion of the workers with the highest knowledge or ability will be the source of knowledge creation and be responsible for enhancing productivity. An aggregated human capital measurement that is based on skill/knowledge/ability and with stronger weight towards the top percentile of the human capital distribution will be a more appropriate measurement.

In this paper, the share of workers in the top 20% of occupations ranked by corresponding cognitive ability is used. There are two reasons for choosing the top 20%: first, as shown in table 3.3a, variable "MSA % of top 20% occ" is highly correlated with all other occupation ability based measures; secondly, it is based on the author's preference for the 80-20 Pareto principle, which states that roughly 80% of the effects come from 20% of the causes. Choosing other measures that also give more weight to high skilled workers (such as top 5% or top 1%) does not change the overall finding.

In figure 3.1.b, metropolitan areas' average wage adjusted for workers' characteristics[10] is plotted against the metropolitan areas' share of top 20% occupations. The adjusted R-square for this simple two-variable regression is 24.69%. In figure 3.1.c, metropolitan areas' adjusted wage is plotted against the metropolitan areas' share of college degree holders; the adjusted R-square for this regression is 45.25%. In figure 3.1.d, metropolitan area's adjusted wage is plotted against the metropolitan areas' log of population. The adjusted R-square for this regression is 50.41%.

If the share of college degree holders predicts metropolitan areas' wage better than the share of top 20% occupation, why use the later measurement? There are two reasons: first, to avoid the high correlation between population size and share of college degree holders; secondly,

[10] The metropolitan area average wage adjusted for workers' characteristics is done by running a hedonic wage equation with metropolitan area dummy variables. Other control variables are: years of education, age, race, sex, marital status, and observation year dummies.

is to avoid reverse causality of the impact from productivity enhancing to obtain a higher level of education. In the correlation coefficient table 3.3b, the correlation between share of college degree holders and share of top 20% occupations is 0.867; however, the correlation between college share and population size is larger (0.503) than the correlation between share of top 20% occupation and population size (0.304). In order to better differentiate the human capital and population size dimensions of a local labor market and to avoid the high correlation between population size and share of college degree holders, this research prefers to use a share of the top 20% occupations to measure the human capital.

The other important reason to use a share of the top 20% occupations is to avoid the reverse causality issue. As pointed out by Duranton (2006), because education can be viewed as a normal consumption good, it is likely that productivity growth (income growth) will induce people to want to obtain more education (one type of consumption). Therefore, the observed positive correlation between education level growth and income growth, could be a result caused by income growth, not the other way around. Using a share of top 20% occupations can help to ease reverse causality concern. The share of top 20% occupations increase is a labor market demand factors, it is not directly driven by income growth.

3.3 Identification strategy, empirical model and data

3.3.1 Identification strategy

One of the biggest challenges to the human capital externality and urban wage premium literatures are unobserved personal characteristics and sorting effects. It is acknowledged that many personal characteristics, such as cognitive ability, non-cognitive ability, and effort are difficult to observe by researchers and these characteristics have strong influence on labor market outcome (Heckman, *et al*., 2006). These unobserved characteristics could be important in determining workers' wage levels and it could also impact workers' location decisions. It is likely that workers receive higher wages in larger urban areas with higher levels of aggregated human capital as a result of workers being able to sort themselves to those larger local labor markets. Therefore, without control for this locational **sorting effect** based on personal characteristics, the estimations of human capital externality and labor market matching effects could be biased. This study does not directly address the spatial/human capital aggregation problem. The sorting effect is indirectly addressed by looking into the difference in impact of human capital externality between stayers and movers.

The core identification strategy in this paper relies on **occupation-based sorting**. Moretti (2004) provides an example of two high school graduates, one works as a lab technician in a San Diego bio-tech firm and one works in a shoe factory in Miami. Using education attainment, high school diplomas in this case, a researcher cannot tell the human capital different between these two workers. However, by occupation requirement, bio-tech lab technician and shoe manufacturing in this case, a researcher knows more about the productive human capital requirement in these two occupations. As argued by Gibbson and Waldman (2004) "human capital is specific to the nature of the work,", and job tasks or occupations are better proxies for the nature of the work compared with other proxies such as education level and test scores (such as AFQT[11] test).

Therefore, this chapter proposes using occupation fixed effects to control for individual unobserved characteristics that are related with occupation. The logic behind this argument is that occupation is a labor market matching outcome: employers signal their willingness to pay for a

[11] The Armed Forces Qualification Test (AFQT) is covers four sections: world knowledge, paragraph comprehension, arithmetic reasoning, and mathematics knowledge. The AFQT scores is a Military Entrance Score. In human capital research, AFQT score is widely used as measurement for skill (Carneiro & Heckman, 2003).

certain job position and will always try to find the most able worker given their willingness to pay. On the other hand, given the ability level of a worker, he/she will always try to find the job position that rewards his/her ability the most. Therefore, the wage offered/accepted in this job matching process can be viewed as the reward for worker's ability, and the revealed indication of this worker’s ability in this case is the job position offered/accepted.

An important characteristic of the matching process described above is that it does not only refer to the hiring process, it is a dynamic process. As the employer knows more about the employee’s ability, the employer’s willingness to pay and the employee’s job position can change over time. Therefore, even without individual level panel data, with detailed occupation information, both time-invariant and time-variant individual unobserved characteristics could be controlled to a certain degree. Of cause, there are maybe other individual unobserved characteristics that are not related to occupation. However, it may not create a problem for the estimation if those unobserved characteristics are not related to both the variables of interest and dependent variable.

Identification in this research also relies on location. Assume there are two high school graduates, both work as lab technicians in bio-tech firms, one firm located in San Diego, and one firm located in Miami. San Diego is a hub for bio-tech research, it accounts for a higher share of total regional economic activity compared with Miami. Assume the lab technician in San Diego has a higher wage than the lab technician in Miami. Is it because the lab technician, with higher level of productive human capital, sorts himself to San Diego? Or is it because San Diego, a hub for bio-tech research, makes similar worker more productive? The first case is migration sorting, while the second case is the knowledge spillover effect that is the topic of interest.

