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The Responsiveness of Migration to Labor Market Conditions

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THE RESPONSIVENESS OF MIGRATION TO LABOR MARKET CONDITIONS

DISSERTATION

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

By
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ABSTRACT OF DISSERTATION

THE RESPONSIVENESS OF MIGRATION TO LABOR MARKET CONDITIONS

This dissertation explores how migration responds to economic conditions, particularly differences in responsiveness for various segments of the population. After a brief introduction and motivation of my work in Chapter One, Chapter Two estimates the responsiveness of households' interstate migration to origin state labor market conditions and surrounding state labor market conditions. Each percentage point increase in origin state unemployment insurance claims leads to a 3.2 percent increase in household's propensity to migrate interstate and each percentage point increase in the unemployment insurance claims rate of surrounding states reduces interstate migration propensity by 5.2 percent. I then examine how this responsiveness varies by demographics and how it has changed over time. I determine that the responsiveness of migration to labor market conditions is weaker for several groups at high poverty risk, including less educated, non-employed and rural households and households with children present. I also show that between the early 1980s and mid 1990s labor market conditions became a smaller factor in household migration decisions, but since then labor market conditions have gained in importance.

While Chapter Two examines short-run migration responsiveness, Chapter Three explores the size of the long-run outflow (or inflow) of skilled labor occurring in local areas in response to economic conditions, amenities and other area characteristics. I estimate the extent of this brain gain and brain drain within localities in the United States between the early 1990s and late 2000s, describing both absolute changes (percentage growth in the stock of educated individuals) and relative changes (growth in the share of educated individuals). For each of three measures of brain gain estimated, I show substantially more positive flows of educated individuals towards local areas with strong initial economic conditions. I also show that non-metropolitan areas are more likely to experience all three measures of brain drain. I present evidence that nonmetropolitan areas' inability to attract and retain educated individuals stems primarily from labor market disparities including the urban-rural wage differential.

KEYWORDS: Internal Migration, Labor Market Conditions, Human Capital, Brain Drain, Poverty

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1 INTRODUCTION

The following two chapters consider migration's responsiveness to economic conditions and other area characteristics, focusing on how individual characteristics affect this responsiveness. Both of these chapters particularly emphasize education's effect on migration's responsiveness to economic conditions. In Chapter Two the unit of analysis is the household (head) and I examine: 1) the effect of short-run changes in origin and surrounding state labor market conditions on households' propensity to migrate, 2) how demographic characteristics, including education, influence the relative importance of labor markets in the migration decision, and 3) how the effect of labor market conditions on migration has changed over time. An important finding in this chapter—and what helps motivate Chapter Three—is that labor markets play a larger role in the migration decisions of more educated households. Coupled with educated labor's high base migration rates, this suggests that, over time, spatial differentials in labor market conditions within the United States could lead to sizeable net flows of educated labor from depressed areas to thriving areas. In light of my findings in Chapter Two, Chapter Three then examines the issue from the perspective of local areas (counties and groups of less populous counties). To what extent do local area characteristics, including economic conditions, determine whether an area attracts and retains human capital over a period of almost two decades?

Chapter Two uses three different measures of state labor market conditions—the unemployment insurance claims rate, unemployment rate, and employment growth rate—with few qualitative differences in the results. I find that a percentage point increase in the origin unemployment insurance claims rate of the median household increases their propensity to migrate interstate by 3.2 percent. Likewise a percentage point increase in the unemployment insurance claims rate in surrounding states (within a 1,000 mile radius) decreases migration propensity by 5.2 percent. The relative importance of labor markets in influencing migration decisions fell between 1982 and the mid-late 1990s, but increased from the late 1990s through 2012. This responsiveness also varies considerably according to demographic characteristics. Household heads who are college educated, labor force participants, metropolitan and those without children present are especially responsive to labor market conditions. Interestingly the household characteristics associated with *lower* responsiveness also imply higher poverty risk. Chapter Three shows that the differential responsiveness of more and less educated individuals has lasting effects on the distribution of human capital in the United States. The results suggest that, *ceteris paribus*, a typical county with a one percentage point higher unemployment rate and a one percentage point higher poverty rate in the early 1990s would have 3.2 percent fewer 30-something high school graduates in the late 2000s. Similarly such counties could expect the share of individuals with high school diplomas and college degrees to both increase by 0.4 percentage points *less* over the period among the cohorts being tracked. Nonmetropolitan areas similarly struggle to attract and retain human capital.

The propensity of households to migrate in response to labor market conditions—and any changes in this propensity—may affect the efficiency of national labor markets by affecting the likelihood that labor is located where it can be most productively employed. A perceived strength of U.S. labor markets is their flexibility (Partridge, et al., 2012); migration's responsiveness to labor market incentives is an important aspect of this flexibility. The demographic differences in migration's responsiveness found in this dissertation—high poverty groups having only a weak tendency to move out of poor labor markets and towards thriving ones—should be of concern to policy-makers in economically depressed states, counties and cities. On top of slow or non-existent growth of tax bases due to a weak economy and net outmigration, detrimental demographic shifts may cause short-run and long-run harm to public finances in these places. Differential migration responses to labor market conditions may also contribute to long-term divergence in economic growth and productivity. Although there is disagreement among economists about the relative importance of the various mechanisms underlying human capital externalities, large net flows of educated labor across labor markets certainly affect the existing residents of both brain gain areas and brain drain areas in some way. A better understanding of exactly how human capital spillovers arise is necessary before judging the efficiency of these net flows of human capital. Although the particular policy implications of the following chapters are not obvious, the findings in this dissertation may be informative for understanding the benefits and costs of place-based policies, tax deductions for moving expenses, and education subsidies in rural and depressed areas.

The recent economic literature is broadly in agreement that migration responds to both general labor market conditions and the particular economic incentives faced by individuals (Saks and Wozniak, 2011; Wozniak, 2010; Bound and Holzer, 2000; Kennan and Walker, 2011; Sasser, 2010). Therefore I look at the general effect of labor market conditions on migration as a starting point for my study, not as a unique contribution. There has been considerably less research differentiating between the responsiveness of various groups. Wozniak (2010) shows using Census data that among individuals with five to eight years of potential experience, their state of residence is more sensitive to state labor market conditions at the implied time of labor market entry (based on Mincer Equation) if the individual is college-educated. By looking at changes in residence state over a twelve month period (and by not assuming that one's birth state was their state of residence at the time of labor market entry), I more directly estimate differences in migration's responsiveness to current labor market conditions by educational status. I also am able to identify previously unidentified differences in responsiveness along other demographic characteristics: labor force participation, presence of children, and metropolitan status. While previous research (Partridge et al., 2012) showed labor demand shifts led to smaller net population shifts in the early 2000s (2000-2007) than in the 1990s, I show that the *relative* role of (general) labor market conditions in determining household migration decisions *increased* in the 2000s. So while my dissertation is silent on what caused the secular decline in interstate migration in the 1990s and 2000s, it shows that the primary reason for the decline is *not* a reduced responsiveness to labor market conditions. Finally, the third chapter contributes to our understanding of the determinants of brain gain and brain drain within the United States by tracking specific cohorts over time. Previous research looking at the determinants of areas' human capital accumulation has often looked at changes in educational attainment among the population as a whole (Artz, 2003; Bound and Holzer, 2000; Berry and Glaeser, 2005) rather than tracking changes over time among specific cohorts. Such a strategy may conflate net inmigration of educated labor with either: 1) reductions over time in the net outmigration of educated labor or 2) improvements in the educational system leading to higher rates of high school graduation and college attainment.

2 WHICH LABOR MARKET CONDITIONS AFFECT MIGRATION AND WHOSE MIGRATION IS AFFECTED?

2.1 Introduction

Almost 53 percent of all working-age households migrating to a different state between 2011 and 2012 cited work-related factors as the main reason for their move.[1] It should come as little surprise then that migrants are more likely to move from areas with poor labor market conditions to areas with strong labor market conditions. The size of migration's responsiveness to state labor market conditions—and *whose* migration responds—has important implications on public policy. Free mobility of labor is generally regarded as efficiency-enhancing: workers move from regions with a surplus of labor to regions where labor is in more demand (Marston, 1985). Reductions in barriers to migration, such as tax deductions for moving expenses, are then defended as promoting labor market efficiency. But if factors other than labor market conditions prompt most moves, such policies may just subsidize consumption of area amenities over consumption of other goods and services without having leading to a more efficient allocation of labor. Migration's responsiveness to labor market conditions may also be relevant when considering the merits of place-based policies. Place-based policies, which direct federal funds toward economic development in the neediest areas, are one set of tools policy makers use to reduce inequality. Such policies could be misguided if they substantially counteract migration's natural response to spatial differences in labor market conditions. This chapter shows that low poverty groups are more likely to

[1] Author's tabulation based on household heads age 18-65 surveyed in the 2012 Annual Social and Economic Supplement to the Current Population Survey (the March CPS). Employment related factors include: New job or job transfer, to look for work or lost job, to be closer to work/for easier commute, retired, and other job related reasons.

migrate in response to labor market conditions. This result suggests the possibility that if place-based policies improve *general* economic conditions in an area (rather than targeting job growth among groups at high poverty risk), they may have a particularly large effect on the migration of low-poverty groups.

Also, if labor market conditions drive the migration of skilled workers more than unskilled workers, then states whose employment prospects are historically the bleakest may wind up with an even less employable workforce than if no differentials in responsiveness existed. Therefore, beyond potentially influencing the effectiveness of place-based policies, differences in demographic groups' migration response to economic conditions may also prolong or compound chronic labor market differentials across states. The loss of a state's skilled and high-income workforce and the retention of the high poverty population could also cause additional strain on the budgets of state governments facing tight labor markets.

In this chapter I show that demographics do lead to stark differences in households' migration response to transitory changes in labor market conditions. In general, the migration of groups at highest poverty risk is the least responsive to labor market conditions. Researchers have previously identified a positive relationship between educational attainment and responsiveness of migration to labor market conditions (Bound and Holzer, 2000; Wozniak, 2010). This essay, though, is the first I am aware of to verify this result using yearly microdata.[2] Using a household level migration model of migration and controlling for year-to-year changes in unemployment,

[2] Bound and Holzer (2000) looked at how differences in MSA labor demand affect the net population changes of different subpopulations. Wozniak (2010) finds that workers with some higher education are more likely to be located in a state which had high labor demand when they entered the labor market, controlling for state of birth.

I determine how much educational attainment affects the responsiveness of migration to differentials in labor market conditions. I also find that non-employment, children in the household, and living in nonmetropolitan areas all reduce migration's responsiveness to labor market conditions. Inability or unwillingness to relocate to strong labor markets may therefore be another factor contributing to high poverty among household heads who experience employment gaps, are less educated, live in rural areas, or have children. Surprisingly, the economics literature has been relatively silent on this issue. Finally, I also present evidence that household migration propensity became less responsive to labor market conditions through the 1980s and into the 1990s, but increased thereafter.

2.2 Literature Review

Most research on labor markets' influence on internal migration addresses (at least) one of three general questions.[3] First, considerable research explores how migration into and out of a state (or other geographic unit) responds to local labor market conditions—typically defined by some measure of unemployment, employment growth, real wages, industry specific wages, shocks to labor demand, or a combination of similar variables—or to differentials in labor market conditions (Blanchard et al., 1992; Bound and Holzer, 2000; Greenwood and Hunt, 1984; Hughes and McCormick, 1989; Kennan and Walker, 2011; Partridge and Rickman, 2006; Pissarides and Wadsworth, 1989; Wozniak, 2010). Second, some of the literature estimates migration's response to changes in national labor markets (Pissarides and Wadsworth, 1989; Saks and Wozniak, 2011). Third, some researchers examine how migration is affected by labor policies and

[3] A complementary literature looks at the effect of migration on labor markets. Many of these papers seek to determine the effectiveness of migration in bringing spatial equilibrium when heterogeneous shocks occur across labor markets (Blanchard et al., 1992; Partridge and Rickman, 2006).

institutional features of labor markets, including welfare policies (Gelbach, 2004; Kaestner et al., 2003; McKinnish, 2005), regional transfers (Obstfeld and Peri, 1998), state tax policies (Conway and Rork, 2012; Coomes and Hoyt, 2008; Young and Varner, 2011), and unemployment insurance benefits (Day and Winer, 2006), to name a few. This chapter focuses primarily on the first category of research, the responsiveness of migration to local labor market conditions in origin, destination, and other surrounding states, and briefly addresses the effect of national conditions on migration.

Most early research concluded that migration is only slightly—if at all—more likely to occur from high unemployment areas to low unemployment areas (Gallaway, et al., 1967; Rogers, 1967; Wadycki, 1974). Another common feature of early papers was the finding that even when researchers found that inmigration decreased with local unemployment (as expected), outmigration unexpectedly decreased with local unemployment (Greenwood, 1975). Lansing and Mueller (1967) claimed that early studies found that area unemployment has a perverse effect on outmigration because high unemployment is most prominent among less educated, less skilled workforces, but such workers also tend to be less mobile. With greater controlling for the demographics of an area, and more widely available individual and household level data, more recent research typically finds unemployment significantly affects outmigration and inmigration in the expected directions (Bound and Holzer, 2000; Greenwood and Hunt, 1989; Saks and Wozniak, 2011; Sasser, 2010.) The results in this chapter are based on three decades of micro data, allowing for detailed household controls.

Research examining the procyclicality of migration with respect to aggregate labor market conditions typically finds that improvements in national conditions are associated with higher migration (Pissarides and Wadsworth, 1989; Saks and Wozniak, 2011), though until recently studies (particularly in the U.S.) have been limited by the availability of microdata or sufficient longitudinal data to draw strong conclusions. Moreover, the recent secular decline in interstate migration (falling from an annual rate of 3.5% to 1.5% between 1982 and 2012)[4] further complicates researchers' task of deciphering the influence of aggregate labor market conditions on migration, particularly when relying on macrodata. In perhaps the most exhaustive attempt yet to examine the relationship between the aggregate business cycle and migration, Saks and Wozniak (2011) conclude that migration is indeed procyclical. However, using household level data from the March Current Population Survey, their estimates imply that the procyclicality of interstate migration applies only to household heads aged 18-35.

Relatively little is known about demographic differentials in migration's elasticity with respect to labor market conditions. Bound and Holzer (2000) demonstrate that the growth rate of the college-educated population in a MSA between 1980 and 1990 was more responsive to changes in MSA labor demand than the growth rate of the high school-educated. Similarly they show that the growth rate of the young populations in a MSA appear to be especially sensitive to changes in labor demand. They find inconclusive evidence regarding the responsiveness of blacks. Wozniak (2010) shows that individuals' current state of residence is more responsive to initial state labor market conditions (at the time of labor market entry) if the individual is college-educated. Saks and Wozniak (2011) find that the migration of blacks, women, labor force participants, and college-educated are more responsive to changes in the *national* business cycle,

[4] Author's tabulations based on household heads aged 18 to 65 in the March CPS. Imputed observations are dropped, based on the findings of Kaplan, and Schulhoger-Wohl (2010).

ceteris paribus, but they do not test for differential responsiveness to local labor market conditions. I am unaware of research which examines how family structure (marital status and presence of children) or metropolitan status affects the responsiveness of migration to local labor market conditions.

There has also been limited research explicitly examining how migration's responsiveness to labor market conditions has changed over time. Partridge et al. (2012) find that county population growth (a proxy for net migration) became significantly less responsive to shocks in labor demand (based on predicted employment growth rates for a county's industrial composition) between the periods 1990-2000 and 2000-2007. With dramatically lower migration rates in the latter period, it is perhaps unsurprising that labor demand shocks (or any other impetus to move) exhibit reduced effects on population growth. Households are much less likely to migrate than they were in 1990. This could be because people are not as responsive to labor market incentives to move, because people are not as responsive to *non*-labor market incentives to move, *or* because the incentives to move have declined (i.e. the benefits of moving have declined relative to the costs). For instance, any non-labor factor that increased the costs of moving during this period may have reduced internal migration, making it appear that household migration became less responsive to labor market conditions. Besides changes in migration's responsiveness to labor market conditions, several other theories have been put forth that might explain the decline in migration.[5] The findings of Partridge et al. certainly do not imply that labor market conditions are a less important factor in households' migration decision than they were in 1990. By looking at the effect of labor

[5] Kaplan and Schulhofer-Wohl (2013), for instance, present evidence that migration rates fell largely because labor markets have become less heterogeneous in returns to occupations and because of improvements in information and communication technology.

market conditions on *household's* (log) propensity to migrate, this chapter *will* explore how the importance of labor market conditions in the migration decision has changed relative to other factors in the migration decision.

2.3 Model and Empirical Strategy

Recently some researchers—notably Kennan and Walker (2011)—have modeled the household migration decision using a structural approach, though reduced form modeling remains the dominant approach in literature examining the effect of labor markets on migration (Molloy et al., 2013; Partridge et al., 2012; Saks and Wozniak, 2011; Sasser, 2010; Wozniak, 2010). This essay also adopts a reduced form model of migration. Modern economic literature examining the effect of labor market conditions (henceforth LMCs) on migration generally assumes, explicitly or implicitly, that individuals or households make migration decisions to maximize utility. Household i's expected utility in some locale, s, is a function of real after-tax income ($Y_{i,s}$), transitory labor market conditions (LMC_s), moving costs ($C_{i,s}$), state attributes ($A_{i,s}$), and household characteristics (X_i):

$$EU_{is} = E[U\big(Y_{i,s}(LMC_s, X_i) - C_{i,s}(X_i), A_{i,s}(LMC_s), X_i\big)] \qquad (2.1)$$

$A_{i,s}$ represents household i's valuation of fixed characteristics of state labor markets and measurable amenities like climate, average commute time, school quality, and proximity to water and recreation. $A_{i,s}$ also includes amenities that are typically unobservable such as family, social networks and scenic quality. I postulate that transitory changes in LMCs affect a locale's amenity value, because of their effect on governments' budgets and hence their ability to fund programs that enhance residents' quality of life. Letting the subscript o denote household i's origin state, I assume that $C_{io} = 0$. If $s \neq o$, then $C_{is} > 0$ and C_{is} increases with s's distance from the origin. Transitory increases in local unemployment are also associated with transitory decreases in real income, because workers face a higher probability of not having labor income and because the wages of workers tend to decrease in slack labor markets. This chapter utilizes three measures of LMCs: unemployment insurance claims rates (UI claims rate for short), unemployment rates, and employment growth rates.

Household migration is observed as a binary variable. Let $M_i = 1$ if household i moves across state borders during a 12 month period, and let $M_i = 0$ otherwise. Suppose s^* represents the most attractive potential destination for a household considering a move:

$$EU_{is^*} = Max[EU_{is}] \quad \text{for all } s \neq o \tag{2.2}$$

Household i's migration decision, then, is based on whether the latent variable $M_i^* > 0$:

$$M_i^* = EU_{i,s^*} - EU_{i,o} \tag{2.3a}$$

$$M_i = \begin{cases} 0 & \text{if } M_i^* \leq 0 \\ 1 & \text{if } M_i^* > 0 \end{cases} \tag{2.3b}$$

Based on this framework, the household outmigration decision can be modeled approximately by the general equation shown in (2.4).

$$M_i = M\left(LMC_o, LMC_{-o}, A_{i,o}, A_{i,-o}, C_{i,-o}, X_i\right) \tag{2.4}$$

LMC_{-o} refers to labor market conditions in all states besides the origin which are relevant to the migration decision. In cross-sectional analyses of household migration researchers face the task of controlling for all relevant amenity variables and for the cost of migration between various states. However when longitudinal or panel data is available, as in this essay, it is possible to simply include state dummies, if one assumes that the amenity value and moving costs of different states do not vary considerably over the sample period.[6]

Consistent with theory, most recent evidence indicates the propensity of households to migrate increases as origin LMCs deteriorate or as potential destinations' LMCs improve. In modeling the effect of LMCs on migration, an important, unresolved question is which non-origin states' LMCs are actually relevant to the household migration decision, especially given the concentration of interstate moves to nearby states. Some past empirical work allows for LMCs in closer states to be more important to the migration decision (Hughes and McCormick, 1989; Saks and Wozniak, 2011), typically controlling for potential destinations' LMCs using a gravity model or by applying weights based only on distance. I explicitly test for the effects of LMCs at different distances from the origin. I model the household migration decision using a logistic (logit) model, so it is assumed that household i's propensity to migrate across state lines is equal to:

$$P\left(M_{i,t} = 1\middle|\boldsymbol{Z}\right) = P\left(M_{i,t}^{*} > 0\middle|\boldsymbol{Z}\right) = \frac{\exp(\boldsymbol{Z\beta})}{1+exp(\boldsymbol{Z\beta})} \tag{2.5}$$

Household interstate migration, $M_{i,t}$, takes a value of one if migration occurs, zero otherwise. The latent propensity variable, $M_{i,t}^{*}$, is unbound and equals:

$$M_{i,t}^{*} = \boldsymbol{Z\beta} = \beta_0 + \beta_1 LMC_{o,t} + \beta_2 LMC_{-o,t} + \beta_3 X_{i,t} + \beta_4 \tau_t + \sigma_o + \epsilon_{iot} \tag{2.6}$$

$M_{i,t}^{*}$ describes the propensity of household i to outmigrate from state o between years t and $t+1$. The term $LMC_{o,t}$ denotes the UI claims rate, unemployment rate, or

[6] Even if this assumption is invalid, it is possible to allow for state specific time trends that capture changes in amenities and moving costs over time. State-specific time trends were tried but excluded for parsimony because they had little effect on results when they were added to the model.

employment growth rate in household i's origin state o in year t. The term $LMC_{-o,t}$ describes the (population-weighted) average of the UI claims rate, unemployment rate, or employment growth rate of states within some distance of the origin state (excluding the origin state). Several variations on the spatial specification of $LMC_{-o,t}$ are considered, though I use a radius of 1,000 miles in my preferred specification. The term $X_{i,t}$ includes various individual (household head) characteristics largely corresponding to the individual controls used by Saks and Wozniak (2011), including gender, education, race, employment status, metropolitan status, marital status, presence of children and a cubic in age.[7] In the specification that uses employment growth as the measure of LMCs, I also include controls for population growth in the origin and in surrounding states. The concern is that even population growth that is not caused by shocks to labor demand will still lead to employment growth. By controlling for population growth, I differentiate between shocks to labor supply and shocks to labor demand. Finally, origin state dummies, denoted by σ_o, are included in every specification and a cubic in year is included in the preferred specification. I also consider alternative controls for year.

The baseline model in (2.6) resembles the final model in Saks and Wozniak (2011) with two primary differences[8] which in part reflect the different objectives of our essays—Saks and Wozniak seek to identify the effect of *national* LMCs on migration propensity, while this chapter primarily focuses on the effect of relative *area* LMCs on migration. First, Saks and Wozniak control for aggregate U.S. LMCs, whereas I separately estimate the effects of non-destination LMCs at various distances from the

[7] I also considered including an index of state and national home prices, but these controls proved inconsequential in the model. They were therefore omitted for parsimony.
[8] Two other differences should be noted: Saks and Wozniak (2011) employ a linear probability model (not a logit) and instead of taking the natural logarithm of UI claims rates, they normalize UI claims rates to have a mean zero and standard deviation of one.

origin. Second, Saks and Wozniak control for migrants' destination state LMCs, whereas I control for origin state LMCs.[9] Explicitly controlling for both origin and destination LMCs proves problematic within this model. Depending on the year, upwards of 98% of households do not move to another state within a 12 month span, so measures of origin and (actual) destination LMCs are identical for most households. Multicollinearity therefore becomes a major problem if origin and destination LMCs are both included. I include origin LMCs (instead of destination LMCs) because potential migrants have better information about LMCs in the origin than anywhere else and because potential destinations' LMCs are partially controlled for in (2.6) with $LMC_{-o,t}$. The effects of the *actual* destination and *potential* destinations are not, however, separated in this model. As a result, the significance of $LMC_{-o,t}$ may depend on its ability to capture the LMCs of *actual* destination states. I will present evidence in subsection 2.5.3 that $LMC_{-o,t}$ is a good proxy for destination state conditions.

Within the framework of (2.6), if the relevant labor market conditions are being captured by $LMC_{o,t}$ and $LMC_{-o,t}$, it is also possible to test whether migration is procyclical with respect to aggregate LMCs by summing the coefficients on $LMC_{-o,t}$ and $LMC_{o,t}$ (i.e. $\beta_1 + \beta_2$). Procyclical migration implies that a uniform increase in national unemployment should reduce households' propensity to migrate, so $\beta_1 + \beta_2$ should be negative when LMCs are measured with the UI claims rate or the unemployment rate.