To correct the bias caused by **migration sorting**, a longitudinal data set is required. The widely used longitudinal data in US are Panel Study of Income Dynamics dataset by University of Michigan and National Longitudinal Surveys dataset by Bureau of Labor Statistics. However, the numbers of observations are limited in these two databases. As discussed later in this section, the identification in this paper relies on using an occupation*region fixed effect. The numbers of observations in these two databases are not sufficient to support the identification strategy. Therefore, instead of using longitudinal data to correct migration sorting effect, results based on people who were born and work in the same state (stayers) and people who work in the state that is not their birth place (movers) are presented in the robust check section. As discussed in section 5, without control for migration sorting, the results presented in section 4 are slightly upward biased. The results based on stayers in section 5 can be used as lower bound estimation results.

Two methods are used to control for locational characteristics. For time invariant characteristics, such as natural amenities, are controlled by using a **locational fixed effect**. For **time variant location characteristics** that are related to independent variable (productivity) and dependent variables (human capital and labor market size), a list of time-variant variables, as discussed later in this section, are introduced to provide a more precise estimation results.

An identification strategy based on locational and occupational fixed effects can help to distinguish a shoe factory worker from a bio-tech lab technician, and also a worker in Miami from a worker in San Diego. However, it is not able to distinguish two bio-tech lab technicians, one from Miami and one from San Diego. Therefore, a regional*occupation fixed effect identification is used in the empirical estimation. A total of 283 Metropolitan statistical areas and 426 occupations at five-digit level standard occupation classification identified in the data used in this research yield 120,558 potential groups for fixed effect. The performance of this identification strategy is robust under different empirical specification as presented in the robustness check section.

3.3.2 Empirical model and data

The empirical model adopted by this research is the Mincerian wage equation with human capital externalities developed by Rauch (1993). Ciccone and Peri (2006) criticized how this approach was used by Acemoglu and Angrist (2001) and Moretti (2004) for they did not consider the labor market composition effect and with the potential for an upward bias in estimation results. In this paper, the Mincerian approach is used for its flexibility, while the labor market composition effect is controlled by using an occupation fixed effect. Following Moretti (2004), the empirical model is:

$$\ln\left(w_{i,o,m,t}\right) = X_{i,o,t}\beta + Z_m\alpha + d_t + d_{m*o} + \mu_{i,o,m,t} \qquad (2)$$

where $w_{i,o,m,t}$ is the hourly wage of individual *i* working in occupation *o* living in metropolitan area (MSA) *m* in time period *t*; $X_{i,o,t}$ is a vector of the individual characteristics of the worker, including years of schooling, potential experience, and square of potential experience, race, sex, and marital status; Z_m is a vector of time variant MSA characteristics that include MSA level potential knowledge spillover measures, labor market matching measures, and labor market demand shock measures, unemployment rate, and median rent level; d_{m*o} represents MSA*occupation fixed effect; and d_t is a time fixed effect.

In the identification section, detailed arguments were presented about why using MSA*occupation fixed effect to control for MSA and occupation time invariant characteristics. In this section, the MSA level time variant variables will be presented and discussed in detail. There are three time-variant MSA variables, except for the two key variables (share of top 20%

occupation and log of population size), are considered in this chapter: labor demand shock, unemployment rate, and housing cost/rent.

The **labor demand shock** measure was originally proposed by Katz and Murphy (1992) and it is used by Moretti (2004) to capture the exogenous shifts in the relative demand for different skill groups.

$$shock_{j,m} = \sum_{s} \eta_{s,m} \Delta E_{j,s} \qquad (3)$$

where *j* represents skill groups, *s* is the two-digit level industries defined by NAICS, $\eta_{s,m}$ is the share of employment by industry *s* in region m, and $\Delta E_{j,s}$ is the nationwide change in employment for skill group *j* by industry *s*. $shock_{j,m}$ represents the labor demand shock of skill group *j* in regions *m*, based on the industry structure of region *m* and nationwide industry growth. The labor demand shock is expected to be positively correlated with productivity growth.

Metropolitan area **unemployment rates** change over time, high unemployment indicating a distressed labor market. Therefore, it is likely that the unemployment rate is negatively related to productivity growth. **Housing cost/rents** increase with a positive labor demand shock and productivity growth (Roback, 1982). It is expected that rent is positively related to productivity growth. When the housing supply elasticity is low, the housing rent raise even fast than the productivity growth (Glaeser, *et al*., 2006). Housing cost can also capture the changes in consumer amenity. According to the Roback's compensational difference spatial equilibrium model, an increase in consumer amenity would be capitalized into the housing cost.

The micro data used in this study is obtained from IPUMS USA project (Ruggles et al., 2010). The 2000 5% US Census, and 2005-2011 1% America Community Survey micro-data are grouped into three time periods: 2000, before financial crisis 2005-2007, and after financial crisis

2008-2011. The data are also split into 5 skill groups based on education attainment, EDU1 to EDU 5 are representing, high school dropouts, high school graduates, some college education, college degree holders, and post graduate degree holders, respectively**.** In the empirical analysis, this chapter focuses on individuals who are at least 22 years old, in the labor force and have wage income. The hourly wage rate is calculated by using the information on annual wage, weeks worked last year, and usual hours worked per week. Wage and rent in this study are not adjusted for inflation. The only other source of data is the population by metropolitan areas from Bureau of Economic Analysis.

From the first period 2000 to the third period 2008-2011, share of top 20% occupation increased from 22.4% to 28.0%, while the median population size increased by 9.1% during the same time period.