[9] In unreported results I find that use of origin state characteristics instead of destination state characteristics affects estimates of the procyclicality of migration with respect to the national labor market. However, including origin state characteristics also comes at a cost. Ten years of potential observations must be dropped (1964-71, 1976 and 1981) because until 1982 the CPS did not ask migrants where they lived one year prior. Individual outmigration data is missing altogether in the years 1972-1975 and 1977-1980, so these years are not used by Saks and Wozniak (2011). In a replication of Saks and Wozniak, I show that the results are not substantially altered by the omission of pre-1982 data. Data limitations in this paper are alleviated somewhat because three additional years of data have come available (2010-2012) that were not used by Saks and Wozniak (2011).

Similarly, procyclical migration would imply that $\beta_1 + \beta_2$ should be positive when LMCs are measured with employment growth.

I then extend the model described by (2.6) to allow for the possibility that LMCs' effects vary by household characteristics and by year. Equation (2.7) describes this regression.

$$\begin{aligned} M_{i,t}^{*} = \beta_0 + \beta_1\left(LMC_{o,t} - LMC_{-o,t}\right) + \beta_2 X_{i,t} + \beta_3 \tau_t \\ + \beta_4\left(LMC_{o,t} - LMC_{-o,t}\right) \times X_{i,t} \\ +\beta_5\left(LMC_{o,t} - LMC_{-o,t}\right) \times \tau_t + \sigma_o + \epsilon_{i,o,t} \end{aligned} \tag{2.7}$$

Equation (2.7) models household migration as a function of differentials in LMCs (origin state conditions relative to surrounding states), household characteristics, year, interactions between LMC differentials and household characteristics, interactions between LMC differentials and year, and origin state indicators. If a particular demographic subgroup is especially likely to migrate interstate when origin LMCs are weak relative to their states' neighbors, this will be revealed by significantly positive (negative) values in β_4 when LMCs are a measure of unemployment (employment). The coefficient β_4 measures each group's LMC-driven migration: how important are LMCs in the migration decision (relative to non-labor factors)? Groups with high labor force attachment and those facing large potential economic gains to migration theoretically should have more LMC-driven migration. Conversely, low levels of LMC-driven migration might be expected, for example, among groups who are especially reliant on family and social networks and who therefore face higher social costs of migration. Finally, if migration's responsiveness to LMCs has changed over time, this will be captured in the coefficients on the interactions of LMCs with year (β_5).

Each of the measures of LMCs used control for *general* changes in state labor demand and cannot be used to distinguish between different causes of shifts in labor demand, nor can the measures help distinguish between labor demand shocks that differentially affect different types of labor. Technological innovation, labor supply shocks, changes in consumer tastes and changes in the prices of production inputs will have different impacts on the demand for an individual's labor depending on their education, experience, industry and occupation. It cannot necessarily be assumed, then, that any differences in responsiveness to general labor market conditions that are observed across groups imply that the groups differ in their responsiveness to the particular labor market incentives that they face. Because of heterogeneity in demand for different types of labor, some states may have strong employment opportunities for certain subpopulations despite a weak overall economy. However there is reason to suspect that the measures of unemployment better capture the labor market opportunities of high poverty groups, because skilled labor is less prone to unemployment than unskilled labor.[10] Thus, if anything, it is likely that there is a bias towards finding *higher* responsiveness among less educated and other high poverty groups.[11]

The final model employed in this paper allows me to separate the effects of LMCs

[10] According to the Bureau of Labor Statistics, high school dropouts in 2013 had an unemployment rate of 11.0%, high school graduates had 7.5% unemployment, individuals with an associate's degree had 5.4% unemployment, individuals with a bachelor's degree had 4.0% unemployment, individuals with a master's degree had 3.4% unemployment, and individuals with a professional degree or doctoral degree had 2.3% unemployment.

[11] A concern unique to the measure of UI claims is that states with generous unemployment insurance might also have more generous welfare systems. Could an apparent diminished responsiveness among high poverty groups arise because increases in UI claims coincide with increases in welfare generosity that are in actuality what prevent high-poverty groups from out-migrating? Although I cannot rule out this effect entirely, I think it is unlikely that this is driving my results. The most obvious reason is that the results that follow are largely consistent across the three measures of LMCs, and such a concern does not apply to the unemployment rate and employment growth rate. Second, since the UI claims rate measures the rate of *initial* claimants, many common changes to UI rules, such as extending UI benefits for additional weeks, would not effect this measure. Finally, any persistent difference in UI rules such as higher replacement rates would be captured by the state dummies.

in the destination state from the effects of LMCs of other surrounding states. The model closely corresponds to (2.6) but instead of predicting whether *any* interstate move will occur, it predicts whether a household will move into a *specific* state, d.

$$M^*_{i,d,t} = \boldsymbol{Z\beta} = \beta_0 + \beta_1 LMC_{o,t} + \beta_2 LMC_{d,t} + \beta_3 LMC_{-o,t} + \beta_4 X_{i,t} + \sigma_o \qquad (2.8)$$

$$+t + t^2 + \epsilon_{ist}$$

The dependent variable, $M^*_{i,d,t}$, describes households' propensity to move *to* state d. Because of the small number of migrants to most states observed in the CPS, I limit the number of potential destination states being considered to the 12 most common destinations in my sample. Each of these 12 regressions model migration *into* one particular state. The only difference in independent variables between (2.6) and (2.8) is the inclusion of $LMC_{d,t}$ in (2.8).[12] This variable captures the effect of a state's LMCs on the propensity of households to migrate *to* that state. Thus, in this model, β_1 and β_2 describe, respectively, the push effect of origin LMCs and the pull effect of destination LMCs, while β_3 describes the effect of *other* states' LMCs on migration to d. Note that households from state d *and* households from states with fewer than 20 observed migrants to d over the period 1982-2012 are omitted from the regression modeling migration into state d.[13] This implies non-random sampling of households in each state's regression, with heavier sampling from nearby states and more populous states. As a result, the coefficients may be biased estimates of the population parameters. The direction of any potential bias is not obvious. Nonetheless, the relative sizes of β_2 and β_3 and the regressions' sensitivity to the inclusion of $LMC_{d,t}$ and $LMC_{-o,t}$ will be instructive

[12] Note also that by design (2.8) controls for trends in flows to particular states whereas (2.6) only captures migration trends within the nation as a whole.
[13] The migration regressions to each state d include households from an average of 8.1 other states. All others must be omitted due to an insufficient number of observed moves to state d.

in determining: 1) the relative extent to which the labor markets in d and $-o$ affect the migration decision and 2) whether $LMC_{-o,t}$ acts as an adequate proxy for $LMC_{d,t}$ in (2.6) and (2.7).

In addition to reporting results from regressions for each destination state, I also report results of a logistic regression in which each of these destination state-specific regressions are pooled together into one regression.

$$M^*_{i,d,t} = \beta_0 + \beta_1 LMC_{o,t} + \beta_2 LMC_{d,t} + \beta_3 LMC_{-o,t} + \beta_4 X_{it} \quad (2.9)$$

$$+\beta_5 Ln(distance) + \sigma_o + \sigma_d + t + t^2 + \epsilon_{ist}$$

The unit of observation in this pooled regression is not the household, but the household-potential destination state interaction.[14] This pooled regression includes each distinct household—whether they moved or not—as up to 12 different observations (once for each potential destination state). An observation takes the value of one if the household moved to d, a value of zero otherwise, but d takes each of 12 values for different observations. Two additional controls are necessary in (2.9) to control for heterogeneity in moving costs between states: a dummy for the potential destination state being considered and the log of the distance between the household's origin state and the potential destination state. These controls would be superfluous in (2.8) where a single potential destination is considered in each regression. Since the potential destination state is designated a priori for each observation (independent of the household's eventual migration decision) a clear distinction is made between the labor markets of the origin

[14] Since each household can only move to a maximum of one state, each household-potential destination state observation is not independent of all other observations. Ideally this would be remedied by clustering standard errors by household, but it is not feasible to run regressions with more than a million clusters. Instead I continue to cluster standard errors by origin state. Because all variables based on this regression are either highly statistically significant or not remotely significant (see Table 2.7), qualitative results likely would not be affected by the violation of independent observations.

state, the potential destination state, and "other" surrounding states. In contrast, since over 98% of the sample lives in the same state at the end of the period as they did at the beginning, if $LMC_{d,t}$ was added to (2.6), origin and destination LMCs would be identical for most observations, thereby creating collinearity problems. By allowing for the inclusion of both $LMC_{d,t}$ and $LMC_{-o,t}$, (2.9) provides a test of whether only origin and destination states' LMCs affect household interstate migration propensity, or whether LMCs in other surrounding states have some additional effect on households' migration decisions. Knowing whether "other" states affect migration flows may offer insights into the mechanism through which labor markets influence migration and can inform future modeling of the effects of LMCs on migration.

2.4 Data

All household level data comes from the 1982-2012 Annual Social and Economic Supplement of the Current Population Survey (the March CPS). Household data are restricted to heads between the ages of 18 and 65.[15] Each state's UI claims rate is defined as the ratio of the number of initial claimants in a year to the sum of public employment and covered private employment. Initial claimants and covered private employment data are available from the Department of Labor in the *Unemployment Insurance Financial Data* Handbook. State unemployment rates, employment growth rates, and (civilian non-institutionalized) population growth rates are reported by the Bureau of Labor Statistics.

By measuring how many people are claiming unemployment for the first time in a period, initial UI claims rates may measure *current* conditions for potential migrant job

[15] Furthermore I drop observations where the origin or destination state is imputed to a household.

seekers better than unemployment rates, which measure the stock of unemployed workers rather than the flow into or out of unemployment at a point in time. Employment growth, similarly captures the flow into and out of employment. However, unlike employment growth and unemployment rates, UI claims rates have the added advantage that they are based on the state in which a job was lost. Thus, the initial UI claims rate is unaffected by whether someone who loses their job subsequently migrates (making it less susceptible to endogeneity concerns). For these reasons, the preferred specifications in this paper will utilize the initial UI claims rates as the measure of LMCs, though I also explore how migration is affected by unemployment rates and employment growth.[16]

The March CPS asks households about any changes in residence between March of year $t-1$ and March of year t, so it is difficult to pinpoint the exact timing of the LMCs that were most relevant to the move, though it seems sensible to allow for some lag between a change in LMCs and a resulting move. Monthly and quarterly state UI claims data are not available, so I predict migration in the March CPS as a function of the average of the UI claims rate in year $t-1$ and year $t-2$.[17] The Bureau of Labor Statistics reports monthly estimates of state unemployment rates and employment levels. To predict moves between March of $t-1$ and March of t, I use estimates of employment growth between March of $t-2$ and March of $t-1$. I use a somewhat later measure of unemployment—March of $t-1$—since the current share of unemployed workers is the result of several lags of accessions and separations.

[16] Some states may have persistently high unemployment rates and high unemployment insurance claims rates. The risk of unemployment in such states may be balanced by other considerations such as high wages or state amenities. Therefore outmigration from a state would not necessarily be associated with high unemployment, but with *increases* in unemployment. However, it is not necessary to model LMCs using *changes* in the unemployment rate or the UI claims rate because persistent differences in the level of unemployment across states will be captured by the state dummies.
[17] Results were insensitive to variations in the weighting of UI claims in $t-1$ and $t-2$.

When constructing $LMC_{-o,t}$, state weights were determined based on 2000 Census data on state populations and distances between state centers of population (e.g. to determine the states within a 1000 mile radius of the household's origin). Distances between states are based on estimates of the latitudes and longitudes of each state's population center in the 2000 Census's State Centers of Population dataset.

Table 2.1 reports summary statistics of household characteristics, disaggregated by migrant status (non-migrant, intrastate-intercounty migrant and interstate migrant). This table reveals several well-known statistical differences between migrants and non-migrants. Compared to non-migrants, interstate migrants between 1982 and 2012 were on average 7.5 years younger, 80% more likely to be unemployed and 44% more likely to have a college degree. Migrants were also more likely to be white, unmarried and to have no children present. As expected, interstate migrants' destination states had better LMCs (whether measured with UI claims rate, unemployment rate, or employment growth) than their origin states.[18]

Figure 2.1 describes the proportion of household heads aged 18-65 migrating across various distances and jurisdiction lines and how these migration rates have changed over time. Notice the large drop in all definitions of household mobility in the last 30 years. Short and long distance migration experienced comparable steady declines, with every category of moves falling by more than 50% over the period 1982-2012. Figure 2.1 also shows that most moves cover relatively short distances. Between 1982 and 2012, roughly one third of all moves crossed county lines. The figure then shows

[18] Note that initial UI claims rates and interstate migration rates both trended down since 1982, so there are relatively more interstate migrants in the early part of the period 1982-2012, which also tended to have high UI claims. This has the effect of inflating the average UI claims rates of interstate migrants relative to non-migrants.

that of those crossing county lines each year, fewer than half crossed state borders. While about half of all of the $\frac{48\times 47}{2}$ pairs of state population centers (excluding Alaska and Hawaii) are more than 1,000 miles apart, only about a quarter of *interstate* moves in a typical year are between states separated by more than 1,000 miles, suggesting interstate migrants tend to migrate to nearby states. In sum, fewer than 4% of *all* moves cover more than 1,000 miles.