3.4 Results

The baseline estimation results is presented and discussed in this section. The estimation results for the individual productivity models are presented in table 3.4. The second column shows the results all the observations are pooled together. Columns 3-7 presents the results for 5 educational groups.

The result for all observation is as expected (column 2 in table 3.4). The growth of the top occupation share and population size both positively contribute to productivity growth. The coefficient of MSA population (log) is 0.0642: doubling population size would increase productivity for 6.42%. This result is comparable to other urban agglomeration literature, where most literature arrive at an elasticity of urban agglomeration 3 to 8% (Bettencourt & West, 2011; Melo et al., 2009). Given the average population growth from 2000 to 2008-2011 periods is 9.1%, the contribution of population growth to productivity growth is 0.56%.[12] The coefficient of human capital externality (MSA share of top 20% occupations) is 0.363: a 1% increase in the share of the top 20% occupations is associated with a 0.36% increase of productivity. Given the average 5.6% increase in share of top 20% occupations from 2000 to 2008-2011 periods, the contribution of human capital externality to productivity growth is 2.05%.[13] The contribution of human capital externality is 3.7 times the contribution of labor market matching.

Three key results are plotted in figure 3.2. In figure 3.2a, compare 2008-2011 with 2000, wage growth for the EDU1, EDU2, and EDU5 are higher than wage growth for EDU3 and EDU4. This U-shaped trend of wage growth has been investigated by Autor and Dorn (2009), where they use the increase use of computer technology as a mechanism to explain the polarization of the labor market. They argue that computer technology is complementary to higher-skilled workers, and it is also complementary to the portion of low-skilled work that focuses on non-routine job tasks. On the other hand, computer technology is substitutable for routine job tasks, usually performed by median-skilled workers.

One of the key challenges to Acemoglu & Angrist (2001) and Moretti's (2004) empirical strategy is that they could not separate the effects of increasing share of high skilled workers on the productivity gain and the imperfect substitutions between high skilled workers and low-skilled workers. The argument is that, besides productivity gains, an increasing share of high skilled workers could bring a negative effect to high skilled workers because of the downward sloping demand curve. On the other hand, an increasing share of high skilled workers could bring a positive effect to demand for the low-skilled worker. This positive imperfect substitution effect

[12] 1.091^0.0642-1=0.56%

[13] Exp(0.363*0.056)-1=2.05%

was also identified by Barbara Bergman in the 1960s/1970s (Hewings, 1977). Moretti (2004) shows in his study that the human capital externality is the strongest for the least educated group of workers because this group benefits from both positive human capital spillover effect and positive imperfect substitution effect from the increasing demand of high skilled labor.

As shown in figure 3.2b, the human capital externality increases as the educational level increases, with the exception of the least educated group. This positive association could be driven by differentiated human capital spillover effects for different groups. As argued by Autor & Dorn (2009), technology improvements bring more benefit to highly skilled group whose job tasks are complementary to new technology. The same logic applies here; the human capital externalities, that are partially facilitated by technology improvements, also bring more benefit to more highly skilled workers. The only exception is that the human capital externality for EDU1 group is larger than that for the EDU2 group. This could be evidence that, for the least educated group, the imperfect substitution effect is a significant component of observed human capital externalities. Moretti (2004) also finds evidence that the increasing human capital imperfect substitution effect benefit the lowest educated group the most.

Wheeler (2001) demonstrated that different segment of labor market could have different urban agglomeration effects. He argued that the matching effect should be the largest for the most educated group of workers where the firm capital and worker skill are complementary in production. In his empirical model, he finds that the matching effect is the greatest for the group of workers with college degrees and above. In contrast, the group of workers with less than 8 years of schooling does not have a significant matching effect. The results here are similar to those of Wheeler (2001): there is a positive association between matching effect and education level. As show in figure 3.2c, the trend is not as clear cut as shown in Wheeler: the labor market matching effect is the biggest for the group with some college education; while the labor market matching effect is not significant for the group without high school diploma. However, the difference among EDU3, EDU4, and EDU5 are not statistical significant at the 5% level.

To better understand the transition between 2000 to 2008-2011 in the way human capital externality and labor matching are contributing to the productivity growth for different groups, two shocks are applied to the estimated models in table 3.4. The following shock values are based on observed difference for share of top 20% occupation and population size between 2000 to 2008-2011 periods. The first shock is to apply a 5.6% (22.4% to 28.0%) increase in the share of top 20% occupations holding everything else constant. The productivity growth from this shock are, 2.72%, 1.31%, 2.09%, 3.39%, and 6.32%, for EDU1 to EDU5, respectively. The second shock is to apply a 9.1% increase in population holding everything else constant. The productivity growth from population increase shock are, 0.19%, 0.46%, 0.61%, 0.40%, and 0.40%, for EDU1 to EDU5, respectively.

The total productivity growth for the five education groups are 2.91%, 1.77%, 2.71%, 3.79%, and 6.72%, respectively. The contribution from the human capital externality dominates the contribution from the labor matching effect for all the groups; especially the lowest and highest educated groups both 94% contribution from human capital externalities. One possible explanation could be that local labor market size is become less important for labor matching process in the post 2000 period, because the development and wide use of internet for information exchange. Labor matching (firms post job vacancy information and workers search for available jobs) could be easily done via internet. However, the human capital externality is still dominantly working through a face to face interaction method.

Other baseline results are consistent with expectation: MSA level unemployment rate is negatively related with productivity growth; MSA level labor demand shock is positively related with productivity growth; and MSA level median rent is also positively related with productivity growth. In the robustness check section, only the results of key interest will be presented.

3.5 Robustness check

In this section, alternative specifications are designed to probe the robustness of the main results. These sets of robustness checking results can also shed some light on how human capital externalities and labor market matching could impact different segments of the labor market. The angles of different segments can help to facilitate more targeted policy discussion.

First, the sample is split into male and female. Second, the manufacturing workers and professional workers are pulled out to be investigated. Third, the sample is split into workers who are younger than 35 and older than 55 (and those between 35 and 55 are disregarded). Fourth, the sample is split into homeowners and renters. Finally, the sample is split into stayers (people who were born and work in the same state) and movers (people who were born and work in different states). These robustness checking results are presented in table 3.6. The third column shows the overall trend: that human capital externality is much more important in enhancing productivity compared with labor market matching for all ten specifications expect for in the younger workers group.

Wheeler (2006), in his study of wage growth among young workers, also finds labor market matching to be more important than human capital externalities for young workers' wage growth. He finds that between-job (job change) wage growth is more significant than within-job wage growth. Larger cities have more job hopping opportunities and young workers change jobs more frequently in urban areas (Finney & Kohlhase, 2008). Furthermore, Bleakley and Lin (2012) find that labor market size has a negative impact on wages for job-hoppers for all but young workers.

When the comparison is between younger and older workers, it is surprising that in most cases, the human capital externality effects are much larger for the older workers. Older workers, especially older, well-educated workers, experience a larger human capital externalities effect. This evidence suggests that experience and learning could go hand in hand. Munnel and Sass (2009) used this as an argument to suggest that older workers should work longer.

Male workers enjoy a similar level of human capital externalities benefit compared with female workers. The coefficients are 0.407 for male and 0.335 for female. The difference is statistically insignificant at the 5% level. The interesting exception is that, for the group without a high school diploma, female workers enjoy a much larger human capital externality than male workers (0.814 for female EDU1 group vs 0.281 for male EDU1 group). As argued in the last section, a large share of the human capital externality for low-skilled workers is driven by imperfect substitution of high skilled for low-skilled workers. The results here suggest that it is possible that low-skilled female workers are the major cause of the imperfect substitution, and they are more complementary to high skilled labor. According to Cortes (2008) based on 2000 Census data, the top two industries for low-skilled female is the apparel / textile industry and working in private households, while the top two industries for low-skilled male is landscaping services and car wash. The income elasticity of demand is likely higher for private households than for landscaping services.

The labor market matching effect is larger for male workers than for female workers, especially for workers with college degrees and above. This result suggests that labor market matching effect could be a potential source of the gender wage gap for high-skilled workers. To the best of my knowledge, there is no research that has examined this issue.

Comparing stayers and movers is part of the identification strategy to gauge the impact of the migration sorting effect. Members of the stayers group were born and work in the same state, while members of the movers group moved at least across a state line at some point in their lives. Results presented in table 3.6 indicate a large difference in the human capital externality effect for the two groups, 0.275 (stayers) and 0.591 (movers), respectively. The human capital externality for the entire population is 0.363 as presented in table 3.5. This difference could be an indication of sorting effects: people who made a long distance move are more able people (with higher ability level) when compared with people who did not make a long distance move. This endogenous self-selection could explain why observed human capital externalities are higher for movers. In section 4, the human capital externality for the entire population without considering the sorting/self-selecting effect could be upwardly biased. Therefore, estimation results for stayers can be used as lower bound estimates for the human capital externality effect.

The sorting effect is most likely driven by lower-skilled workers. As presented in table 3.6, the human capital externality movers in EDU1, EDU2, and EDU3 groups are significantly larger than the corresponding stayers groups. This result is as expected. High-skilled workers have the ability to search for jobs at a national or regional level, while low-skilled workers usually search for jobs at a local level. It is more difficult for low-skilled workers to move across state boundaries than high-skilled workers. Therefore, for a low-skilled worker who moves across a state boundary, it is an indication that the worker may have a higher ability than a low-skilled worker who was born and worked in the same state. In this case, a low-skilled mover demonstrates a sorting effect. The estimated coefficient for human capital externalities is likely upward biased for low-skilled movers.

When manufacturing workers are compared with professional workers, overall, the human capital externalities and labor market matching effect are similar for workers in these two industries. Comparing owners to renters, the overall externalities are also similar.

To summarize the findings of this robustness check section, the overall findings are similar to the baseline result. Secondly, younger workers benefit more from labor market matching effect while older workers benefit more from human capital externalities. Thirdly, a large urban wage premium for a man could be a cause of the observed gender wage gap, especially for the highly educated groups. Finally, sorting seems to be a strong cause for the observed human capital externality effect for the groups without college degrees.

3.6 Summary and Conclusion

The goal of this chapter is to explore two potential causes of labor market productivity externalities in the post-2000 US labor market. The baseline results indicate that, while both human capital externalities and labor market matching effect are positively contributing to productivity growth, the contribution of human capital externalities is at least three times larger than the contribution of labor market matching. Migration sorting and imperfect substitution do positively contribute to the productivity externalities. However, after taking these two factors into consideration, the effects of human capital externalities and labor market matching are still very significant in enhancing productivity growth.

The empirical strategy and modeling structure presented in this paper provide an opportunity to explore different segments of the labor market, as presented in the robustness check section. Also, the use of post-2000 data could shed some light on the most recent labor market issues.

Comparing with Moretti (2004), where he uses pre-2000 labor market data and finds that human capital externalities are largest for the lowest-skilled group, this study finds that human capital externalities are strongest for the highest-skilled group. It is very likely that the labor market is going through a change where the impacts for high-skilled workers are more captured within high-skilled workers. The research on labor market polarization (Autor & Dorn, 2009) supports findings in this study.

This study finds that younger workers are more likely to benefit from the labor market matching effect while older workers are more likely to benefit from the human capital externalities effect. Among younger workers, the group without a high school degree shows no gain from either human capital externalities or labor market matching effects. This group of low-skilled young adults should be the central focus for human capital policy. Meanwhile, older and highly educated workers seems to gain large benefits from both human capital externalities and labor market matching effects. This group of workers should be encouraged to work longer (Munnell & Sass, 2009).