Table 2.2 shows that among 18-65 year old household heads in the March CPS, intrastate-intercounty migrants were about equally likely to cite housing factors and job-related factors as the reason for moves between 1998 and 2012[19]; interstate migrants were most likely to cite job-related factors. Housing factors are cited as the primary reason for moving among 32.9% of household heads moving to a different county in the same state, among 16.7% of heads migrating to a bordering state, and among 6.1% of heads migrating to non-border states. Job-related factors are cited as the primary reason for moving among 31.8% of household heads moving to a different county in the same state, among half of heads migrating to a bordering state, and among 57.7% of heads migrating to non-border states. Family and “other” reasons together account for roughly one-third of each type of move. The large share of interstate migrants moving for a new job, a transfer or to look for work reveals why differences in state LMCs have the potential to substantially affect interstate migration.

Indeed, Figures 2.2 and 2.3 show preliminary evidence that interstate migrants, on average, are more likely to move from states with poor LMCs towards states with better LMCs. Figure 2.2 plots a time series of the U.S. UI claims rate over the period 1982-

[19] Respondents were not asked to report why they moved prior to 1998.

2012 (plotted against a time series of the interstate migration rate). Figure 2.3 shows (again for 1982-2012) the UI claims rate in interstate migrants' origin state, destination state, and surrounding states, minus the U.S. UI claims rate in the same year. The graph shows that the average migrant's destination UI claims rate is lower than their origin UI claims rate, and their destination UI claims rate is lower on average (by 0.31 percentage points) than the national UI claims rate. This provides preliminary evidence, then, of movement toward states with strong LMCs. However the graph also shows that interstate migrants are somewhat more likely to move *from* states with low unemployment, as origin UI claims rates are on average 0.12 percentage points below the national rate. This is the type of asymmetric response to origin and destination LMCs that early research struggled to explain, but—consistent with the explanation of Lansing and Mueller (1967) described in section 2.2—this asymmetry is much smaller in the regressions of Section 2.5 which include household controls and state dummies.

Though job-related factors are important in migration and though there appears to be a tendency for migrants to move to states with lower UI claims, many migrants move "against the grain" either because of heterogeneity in demand for different types of labor (by education, industry, occupation, or unobservable worker qualities) or because they are moving for housing or family reasons. To examine the state-level relationship between UI claims and migration rates, I plot state population growth against state UI claims rates (based on annual Census estimates) in Figure 2.4, where population growth acts as a proxy for *net* migration.[20] Panels A, B and C show graphs for the periods 1982-1992, 1993-2002, and 2003-2012, respectively. For each of these periods, the years

[20] Birth rates and death rates do not vary considerably across states, so differences in immigration will account for most of the difference between population change and net internal migration.

selected include one business cycle trough, one business cycle peak, and the midpoint between a trough and a peak.[21] In each graph displayed, at least a weak negative correlation exists between state UI claims and population growth, though an especially weak relationship exists in the early 2000s. The graphs displayed are fairly representative of the period. Figure 2.5 graphs the correlation between state UI claims rates and population growth for every year between 1982 and 2012, showing an average correlation of -0.23, with stronger negative relationships in the earliest years shown (1982-1988) and in the most recent years (2006-2012).

Figure 2.4 also reveals regional trends in population growth that appear to be independent of LMCs. Mountain West States like Nevada, Arizona, Utah, Colorado, and Idaho, for example, exhibit consistently more rapid population growth than their UI claims rate would suggest (except in 2009-2010). Conversely, Central Plains States like Nebraska, South Dakota, Kansas, and Iowa have persistently low population growth, regardless of UI claims rate. Amenity differences, differences in state unemployment insurance rules, or persistent differences in real wages may contribute to these differences. A priori, it is unclear whether these effects strengthen or weaken the negative correlation between state UI claims rate and population growth. Therefore, Figure 2.6 aims to filter out relatively permanent differences in states' ability to attract migrants. Each state's UI claims rate (for each year) is normalized relative to that state's average over the 1982-2012 period; likewise each state's population growth is normalized relative to that state's average over the 1982-2012 period. These standard normally distributed variables are then plotted against each other in Figure 2.6.

[21] Identification of troughs and peaks are based on the latest announcement from the NBER's Business Cycle Dating Committee (9/20/2010). Note that the years 1990-1991 actually include both a trough and a peak.

Comparing the graphs of Figure 2.6 to those in Figure 2.4 shows that the negative correlation between the normalized UI claims rate and normalized population growth is stronger than the negative correlation between their un-normalized counterparts. The correlation between normalized UI claims rate and normalized population growth between 1982 and 2012 is graphed in Figure 2.7. The average correlation over the period is -0.42 (compared to 0.23 when the measures are not normalized). These descriptive exercises support the notion that LMCs substantially affect interstate migration, particularly year to year variation in the propensity to migrate. In the following section this is tested more rigorously.

2.5 Results

Subsection 2.5.1 presents results based on the model in (2.6), estimating households' propensity to migrate interstate as a function of origin LMCs, surrounding LMCs and household head characteristics. Interstate migration occurs when a household head reports living in a different state 12 months prior.[22] I examine the robustness of the results to alternative time controls (a quadratic in year, a cubic in year, and year dummies) and I defend the choice of spatial controls (LMCs of states within a 1,000 mile radius) in the preferred specification. Section 2.5.2 describes results from (2.7) where LMCs are interacted with household head characteristics to determine the relative responsiveness of various groups' migration to changes in LMCs and to determine how responsiveness has changed over time. Section 2.5.3 describes the findings from

[22] Ideally migration would be defined as a move to a different labor market, perhaps best described by MSAs or similar metropolitan boundaries. Data limitations in the CPS preclude this. Interstate moves tend to understate the number of moves across labor markets while intercounty moves would overstate the number of moves across labor markets (Molloy, et al., 2011).

regressions based on (2.8) and (2.9), which model household migration separately *into* each of 12 states popular destination states. Based on the results of these 12 distinct regressions, I describe the effect of origin and destination conditions on households' propensity to move to these states (2.8). Then, I examine the effect of "other" (non-origin, non-destination) LMCs using the pooled regression (across all 12 potential destination states) described by (2.9).

2.5.1 Effect of Origin and Surrounding Labor Market Conditions

Table 2.3 displays the key results of the logistic regression based on (2.6), modeling the propensity to migrate interstate as a function of origin LMCs and the population weighted average of LMCs in states within 1000 miles of the origin. Panel A shows results using state UI claims rates as the measure of LMCs, Panel B shows results using state unemployment rates and Panel C shows results using employment growth rates. The highlighted column in the top panel represents the preferred specification where the time control is a cubic in year, the other columns control for time using a quadratic in year and using year dummies. Because I employ a logistic model, regression coefficients have little intuitive meaning. Therefore Table 2.3 and all subsequent tables report the semi-elasticity of household migration with respect to the explanatory variables (evaluated at median or modal values).[23] Below these elasticities I report standard errors. (Appendix Table A.1 presents full results of the regressions described in Table 2.3, including the effects of household characteristics, state and year on household migration propensity.) Panel A of Table 2.3 shows that origin and surrounding states' UI claims

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[23] The median/modal characteristics at which elasticities were evaluated are: employed, some college, unmarried, no children, 42 years old, male, white, metropolitan, resident of California in the year 2000.

rates each affect households' propensity to migrate out of a state in the expected direction. The preferred specification implies that for the median household, a one percentage point increase in the origin UI claims rate increases household migration propensity by 3.2 percent, *ceteris paribus,* while a one percentage point increase in surrounding states' UI claims rates reduces households' migration by 5.2 percent, *ceteris paribus*. Estimates are comparable using the quadratic time controls, but the coefficient on $LMC_{-o,t}$ is substantially closer to zero and statistically insignificant when time dummies are used. Including time dummies has a similar effect on the coefficient on $LMC_{-o,t}$ when measuring LMCs with the unemployment rate or employment growth rate. This seems to be because the year dummies capture the bulk of the between-year variation in national LMCs, which is highly correlated with the LMCs of one's neighbors. This problem grows less stark as $LMC_{-o,t}$ controls for a progressively smaller radius, as more within-year variation exists in $LMC_{-o,t}$, thus limiting the extent to which the coefficients on the time dummies are confounded with the coefficients in $LMC_{-o,t}$. (However, as I will show, narrower spatial definitions of relevant labor markets seem to miss some of the changes in surrounding LMCs that are relevant to potential migrants.) As reported in Appendix Table A.1, controls for household head characteristics generally take the expected sign (consistent with previous research) and are generally highly significant. Higher interstate migration is associated with being male, educated, non-black, non-Hispanic, young, unmarried, and childless.

Note that in each of the panels of Table 2.3, column 2 implies that simultaneously increasing unemployment in a household's origin state and in all surrounding states by one percentage point would have an insignificant effect on interstate migration. That is, since the sum $\beta_1 + \beta_2$ is not significantly different from zero, I cannot reject the hypothesis that interstate migration would be unaffected by a uniform national increase in UI claims. Although statistically insignificant, for each of the three panels the direction and size of the sum of β_1 and β_2 does imply that there may be an economically meaningful increase in household migration when national LMCs improve. In each case, a one percentage point decrease (increase) in unemployment (employment) is estimated to increase household migration propensity by about 2 percent. Moreover, consistent with Saks and Wozniak (2011), if the sample is limited to sufficiently young household heads (ages 18-35) the resulting coefficients do suggest that interstate migration is procyclical with respect to national LMCs.

Though in Table 2.3 I control only for the UI claims rate of the origin state and states within 1,000 miles, this particular classification of "relevant" labor markets is arbitrary. Table 2.4 explores a few alternate specifications which control for different ranges of surrounding LMCs (see Table A.2 for full results.) Otherwise these regressions are identical to column 2 of Panel C (the preferred specification). Column 1 of each panel displays results of a regression including the UI claims rate at the origin ($LMC_{o,t}$), the population-weighted average of the UI claims rate of states within some range of the origin (continue to refer to this as $LMC_{-o,t}$), and the population-weighted average of the UI claims rate of states outside of that range ($FAR_{o,t}$ for short). Column 2 of each panel excludes $FAR_{o,t}$. Each panel classifies near states and distant states using a different range. Panel A classifies surrounding states as those that share a border with the origin state, Panel B classifies surrounding states according to whether their center of population was (as of 2000) within 500 miles of the origin state's center of population, Panel C classifies states—as in Table 2.3—using a 1,000 mile radius, and Panel D controls only for the origin and national UI claims rate. Note that in column 1 of Panels A and B, the coefficient on $FAR_{o,t}$ is substantially larger than the coefficient on $LMC_{-o,t}$. Two things may explain this. First, note from Figure 2.1 that moves to bordering states and moves to states within 500 miles comprise fewer than half of all *interstate* moves. Moreover, because relatively few pairs of states border one another or lie within 500 miles of one another, the average UI claims rate in these groups is measured with more error than the average UI claims rate outside those ranges. Therefore, in these specifications $LMC_{-o,t}$ may actually do a worse job than $FAR_{o,t}$ of approximating the typical LMCs in migrants' potential destinations. In contrast, Panel C shows that the effect of UI claims rates of states within 1000 miles dominates the effect of the more distant states' UI claims rates. It is also problematic for the specifications in Panel A that the coefficient on $LMC_{o,t}$ is somewhat sensitive to the inclusion of the more distant states' UI claims rates. Results are much less sensitive in the preferred specification. When including $FAR_{o,t}$ in the model using the 1,000 mile designation (Panel C), the table implies that a percentage point increase in all UI claims rates decreases household migration propensity by 5.7%. When excluding $FAR_{o,t}$, the same panel implies that a percentage point increase in all UI claims decreases household migration propensity by 5.2%. Note, though, that the inclusion of $FAR_{o,t}$ does increase the collinearity in the model, as evidenced by the higher standard errors on $LMC_{-o,t}$.[24] While this exercise lends support to the notion that the LMCs of the origin and states within 1000 miles of the origin largely capture the relevant factors in household migration, there is nothing

[24] $LMC_{o,t}$ is less susceptible to collinearity than $LMC_{-o,t}$ because the former is not averaged across many states, therefore it exhibits much more variation within year.

magical about this particular radius, as findings were quite similar in unreported results when ranges of 800, 1,200, or 1,500 miles were used instead. Indeed, in subsection 2.5.3 I present suggestive evidence that only the origin and destination states' LMCs matter in the migration decision. Thus, $LMC_{-o,t}$ "works" in this model only by approximating the UI claims rate of migrants' actual destinations (which are concentrated in nearby states).