Further research should further examine the low-skilled young adult group. Is there a strong inflow of immigrants that could be impacting this group? Are white and non-white, low-skilled younger adult labor market performance similar or different? Is there a gender performance difference in the low-skilled young adult group? Looking deeper into these issues can help form better policy to help this segment of the labor market.

3.7 Tables and figures

Table 3.1: Principal component analysis (PCA) for cognitive abilities

Occupation Characteristics	Factor 1	Factor 2	Unexplained
Oral Comprehension	**0.246**	-0.181	0.113
Written Comprehension	**0.248**	-0.182	0.100
Oral Expression	**0.236**	-0.202	0.153
Written Expression	**0.240**	-0.226	0.103
Fluency of Ideas	**0.243**	-0.101	0.199
Originality	**0.234**	-0.102	0.257
Problem Sensitivity	**0.249**	0.077	0.176
Deductive Reasoning	**0.264**	-0.061	0.081
Inductive Reasoning	**0.253**	-0.010	0.166
Information Ordering	**0.254**	0.032	0.155
Category Flexibility	**0.248**	-0.067	0.182
Mathematical Reasoning	**0.209**	-0.109	0.397
Number Facility	**0.195**	-0.090	0.481
Memorization	**0.225**	-0.008	0.336
Speed of Closure	**0.232**	**0.202**	0.179
Flexibility of Closure	**0.219**	**0.257**	0.185
Perceptual Speed	0.172	**0.372**	0.215
Spatial Orientation	-0.042	**0.458**	0.371
Visualization	0.115	**0.357**	0.461
Selective Attention	0.176	**0.344**	0.256
Time Sharing	0.141	**0.293**	0.493
Total explained variance	62.2%	13.7%	

Table 3.2, Data summary by time periods and education attainments

	All	2000	2005-2007	2008-2011	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
Hourly Wage (log)	2.83	2.70	2.89	2.93	2.34	2.61	2.77	3.08	3.37
	(0.76)	(0.73)	(0.76)	(0.76)	(0.68)	(0.66)	(0.67)	(0.73)	(0.77)
Years of education	13.74	13.53	13.83	13.89	8.63	12.00	13.35	16.00	18.00
	(2.63)	(2.60)	(2.60)	(2.66)	(2.19)	(0.00)	(0.48)	(0.00)	(0.00)
MSA % of college degree	34.8%	31.2%	36.6%	37.3%	-	-	-	-	-
	(8.3%)	(7.3%)	(8.0%)	(8.1%)	-	-	-	-	-
MSA % of top20 occ.	25.1%	22.4%	25.3%	28.0%	-	-	-	-	-
	(4.0%)	(2.6%)	(3.2%)	(3.8%)	-	-	-	-	-
MSA population (log)	14.41	14.37	14.41	14.46	-	-	-	-	-
	(1.33)	(1.34)	(1.32)	(1.32)	-	-	-	-	-
MSA median rent (log)	6.48	6.30	6.53	6.64	6.19	6.33	6.48	6.65	6.74
	(0.34)	(0.28)	(0.31)	(0.32)	(0.33)	(0.28)	(0.28)	(0.29)	(0.31)
MSA labor demand shock	0.07	-	0.09	0.12	0.02	0.01	0.06	0.12	0.14
	(0.08)	-	(0.05)	(0.10)	(0.03)	(0.03)	(0.06)	(0.09)	(0.10)
MSA unemployment rate	6.9%	5.7%	6.1%	8.8%	7.1%	6.8%	6.9%	6.9%	6.9%
	(2.1%)	(1.5%)	(1.1%)	(1.8%)	(2.2%)	(2.1%)	(2.1%)	(2.0%)	(2.0%)

Standard errors in parentheses

Table 3.3a, Correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) Hourly wage (log)	1.000							
(2) Years of education	0.365	1.000						
(3) MSA % of college degree	0.176	0.149	1.000					
(4) MSA % of top 20 occ.	0.170	0.126	0.867	1.000				
(5) MSA population (log)	0.116	0.063	0.503	0.304	1.000			
(6) MSA median rent (log)	0.310	0.479	0.659	0.617	0.493	1.000		
(7) MSA labor demand shock	0.259	0.511	0.272	0.402	0.055	0.533	1.000	
(8) MSA unemployment rate	0.037	-0.026	-0.074	0.183	0.068	0.208	0.320	1.000

Table 3.3b, Correlation coefficients

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) MSA % of top 80% occ	1.000						
(2) MSA % of top 60% occ	0.942	1.000					
(3) MSA % of occ above mean	0.911	0.981	1.000				
(4) MSA % of top 40% occ	0.866	0.952	0.983	1.000			
(5) MSA % of top 20% occ	0.689	0.827	0.877	0.911	1.000		
(6) MSA % of top 5% occ	0.345	0.520	0.597	0.653	0.879	1.000	
(7) MSA % of top 1% occ	0.270	0.446	0.526	0.583	0.824	0.985	1.000

Table 3.3c, compare education based measure and occupation based measure

	All	2000	2005-2007	2008-2011
MSA % of college degree	34.8% (8.3%)	31.2% (7.3%)	36.6% (8.0%)	37.3% (8.1%)
MSA % of top20 occ.	25.1% (4.0%)	22.4% (2.6%)	25.3% (3.2%)	28.0% (3.8%)