2.5.2 Effect of Demographics and Year on Elasticity of Migration

Given that household migration changes with origin and surrounding LMCs, it is of considerable interest whether the size of the response varies over time or varies with household characteristics. Based on (2.7), I explore this with a series of regressions which model household migration as a function of LMC differentials ($LMC_{o,t} - LMC_{-o,t}$), household characteristics, a cubic in year, state of origin, interactions of LMC differentials with household characteristics, and interactions of LMC differentials with the year cubic. Coefficients on characteristic interactions with ($LMC_{o,t} - LMC_{-o,t}$) suggest differences across groups in the *relative* importance of LMCs in the migration decision. Full results of this regression are reported in Appendix Table A.3. The effects of demographics and year on responsiveness to LMCs are more succinctly summarized in Table 2.5. For each of the characteristics listed (including year), I report the effect (at the median) of possessing that characteristic (or increasing it by one unit) on the semi-elasticity of migration with respect to LMCs. That is, I report estimates of β_4 (and β_5) in (2.7). Column 1 displays results using UI claims rates as the measure of LMCs, column 2 uses unemployment rates and column 3 uses employment growth. A positive (negative) value in column 1 and column 2 (column 3) indicates that characteristic is associated with a large, "correctly-signed" response to UI claims differentials (that is households with this characteristic are especially likely to migrate interstate when origin unemployment is high and surrounding unemployment is low.) A negative (positive) value in column 1 and column 2 (column 3) indicates that characteristic is associated with an attenuated or perverse response to UI claims differentials. I use the term "LMC-driven migration" to refer to high responsiveness to these differentials.[25] Results in each of the columns are generally qualitatively consistent with one another, and suggest that, *ceteris paribus*, households whose heads are employed, educated, childless, metropolitan, black, and young exhibit more LMC-driven migration than other households. Results in each column also imply that LMC-driven migration declined in the early part of the period 1982-2012 before rebounding in later years.

Groups with the most LMC-driven migration tend to be those with higher potential benefits to job-related migration and those with lower social costs to migration. It is certainly unsurprising that LMCs apparently drive the migration of employed household heads more than labor force nonparticipants, since the latter can only indirectly benefit from living in a state with a strong labor market. It is more surprising that *ceteris paribus,* employed household heads would exhibit more LMC-driven migration than unemployed household heads. However, note that employment status is measured after the potential move would have occurred. The positive effect of employment (relative to unemployment) on responsiveness could be spurious, since employment is based on the week before the survey, after any potential moves could take

[25] Implicit in this terminology is the idea that if interstate migration does *not* respond to differentials in LMCs, then the decision to move must be driven by other factors (amenities, family and social networks, etc).

place.[26] Perhaps the larger responsiveness of employed relative to unemployed reflect that by moving to a state with stronger LMCs, people are more likely to find employment and less likely to become or remain unemployed. A stronger case can be made that the labor force participation of the household head is unlikely to change based on whether or where the household chooses to migrate (at least in the short run). Note that if the household heads are defined only by whether they are labor force participants, the interaction of labor force participation with LMC differentials implies that labor force participants are more responsive to LMCs than nonparticipants.

Higher LMC-driven migration among more educated household heads may stem from higher labor force attachment or from less reliance on nearby family and social networks for support (financial assistance, child care, etc.). Also, educated workers may have skills that are demanded by industries concentrated in particular parts of the country, leading to more variability in their earnings potential in various cities. Seeking the right job *in the right location* may be especially important for educated workers in order to maximize their present earnings and their earnings trajectory. Thus, the potential benefits of LMC-driven migration are higher for educated workers. Households with children present, on the other hand, may face higher costs of LMC-driven migration if moving involves leaving the area of a child's (divorced or unmarried) parent, grandparent or other close family members. More generally, parents with children may be less willing to accept employment in another state because of the disruptive effect of moving on their children's lives and education; the timing and destination of any move for these families will be dictated more by the children's needs and less by area LMCs at a specific time.

[26] Alternatively I could have used responses to whether an individual worked at any time in the last year, but that too would be influenced by current employment.

Residents of nonmetropolitan areas may exhibit an attenuated response to LMCs for several reasons. With fewer high-paying jobs available in rural areas, the choice to live in such a locale may demonstrate a high valuation on amenities or proximity to family and other social networks. It is also possible that the apparent attenuated response for nonmetropolitan households arises because state LMCs do not capture the LMCs of rural areas as precisely as the LMCs of the metropolitan areas. A typical state may have two or three metropolitan areas which comprise the vast majority of the population. States' UI claims rates, unemployment rates, and employment growth rates are largely determined in these metropolitan areas. Moreover there is probably a stronger correlation between LMCs of distinct metropolitan areas in the same state than between a metropolitan and nonmetropolitan area in the same state because nonmetropolitan labor markets are less diverse and more susceptible to shocks to specific industries (e.g. agriculture, coal, forestry, etc.)

It is not immediately obvious why the migration of blacks should be more responsive to LMCs. One possibility is that employers with a "taste for discrimination" face higher costs if they pass over a qualified black candidate when local labor markets are tight than when local labor markets are slack (see Becker, 1971 for a discussion of the economics of discrimination.) In this case, blacks would have especially high returns to LMC-driven migration. Blacks are, however, 40% less likely than non-blacks to migrate interstate, *ceteris paribus*, so the difference between black and non-black migration is that blacks are *less* likely to migrate for *non*-labor reasons (not that they are *more* prone to migrate due to labor considerations.)

In each of the columns of Table 2.5, the interactions with the age cubic suggest that LMC-driven migration falls throughout early adulthood. Panels A, B and C of Figure 2.8 plot the implied semi-elasticity of household migration with respect to each of the three measures of LMC differentials for household heads aged 18-65.[27] All three graphs show high responsiveness for the youngest adults that declines into the 30s or 40s. The three measures of LMCs paint somewhat different pictures, though, for midlife and beyond. Panel A of Figure 2.8 (UI claims) depicts an increase in responsiveness leading up to the retirement years, while the other graphs show more modest changes in responsiveness after age 30.[28] Even 50 years ago economists realized that LMC-driven migration represents an investment in human capital (Sjaastad 1962). Just as young adults invest more in education, they should also be more willing to incur moving costs in order to move to a better job, because they have a longer window to reap the returns on that investment. Young adults may also have fewer familial obligations that keep them tied to a place, such as an aging parent or a child living with another parent.

Panels A, B, and C of Figure 2.9 plot time-series of the implied semi elasticity of household migration with respect to LMC differentials based on the interactions with the cubic in time. These graphs closely correspond with one another. Each graph shows that differentials in LMCs played a large role in determining migration at the start of the period (1982), LMCs decreased in relative importance until the mid-late 1990s, and then increased through 2012. Unlike Partridge et al. (2012) who showed that county population growth (a reasonable proxy for *net* migration) grew less responsive to local labor demand shocks between the 1990s and the 2000-2007 period, these graphs show

[27] Semi-elasticities are evaluated at the median or mode of household characteristics and LMCs.
[28] One explanation for why the graphs do not show declines in responsiveness to LMCs later in life is that the graphs depict semi-elasticities at different ages for individuals *with median and modal characteristics*. The modal employment status is employed, so these graphs represent the semi-elasticity of migration at different ages among *employed* household heads only (ignoring retirees).

that household migration was at least as responsive in the latter period. There are important differences in how our essays define responsiveness to LMCs. Besides differences in the unit of observation (county vs. household), Partridge et al. (2012) consider how labor demand shocks affect *levels of population growth* whereas this paper reports *percent changes* in household migration propensity. Given that overall migration rates fell considerably since the 1990s, it is possible for LMCs to now have a smaller *absolute* effect on net population growth, while simultaneously playing a larger role in determining household migration, *relative to* other factors. In fact simple tabulations in the CPS of the primary reason for interstate moves show a decline in job-related moves but a larger decline in moves for all other reasons. Between 1998-2000 (the first three years the March CPS asked migrants their reason for moving) and 2010-2012, job-related interstate moves fell 38%, while all other types of moves fell 47%.[29] So, apparently while the number of people engaging in LMC-driven migration declined since the 1990s, the number of people migrating for all other reasons declined even more.

2.5.3 Effect of Other Labor Markets

Table 2.6 shows results of the model described by (2.8), estimating households' propensity to move to particular destination states. Recall that households are excluded from a regression if they originate in a state with fewer than 20 observed migrants to the destination state being modeled. Because each person has a very small likelihood of actually migrating to a specific destination state in any given year, the standard error for each individual state regression is large, particularly for less common destinations. So although I ran separate regressions for each potential destination state, I present results

[29] Author's calculations based on household heads aged 18-65.

only for the 12 destination states with at least 500,000 (non-excluded) potential migrants. As I show below, $LMC_{-o,t}$ has an insignificant effect on migration when $LMC_{d,t}$ is included in the pooled model, so for the sake of parsimony I report individual state results only for a preferred specification which includes just $LMC_{o,t}$ and $LMC_{d,t}$. Coefficients on $LMC_{o,t}$ and $LMC_{d,t}$ are reported in columns 1 and 3, respectively, alongside their standard errors in columns 2 and 4 respectively. The coefficient on $LMC_{o,t}$ is significant and positive at the 10% level in 3 of 12 regressions; it is never significant and negative (perversely signed). The coefficient on $LMC_{d,t}$ is significant and negative in 4 out of 12 state regressions and it is never significant and positive. Coincidentally, in spite of large standard errors for the models of migration to each individual state, the estimate of the semi-elasticity of household migration with respect to $LMC_{o,t}$, averaged across these 12 states (0.031) is almost identical to the semi-elasticity reported in the preferred specification in Table 2.3 (0.032). Likewise the average semi-elasticity with respect to $LMC_{d,t}$ for these 12 states is also very close to the estimate of the semi-elasticity with respect to $LMC_{-o,t}$ in the baseline model (-0.050 and -0.052 respectively).

If $LMC_{d,t}$ and $LMC_{-o,t}$ are included together in (2.8) there is more imprecision in the individual destination state regressions due to multicollinearity. To increase precision in determining whether "other" states' LMCs (besides origin and destination) affect migration, Table 2.7 reports results from (2.9), pooling observations from each of the 12 state regressions. Before describing the estimates, it is important to reiterate that most possible state-to-state combinations are not represented in this regression because of data limitations (too few households were observed moving between the states.) Therefore the elasticities reported in Table 2.7 must be viewed with caution, as they may not be representative of the United States. Still, the table suggests that models of interstate migration are far more sensitive to the inclusion of $LMC_{d,t}$ than to the inclusion of $LMC_{-o,t}$ and they also suggest that $LMC_{-o,t}$ serves as an adequate proxy for $LMC_{d,t}$. The first two columns of Table 2.7 show that a one percentage point increase in origin UI claims rate increases the likelihood of a move to other states by about five percent and a one percentage point increase in the UI claims rate in a potential destination decreases the likelihood of a move to that state by just over seven percent. These elasticities are almost identical whether $LMC_{-o,t}$ is included in the model or not, providing evidence that origin and destination LMCs satisfactorily capture the conditions relevant to the migration decision. Column 1 shows that when $LMC_{d,t}$ is included in the model, $LMC_{-o,t}$ has an insignificant effect on households' propensity to move to the destination, with an estimated elasticity very close to zero. This finding is relevant to the literature examining the procyclicality of migration with respect to aggregate LMCs. Note that if the only LMCs that affect interstate migration are those of the origin and the destination, interstate migration can only be procyclical if it responds more to changes in destination LMCs than to changes in origin LMCs. Column 3 estimates the model controlling for $LMC_{o,t}$ and $LMC_{-o,t}$, while excluding $LMC_{d,t}$.[30] When I drop $LMC_{d,t}$ from the model (column 3), $LMC_{-o,t}$ acts as a good proxy for $LMC_{d,t}$; almost the whole effect of $LMC_{d,t}$ is swallowed up in the coefficient on $LMC_{-o,t}$. The coefficient on $LMC_{o,t}$ is only slightly affected by the omission of $LMC_{d,t}$. This suggests that when data or model limitations preclude controlling for destination LMCs (as in subsections 2.5.1 and 2.5.2), including a measure of surrounding LMCs should roughly capture the conditions relevant to the

[30] The demographic controls in Tables 2.6 and 2.7 are identical to those in Table 2.3 and Table 2.4.

household's decision.