Table 3.4, Estimating labor market impact on productivity

	ALL	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
Period 2005-2007	0.0632***	0.0484***	0.0627***	0.0818***	0.0781***	0.136***
	(0.0023)	(0.0069)	(0.0039)	(0.0045)	(0.0149)	(0.0337)
Period 2008-2011	0.0959***	0.117***	0.127***	0.0786***	0.0862***	0.151***
	(0.0040)	(0.0103)	(0.0054)	(0.0091)	(0.0215)	(0.0478)
MSA % of top 20 occ.	0.363***	0.481***	0.233***	0.371***	0.597***	1.097***
	(0.0499)	(0.1210)	(0.0626)	(0.0711)	(0.0986)	(0.1190)
MSA population (log)	0.0642***	0.0216	0.0522***	0.0703***	0.0457**	0.0456*
	(0.0101)	(0.0255)	(0.0134)	(0.0154)	(0.0198)	(0.0270)
MSA unemployment rate	-0.371***	-0.256**	-0.489***	-0.480***	-0.527***	-0.384***
	(0.0419)	(0.1050)	(0.0549)	(0.0658)	(0.0837)	(0.1240)
MSA labor demand shock	0.238***	0.520***	0.416***	0.355***	0.267***	0.0388
	(0.0075)	(0.0876)	(0.0523)	(0.0567)	(0.0973)	(0.2090)
MSA median rent (log)	0.183***	0.0834***	0.187***	0.189***	0.153***	0.135***
	(0.0072)	(0.0191)	(0.0119)	(0.0129)	(0.0156)	(0.0176)
eduyear	0.0324***	0.0178***	-	0.0260***	-	-
	(0.0005)	(0.0005)	-	(0.0009)	-	-
exp	0.0281***	0.0194***	0.0259***	0.0296***	0.0348***	0.0385***
	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0006)
exp2	-0.000412***	-0.000224***	-0.000369***	-0.000445***	-0.000599***	-0.000638***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
female	-0.168***	-0.178***	-0.192***	-0.158***	-0.147***	-0.141***
	(0.0013)	(0.0029)	(0.0017)	(0.0015)	(0.0018)	(0.0023)
black	-0.0484***	-0.0206***	-0.0511***	-0.0457***	-0.0539***	-0.0511***
	(0.0016)	(0.0038)	(0.0018)	(0.0018)	(0.0030)	(0.0044)

Table 3.4, Estimating labor market impact on productivity (continue)

	ALL	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
hisp	-0.0719***	-0.0618***	-0.0853***	-0.0618***	-0.0853***	-0.0848***
	(0.0018)	(0.0038)	(0.0021)	(0.0019)	(0.0028)	(0.0042)
married	0.0933***	0.0931***	0.0813***	0.0789***	0.0999***	0.106***
	(0.0010)	(0.0023)	(0.0013)	(0.0012)	(0.0017)	(0.0025)
MSA*OCC groups	104,586	47,651	86,328	83,971	74,289	53,222
N	9,609,624	682,750	3,221,391	2,324,041	2,132,224	1,249,218
R-sq: within	0.112	0.055	0.076	0.09	0.104	0.095
R-sq: between	0.394	0.104	0.196	0.192	0.145	0.075

(1) All models applied fixed effect at MSA*OCC level, (2) ~ p<0.15, * p<0.10, ** p<0.05, *** p<0.01, Standard errors in parentheses, it is clustered with MSA*OCC groups

Table 3.5, contribution of human capital externality and labor market matching

Change 2008-2011 to 2000		MSA % of top 20 occ.		MSA population (log)		
		5.6%		9.1%		
	ALL	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
MSA % of top 20 occ.	2.05%	2.72%	1.31%	2.09%	3.39%	6.32%
MSA population (log)	0.56%	0.19%	0.46%	0.61%	0.40%	0.40%
Total	2.61%	2.91%	1.77%	2.71%	3.79%	6.72%
HCE share to Total	79%	94%	74%	77%	89%	94%

Table 3.6, Robustness check

	Key variables	ALL	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
Male	MSA % of top 20 occ.	0.407***	0.281*	0.320***	0.484***	0.436***	1.163***
		-0.0563	-0.15	-0.0796	-0.0934	-0.12	-0.153
	MSA population (log)	0.0791***	0.0213	0.0671***	0.0642***	0.0618***	0.0922***
		-0.0116	-0.0311	-0.0169	-0.0192	-0.0233	-0.0342
Female	MSA % of top 20 occ.	0.335***	0.814***	0.170**	0.276***	0.754***	1.052***
		-0.0654	-0.196	-0.0858	-0.0952	-0.127	-0.152
	MSA population (log)	0.0473***	0.0213	0.0330*	0.0760***	0.0241	-0.0149
		-0.0131	-0.0418	-0.0183	-0.0209	-0.0266	-0.0349
Manufacturing, NAICS 31-33	MSA % of top 20 occ.	0.621***	0.352	0.569***	0.607***	0.779***	0.825***
		-0.0871	-0.272	-0.132	-0.17	-0.208	-0.305
	MSA population (log)	0.0534***	0.0747	0.0561**	0.0429	0.118***	0.181**
		-0.0185	-0.0575	-0.0269	-0.0349	-0.04	-0.0714
Professional, NAICS 51-56	MSA % of top 20 occ.	0.589***	1.055***	0.294**	0.444***	0.923***	1.135***
		-0.0877	-0.36	-0.141	-0.154	-0.162	-0.232
	MSA population (log)	0.0696***	0.0401	0.0667**	0.0909***	0.02	0.0748~
		-0.0183	-0.0767	-0.0292	-0.0297	-0.0329	-0.0471
Age <35	MSA % of top 20 occ.	0.0496	0.172	0.0483	0.171*	0.566***	0.504***
		-0.0642	-0.199	-0.0983	-0.104	-0.125	-0.187
	MSA population (log)	0.0895***	0.00521	0.0689***	0.0833***	0.0721***	0.0604~
		-0.0127	-0.0411	-0.0201	-0.0222	-0.0242	-0.0389
Age > 55	MSA % of top 20 occ.	0.621***	0.445~	0.333**	0.471**	1.026***	1.396***
		-0.0935	-0.286	-0.138	-0.188	-0.238	-0.255
	MSA population (log)	0.102***	0.0748	0.0838***	0.124***	-0.0261	0.117**
		-0.0181	-0.0569	-0.0273	-0.0367	-0.0502	-0.0532