2.6 Conclusion

Labor markets drive much interstate migration as households move in an effort to improve their employment prospects. This paper investigated which labor market conditions matter in the household migration decision, how important they are, to whom they are important, and how that importance has changed over time. I find that origin and destination state labor market conditions significantly influence household migration, but that "other" states' labor market conditions are insignificant in the migration decision. "Other" surrounding states' labor market conditions can, however, act as a decent proxy for destination labor market conditions when the latter is omitted. In the baseline model with the preferred specification, I estimate that a percentage point increase in the origin state unemployment insurance claims rate leads to a 3.2 percent increase in household propensity to migrate interstate. I estimate that a percentage point increase in the unemployment insurance claims rate of surrounding states reduces interstate migration propensity by 5.2 percent. Since I find that "other state" labor market conditions have a small, insignificant effect on migration, any procyclicality of interstate migration with respect to *national* business cycle—which I find marginal evidence to corroborate—must arise because the pull effect of improvements in potential destinations' labor market conditions dominates the decreased push effect when households' origin conditions improve.

The migration of household heads with several characteristics that suggest small potential benefits to migration (including less educated and labor force nonparticipants) or high social costs to migration (including children present and nonmetropolitan) are especially unresponsive to differentials in labor market conditions. Importantly, these include several characteristics associated with high poverty risk. One consequence of this low responsiveness to labor market conditions among high poverty groups is that a state experiencing a prolonged economic decline could also undergo a sizeable increase in the proportion of household heads that are uneducated, that have children and whose heads have employment gaps. The high rates of outmigration of low-poverty groups could reduce a state government's ability to remain solvent by reducing the tax base due to: 1) low rates of population growth and 2) declines in per-capita income and wealth due to this demographic shift. The inability or unwillingness of high-poverty groups to escape from states with inferior employment opportunities may also affect our understanding of place-based policies. This chapter suggests that whatever mechanism causes individuals to migrate away from states with a labor surplus to states with a labor shortage has a smaller effect on several high poverty groups. Since high poverty groups move infrequently in response to labor market conditions, place-based policies that stimulate depressed local economies probably have a limited effect on the migration of high poverty groups out of depressed areas, but may help depressed areas attract and retain households at low poverty risk. The welfare effects of such a redistribution of labor are unclear.

The economics literature increasingly differentiates between education-specific labor demand shocks. A fruitful extension of this chapter would allow for heterogeneity in shocks to labor demand by educational attainment and for heterogeneity in shocks based on other demographic characteristics. Also, while this chapter examines the determinants of migration's responsiveness to general labor market conditions, current research does little to address what effect migration has on households. There has been some research to date that shows that migration tends to improve migrants' lifetime earnings (Kennan and Walker, 2010; Kennan and Walker, 2011) and has either zero effect or a negative effect on short-run employment after controlling for selection into migration (Pekkala and Tervo, 2002). There is a clear need for future research that determines how migration affects other outcomes such as health, leisure, income volatility, consumption, fertility, and children's educational attainment. This will improve our understanding of the advantages and disadvantages of policies that affect migration, such as the tax-deductibility of moving expenses and place-based policies that benefit depressed areas.

Tables

Table 2.1 Summary Statistics

VARIABLES	Non-Migrants	Intrastate-Intercounty Migrants	Interstate Migrants
Employed	0.779	0.789	0.745
Unemployed	0.044	0.067	0.079
Not in Labor Force	0.177	0.144	0.176
Female	0.390	0.384	0.372
Less than High School	0.153	0.126	0.109
High School	0.324	0.303	0.260
Some College	0.255	0.283	0.245
College Degree or Higher	0.268	0.288	0.386
Hispanic	0.129	0.090	0.082
Black	0.115	0.088	0.083
Married	0.602	0.447	0.507
Children Present	0.460	0.383	0.394
Nonmetropolitan	0.212	0.241	0.220
Age	42.8	34.2	35.3
Origin UI Claims	7.53%	7.60%	7.59%
Destination UI Claims	7.53%	7.60%	7.45%
UI Claims (1-1000 miles)	7.62%	7.86%	7.85%
Origin Employ. Growth	0.52%	0.67%	0.66%
Destination Employ. Growth	0.52%	0.67%	0.78%
Employment Growth (1-1000 miles)	0.52%	0.66%	0.67%
Origin Unem. Rate	6.41%	6.47%	6.50%
Destination Unem. Rate	6.41%	6.47%	6.26%
Unem. Rate (1-1000 miles)	6.51%	6.62%	6.59%
*Observations	1,301,316	35,174	28,577

Among household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Observations are dropped if state of origin is imputed. CPS weights are applied. Intrastate-Intercounty migrants refers to households that live in a different county within the same state than they did 12 months prior.

Table 2.2: Reasons for Moves: Intrastate-Intercounty Migrants, Contiguous State Migrants, Non-Contiguous State Migrants

Type of Move	Intrastate-Intercounty	Contiguous State	Non-Contiguous State
Work Related	**31.8%**	**49.9%**	**57.7%**
New Job/Transfer	17.2%	35.4%	44.1%
Look for Work	2.2%	4.9%	4.9%
Commute	9.4%	4.3%	1.1%
Retire	0.6%	1.3%	1.6%
Other (Job-Related)	2.6%	4.1%	6.0%
Housing	32.9%	16.7%	6.1%
Family	25.0%	21.7%	21.0%
Other	10.0%	11.7%	15.2%

Authors tabulations based on household heads aged 18-65 in 1998-2012 March CPS data. CPS weights are applied.

Table 2.3 Logistic Regressions of Household Propensity to Move Interstate

Panel A

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves
Origin UI Claims %	0.035*	0.032*	0.035*
(SE)	(0.009)	(0.009)	(0.009)
UI Claims % (1-1000 mi)	-0.059*	-0.052*	-0.016
(SE)	(0.011)	(0.010)	(0.024)
Time Control	Quadratic	Cubic	Year Dummies
Observations	1,365,067	1,365,067	1,365,067

Panel B

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves
Origin Unemployment Rate %	0.016*	0.015*	0.019*
(SE)	(0.007)	(0.007)	(0.007)
Unemployment Rate % (1-1000 mi)	-0.018*	-0.033*	0.061*
(SE)	(0.009)	(0.009)	(0.027)
Time Control	Quadratic	Cubic	Year Dummies
Observations	1,365,067	1,365,067	1,365,067

Panel C

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves
Origin Employment Growth %	-0.033*	-0.031*	-0.034*
(SE)	(0.011)	(0.011)	(0.010)
Employment Growth % (1-1000 mi)	0.072*	0.057*	-0.007
(SE)	(0.014)	(0.013)	(0.047)
Origin Population Growth %	0.007	0.008	0.009
(SE)	(0.013)	(0.012)	(0.012)
Population Growth % (1-1000 mi)	-0.064	-0.030	0.011
(SE)	(0.043)	(0.035)	(0.049)
Time Control	Quadratic	Cubic	Year Dummies
Observations	1,365,067	1,365,067	1,365,067

Results based on household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Reported values indicate the estimated change in (log) household migration propensity associated with a percentage point change in the UI claims/unemployment/employment growth rate, when evaluated at median/modal characteristics and median LMCs. Observations are dropped if state of origin is imputed. UI Claims (1-1000 mi) is constructed by taking the population-weighted average of UI claims rates of states within 1,000 miles of the household's origin. Unemployment Rate (1-1000 mi) is constructed by taking the population-weighted average of unemployment rates of states within 1,000 miles of the household's origin. Employment Growth (1-1000 mi) is constructed by taking the population-weighted average of unemployment rates of states within 1,000 miles of the household's origin. Additional controls include: four indicators for education, a cubic in age, a quadratic in year, and indicators for employed, unemployed, female, black, Hispanic, marital status, presence of children, metropolitan status and state of origin. Standard errors are clustered by origin state. Full results in Appendix Table A.1.

* Significant at 5% level

♦ Significant at 10% level

Table 2.4 Logistic Regressions of Household Propensity to Move Interstate, Alternative Spatial Specifications

Panel A

VARIABLES	(1) Interstate Move	(2) Interstate Move
Origin UI Claims %	0.038*	0.032*
(SE)	(0.009)	(0.008)
UI Claims (Border) %	-0.017	-0.037*
(SE)	(0.008)	(0.007)
UI Claims (Non-Border) %	-0.044*	
(SE)	(0.012)	

Panel B

VARIABLES	(1) Interstate Move	(2) Interstate Move
Origin UI Claims %	0.033*	0.031*
(SE)	(0.009)	(0.009)
UI Claims (1-500 mi.) %	-0.018	-0.039*
(SE)	(0.011)	(0.009)
UI Claims (500+ mi.) %	-0.037*	
(SE)	(0.012)	

Panel C

VARIABLES	(1) Interstate Move	(2) Interstate Move
Origin UI Claims %	0.033*	0.032*
(SE)	(0.009)	(0.009)
UI Claims (1-1000 mi.) %	-0.036*	-0.052*
(SE)	(0.015)	(0.010)
UI Claims (1001+ mi.) %	-0.021♦	
(SE)	(0.013)	

Panel D

VARIABLES	(1) Interstate Move	(2) Interstate Move
Origin UI Claims %		0.036*
(SE)		(0.009)
National UI Claims %		-0.058*
(SE)		(0.011)

Results based on household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Reported values indicate the estimated change in (log) household migration propensity associated with a percentage point change in the UI claims/unemployment/employment growth rate, when evaluated at median characteristics and median LMCs. Observations are dropped if state of origin is imputed. LMC (Border) and LMC (Non-Border) are constructed by taking the population-weighted average of all bordering/non-bordering states' LMCs. LMC (1-1000 mi.) and LMC (1-500 mi.) are constructed by taking the log of the population-weighted average of the LMCs of states within 1000 and 500 miles, respectively, of the household's origin. LMC(1001+ mi.) and (501+ mi.) are constructed by taking the population-weighted average of LMCs of all states over 1000 miles and 500 miles, respectively, from the household's origin. Additional controls include: four indicators for education, a cubic in age, a cubic in year, and indicators for employed, unemployed, female, black, Hispanic, marital status, presence of children, metropolitan status and state of origin. In each panel the number of observations is 1,365,067. Standard errors are clustered by origin state. Full results from the regressions in column (2) are available in Appendix Table A.2.

* Significant at 5% level

♦ Significant at 10% level

Table 2.5 Effect of Household Characteristics on Responsiveness of Household Migration to Labor Market Differentials

VARIABLES	(1) Interaction with Diff. UI Claims	(2) Interaction with Diff. Unemployment Rate	(3) Interaction with Diff. Employment Growth
Employed	0.039*	0.060*	-0.071*
(SE)	(0.007)	(0.013)	(0.022)
Unemployed	-0.040*	-0.045*	0.125*
(SE)	(0.010)	(0.017)	(0.027)
Less than HS	-0.008	0.026♦	-0.006
(SE)	(0.009)	(0.014)	(0.028)
Some College	0.026*	0.035*	-0.002
(SE)	(0.010)	(0.014)	(0.021)
4 Year Degree	0.032*	0.048*	-0.008
(SE)	(0.011)	(0.014)	(0.021)
Married	0.000	-0.003	-0.010
(SE)	(0.007)	(0.010)	(0.015)
Child Present	-0.021*	-0.005	0.030*
(SE)	(0.006)	(0.009)	(0.015)
Age	0.005*	-0.019♦	0.043*
(SE)	(0.001)	(0.011)	(0.015)
Age Squared × 100	-0.019*	0.048♦	-0.099*
(SE)	(0.005)	(0.027)	(0.037)
Age Cubed × 10,000	-0.020*	-0.037♦	0.072*
(SE)	(0.005)	(0.021)	(0.030)
Female	-0.006	-0.004	0.041*
(SE)	(0.006)	(0.011)	(0.018)
Hispanic	0.043*	-0.020	-0.039
(SE)	(0.019)	(0.020)	(0.034)
Black	0.045*	0.015	-0.092*
(SE)	(0.016)	(0.025)	(0.026)
Nonmetropolitan	-0.068*	-0.023	0.129*
(SE)	(0.017)	(0.027)	(0.032)
Time	-0.005	-0.011♦	0.008
(SE)	(0.004)	(0.006)	(0.008)
Time Squared × 100	0.026	0.034	0.009
(SE)	(0.036)	(0.049)	(0.060)
Time Cubed × 10,000	-0.029	0.002	-0.135
(SE)	(0.077)	(0.109)	(0.130)

Results based on household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Observations are dropped if state of origin is imputed. LMC(1-1000 mi) is constructed by taking the population-weighted average of LMCs of states within 1,000 miles of the household's origin. Each regression included the following independent variables: Difference between Origin LMC and LMC(1-1000 mi), all of the household head characteristics and time variables listed above, interactions of the difference between LMCs with household head characteristics and with the cubic in year and indicators for origin state. Reported values indicate the coefficients on these interaction terms. Standard errors are clustered by origin state. All regressions are evaluated at median/modal characteristics and median LMCs. Full results are in Appendix Table A.3.