Table 3.6, Robustness check (continue)

	Key variables	ALL	EDU1: 0-11 years schooling	EDU2: 12 years schooling	EDU3: 13-15 years schooling	EDU4: 16 years schooling	EDU5: 17+ years schooling
Owner	MSA % of top 20 occ.	0.495***	0.496***	0.267***	0.326***	0.686***	1.287***
		-0.0543	-0.16	-0.0709	-0.0802	-0.108	-0.13
	MSA population (log)	0.0607***	0.0191	0.0573***	0.0763***	0.0332~	0.0523*
		-0.0107	-0.0328	-0.0148	-0.0163	-0.0214	-0.0295
Renter	MSA % of top 20 occ.	0.425***	0.515***	0.312***	0.700***	0.605***	0.458**
		-0.0664	-0.171	-0.1	-0.12	-0.157	-0.211
	MSA population (log)	0.0598***	0.0193	0.0450**	0.0611**	0.0692**	-0.00391
		-0.0137	-0.0365	-0.021	-0.0241	-0.0315	-0.0464
Stayer	MSA % of top 20 occ.	0.275***	0.182	0.122*	0.259***	0.503***	0.987***
		-0.0525	-0.207	-0.0731	-0.0872	-0.114	-0.179
	MSA population (log)	0.0446***	-0.0145	0.0301**	0.0468**	0.0436*	0.0492
		-0.0115	-0.0393	-0.0151	-0.0184	-0.0238	-0.0396
Mover	MSA % of top 20 occ.	0.591***	0.654***	0.478***	0.527***	0.675***	0.987***
		-0.0663	-0.15	-0.0933	-0.102	-0.134	-0.142
	MSA population (log)	0.0559***	0.0693**	0.0657***	0.0753***	0.0326	0.0206
		-0.0124	-0.0323	-0.0194	-0.0209	-0.0249	-0.0311

(1) All models applied fixed effect at MSA*OCC level, (2) all the other control variables as show in table 5 are also included in these models (3) ~ p<0.15, * p<0.10, ** p<0.05, *** p<0.01, Standard errors in parentheses, it is clustered with MSA*OCC groups

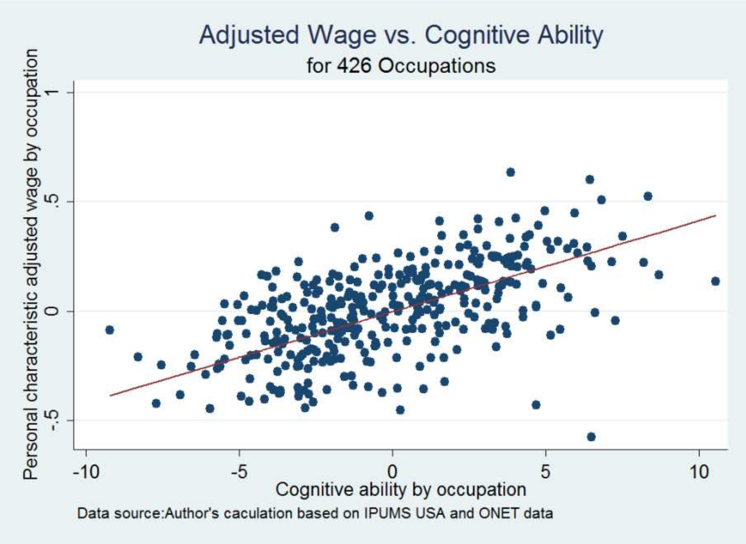

Figure 3.1a

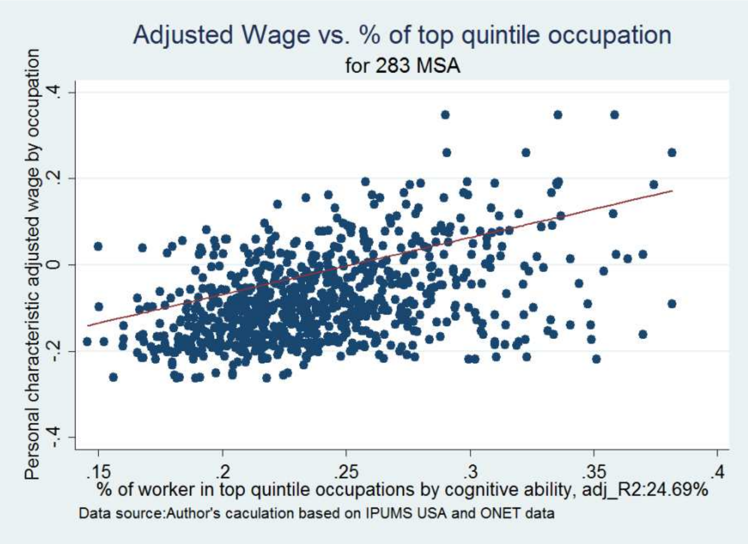

Figure 3.1b

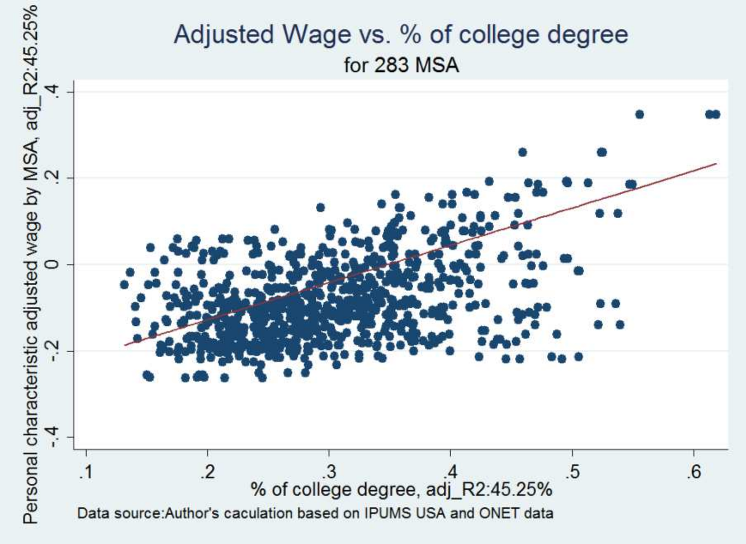

Figure 3.1c

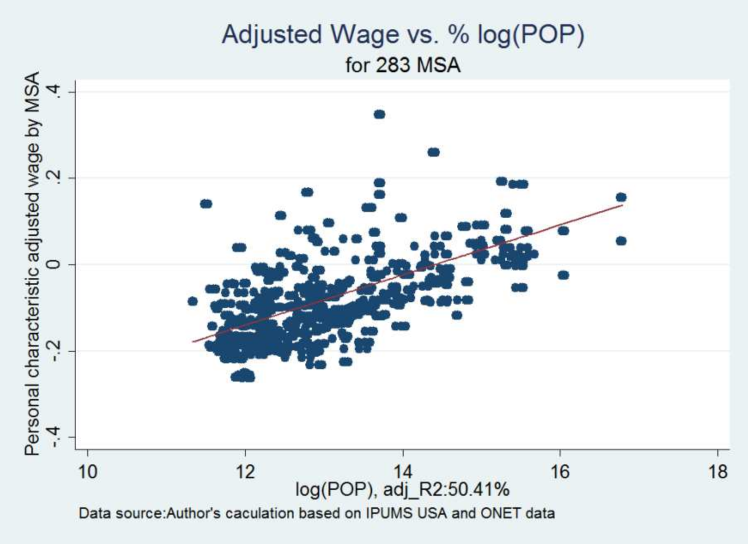

Figure 3.1d

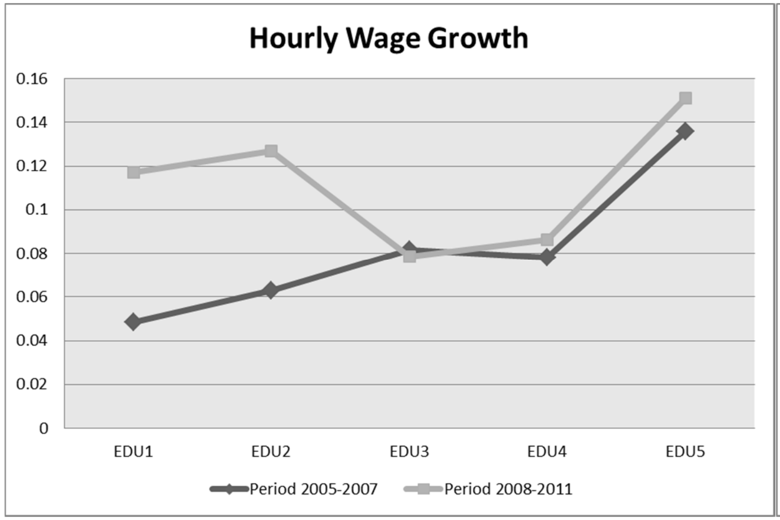

Figure 3.2a

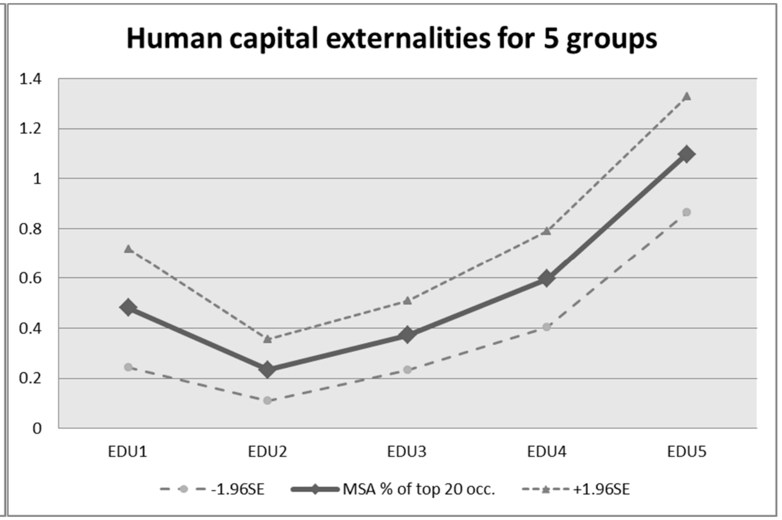

Figure 3.2b

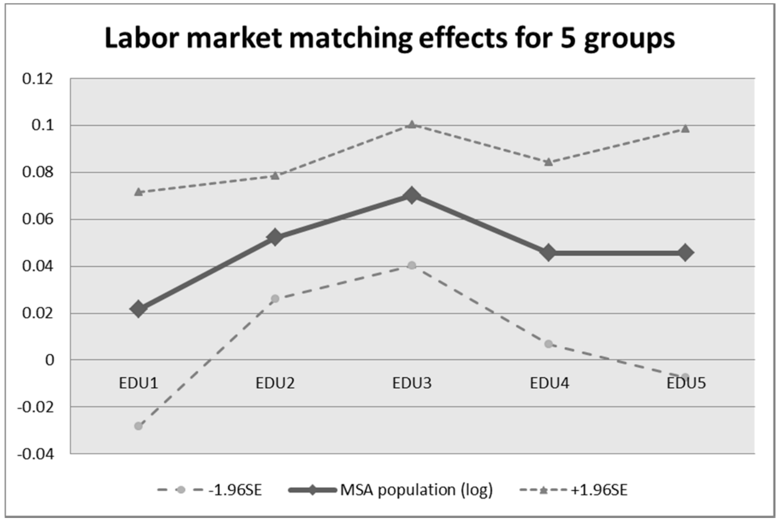

Figure 3.2c

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