* Significant at 5% level

♦ Significant at 10% level

Table 2.6 Logistic Regressions of Household Propensity to Move to Specific States

Dep. Variable: Propensity to Move to:	(1) Indep Var: Ln Orig UI Claims	(2) (SE)	(3) Indep Var: Ln Dest UI Claims	(4) (SE)
California	0.017	(0.028)	-0.023	(0.034)
Colorado	0.039	(0.024)	-0.121*	(0.059)
Florida	0.058*	(0.023)	-.0149*	(0.038)
Georgia	-0.029	(0.035)	-0.069	(0.061)
Illinois	-0.065	(0.055)	-0.009	(0.057)
Massachusetts	0.055	(0.055)	-0.047	(0.059)
Nevada	0.100♦	(0.056)	-0.074♦	(0.045)
North Carolina	0.013	(0.027)	-0.053	(0.036)
Ohio	0.027	(0.046)	0.043	(0.071)
Pennsylvania	0.061	(0.055)	0.006	(0.068)
Texas	0.071*	(0.025)	-0.084*	(0.041)
Virginia	0.027	(0.037)	-0.016	(0.099)
Average	**0.031**		**-0.050**	

Results based on household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Observations are dropped if state of origin is imputed. Only households from states with at least 20 observed migrants to the destination state are considered in each regression. Additional controls include: four indicators for education, a cubic in age, a cubic in year, and indicators for employed, unemployed, female, black, Hispanic, marital status, presence of children, metropolitan status and state of origin. Standard errors are clustered by origin state.

* Significant at 5% level

♦ Significant at 10% level

Table 2.7 Logistic Regressions of Household Propensity to In-migrate, Pooled Across All Potential Destination States

VARIABLES	(1) State to State Move	(2) State to State Move	(3) State to State Move
Origin UI Claims	0.052*	0.049*	0.045*
(SE)	(0.009)	(0.008)	(0.009)
Destination UI Claims	-0.073*	-0.074*	
(SE)	(0.006)	(0.006)	
UI Claims (1-1000 mi)	-0.009		-0.068*
(SE)	(0.015)		(0.013)
Observations	5,648,008	5,648,008	5,648,008
Pseudo R-Squared	0.065	0.065	0.064

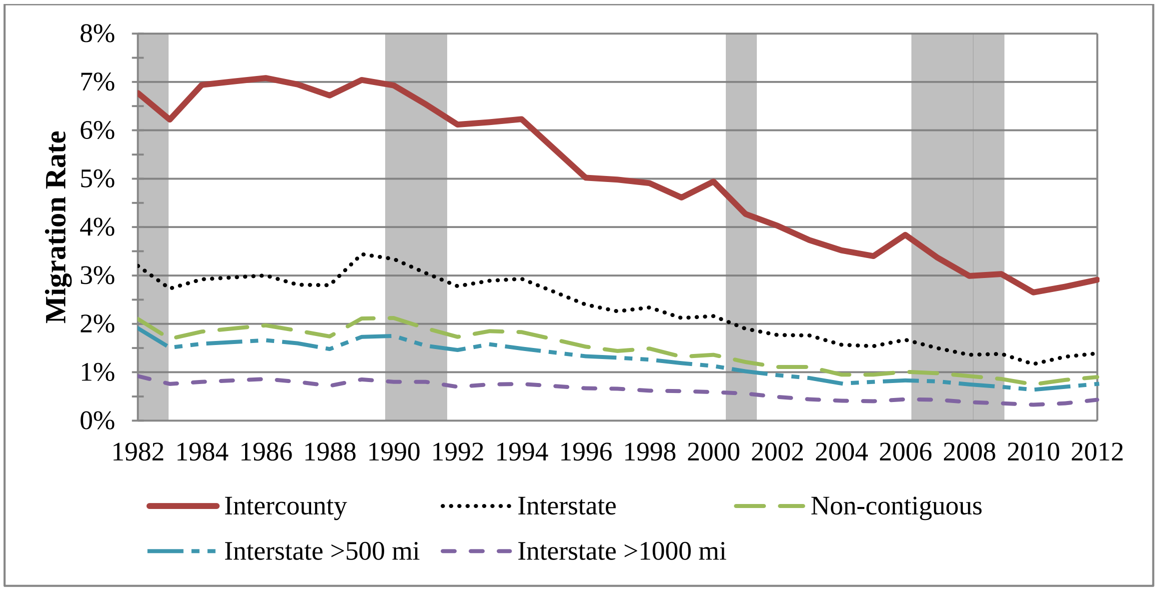
Regression pooled across all state regressions listed in Table 2.6. Unit of observation is the household-potential destination state (equals 1 if the household moved to that state). Results are based on household heads aged 18-65 in 1982-2012 March CPS data, excluding 1985 and 1995. Observations are dropped if state of origin is imputed. Only households from states with at least 20 observed migrants to the destination state are considered in each regression. Additional controls include: four indicators for education, a cubic in age, a cubic in year, and indicators for employed, unemployed, female, black, Hispanic, marital status, presence of children, metropolitan status, state of origin, (potential) destination state, and log distance between origin and potential destination. Standard errors are clustered by origin state.

* Significant at 5% level

♦ Significant at 10% level

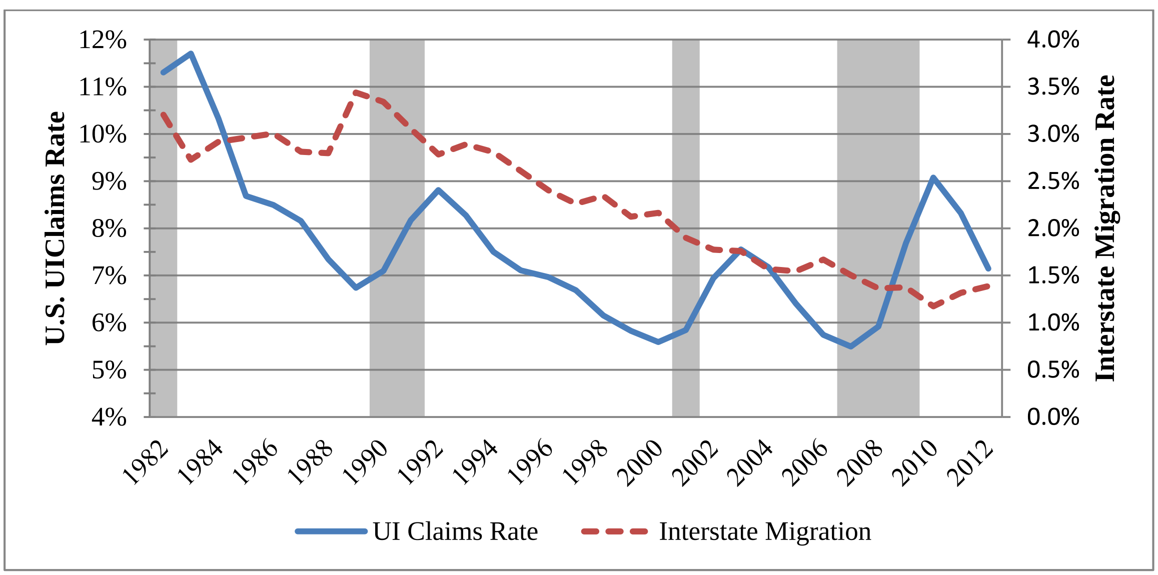
Figures

Figure 2.1: Migration Rates by Year, 1982-2012



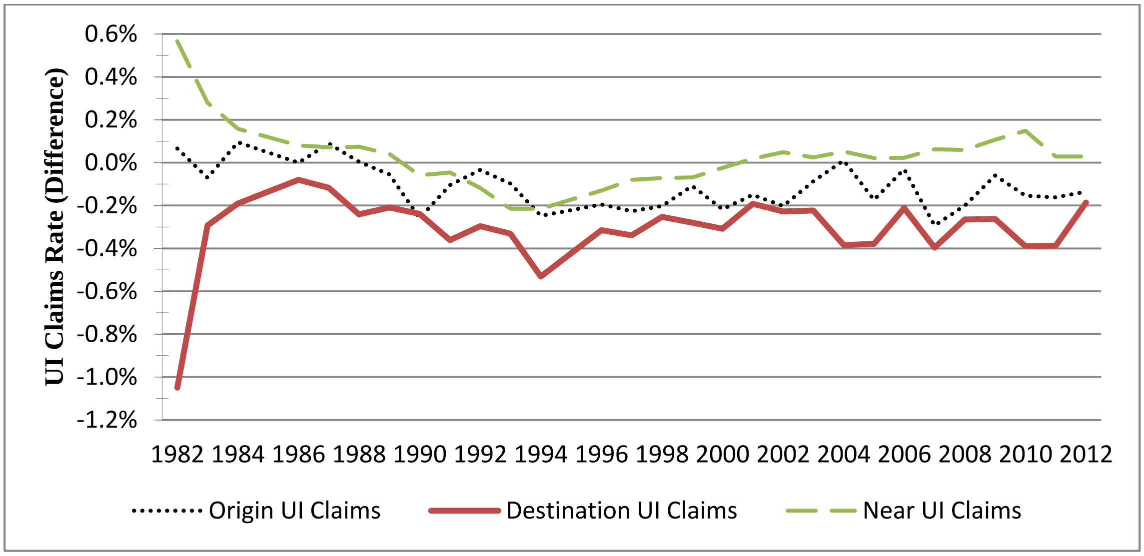
Percentage of households reporting that 12 months ago they lived in a different jurisdiction (county, state, non-contiguous state, state more than 500 miles away, or state more than 1000 miles away), 1982-2012.

Figure 2.2: U.S. Unemployment Insurance Claims & Interstate Migration Rates, 1982-2012



U.S. unemployment insurance claims rate and interstate migration rate—the percentage of household heads aged 18-65 reporting that 12 months ago they lived in a different jurisdiction, 1982-2012. UI claims represents a two year average including the previous year.

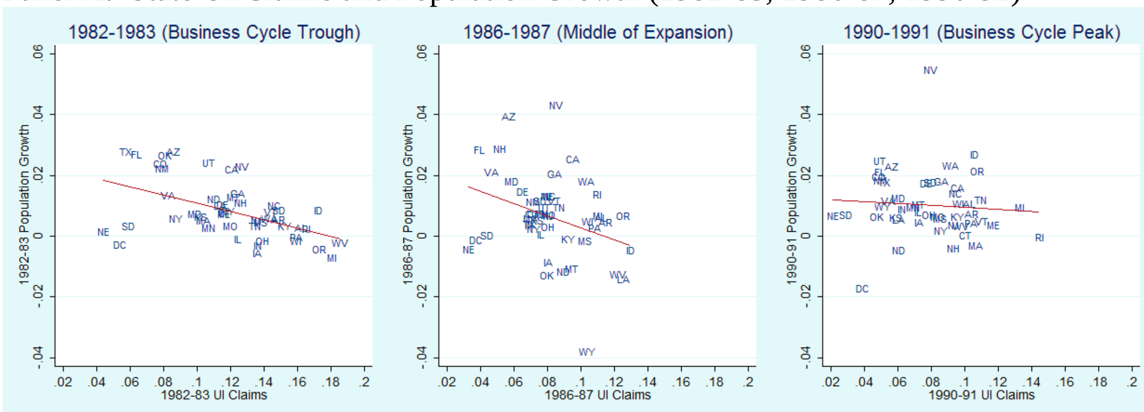
Figure 2.3: Origin, Destination and Surrounding Unemployment Insurance Claims Rates Relative to U.S., Among Interstate Migrants



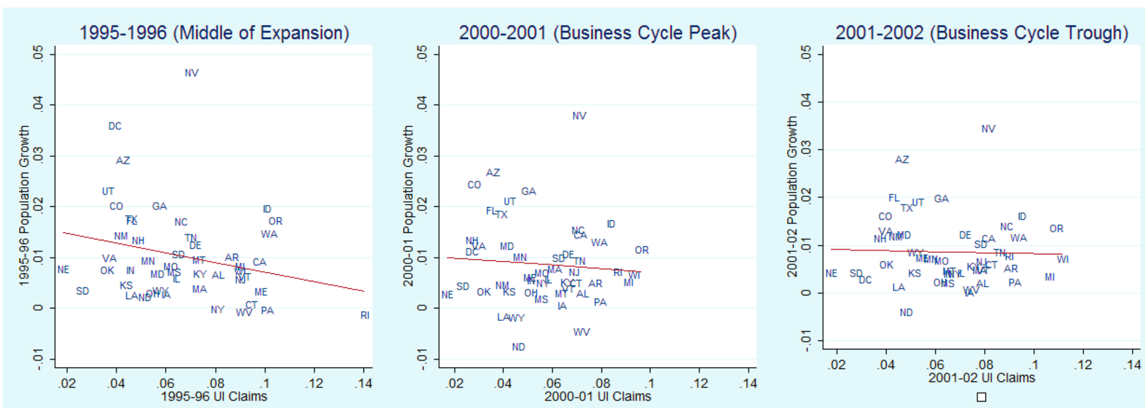
Difference between various unemployment insurance claims rates and the U.S. unemployment insurance claims rate, among interstate migrants 1982-2012.

Figure 2.4: Yearly State UI Claims and Population Growth Scatterplots

Panel A: State UI Claims and Population Growth (1982-83, 1986-87, 1990-91)



Panel B: State UI Claims and Population Growth (1995-96, 2000-01, 2001-02)



Panel C: State UI Claims and Population Growth, (2004-05, 2007-08, 2009-10)

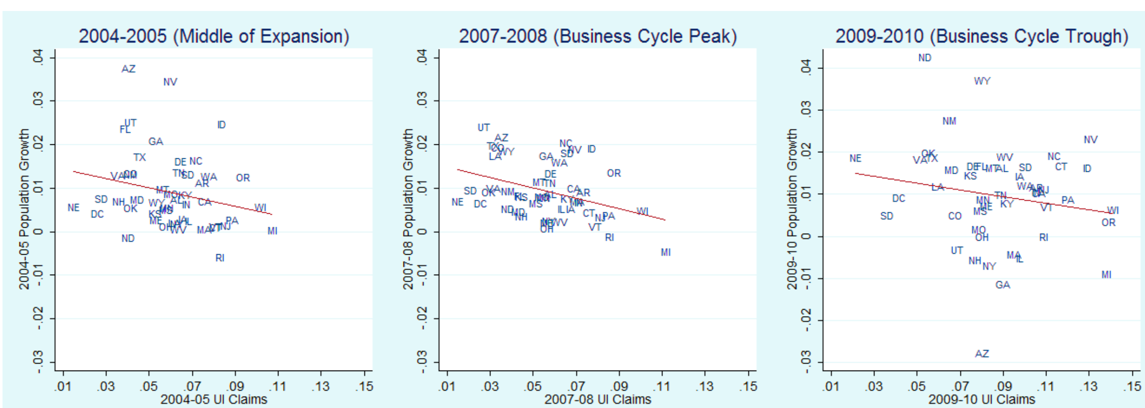
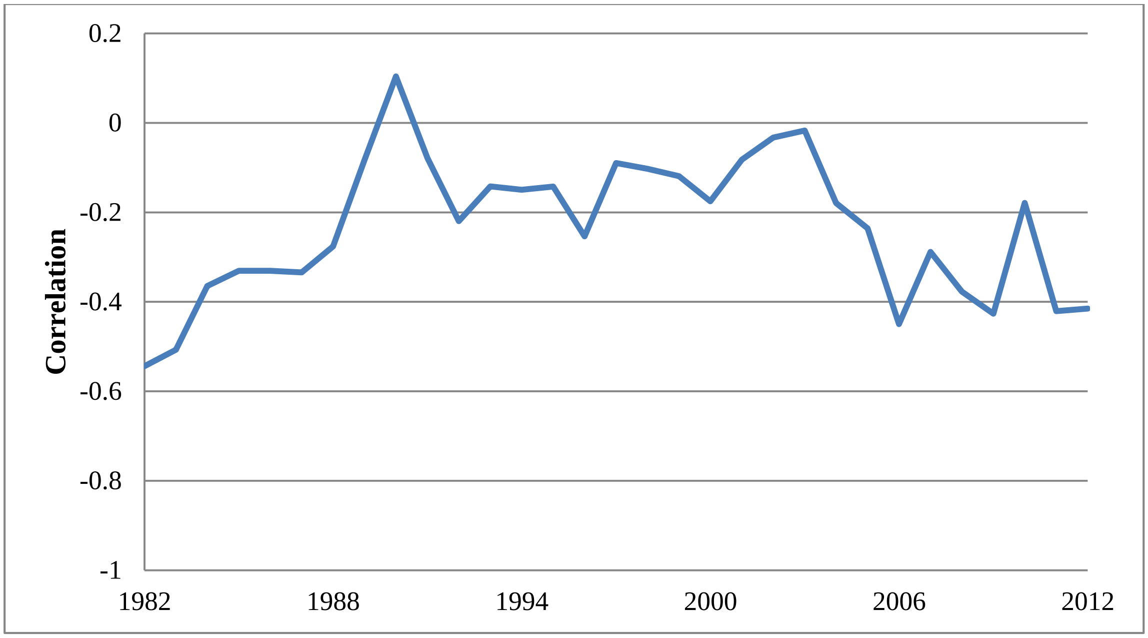


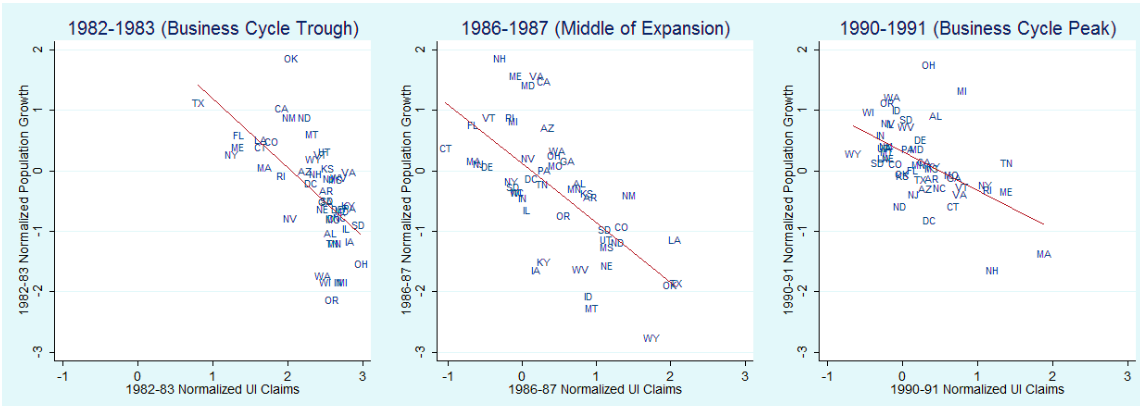
Figure 2.5: Correlation between State UI Claims & Population Growth, 1982-2012



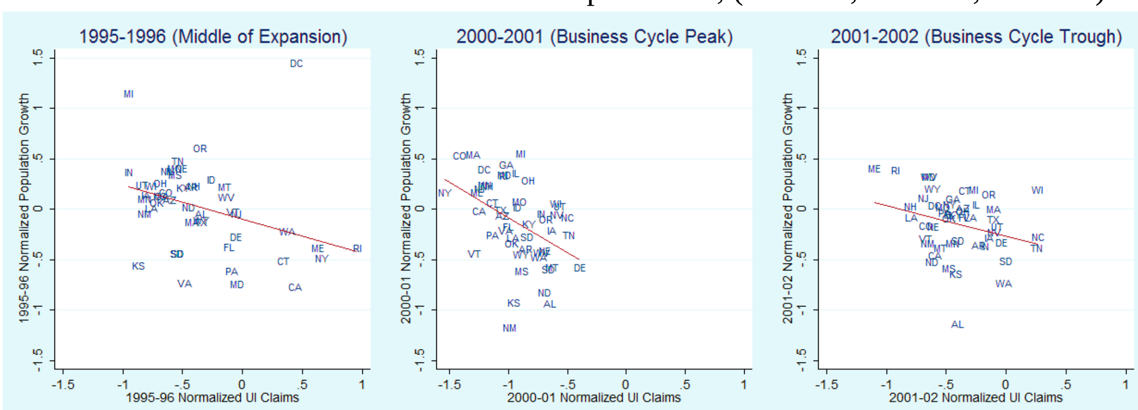
Time series of a simple correlation between two-year average of state's initial unemployment insurance claims rate and state's population growth.

Figure 2.6: Yearly Normalized State UI Claims and Population Growth Scatterplots

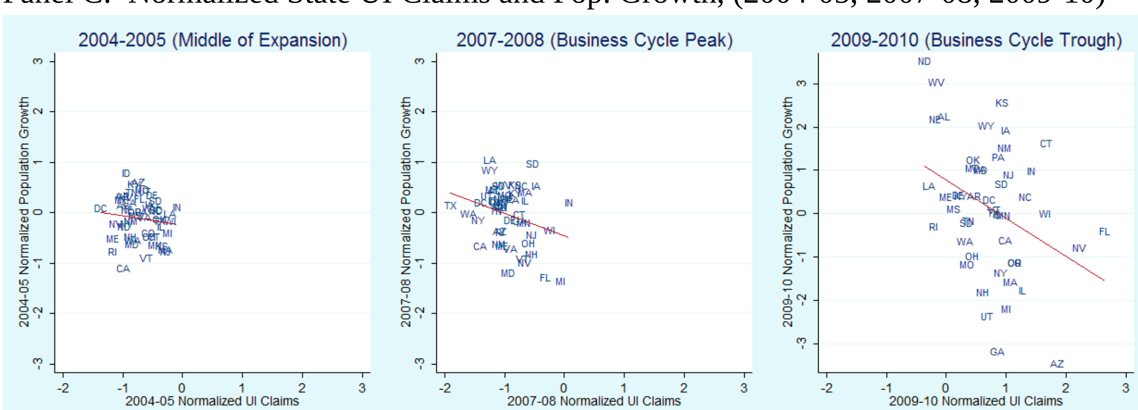
Panel A: Normalized State UI Claims and Pop. Growth (1982-83, 1986-87, 1990-91)



Panel B: Normalized State UI Claims and Pop. Growth, (1995-96, 2000-01, 2001-02)

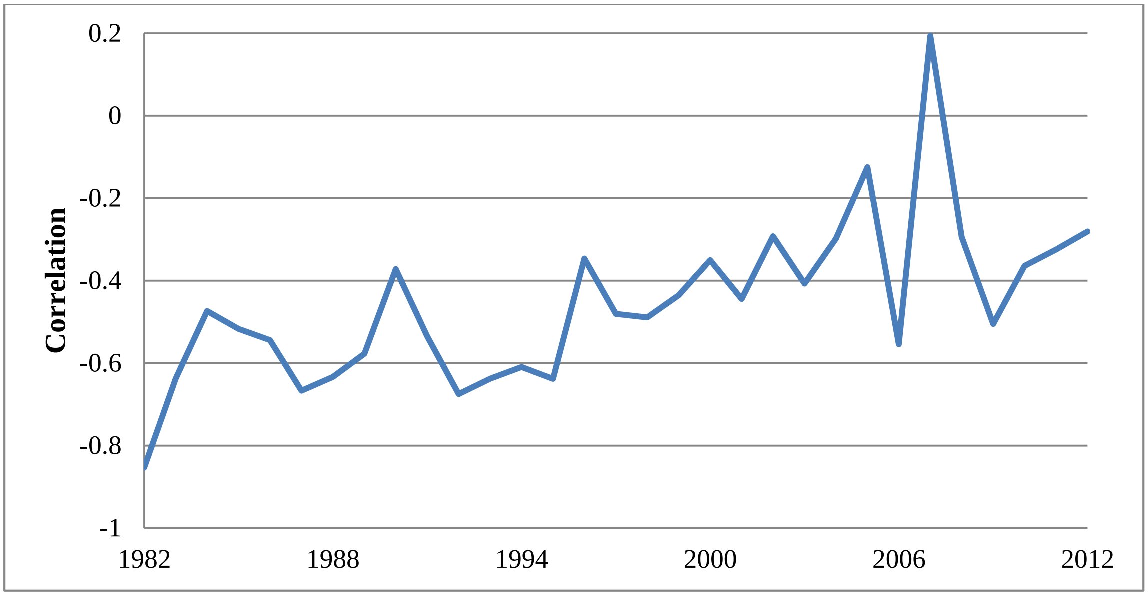


Panel C: Normalized State UI Claims and Pop. Growth, (2004-05, 2007-08, 2009-10)



State population growth and state UI claims are normalized using that state's average and standard deviation values over the period 1982-2012.

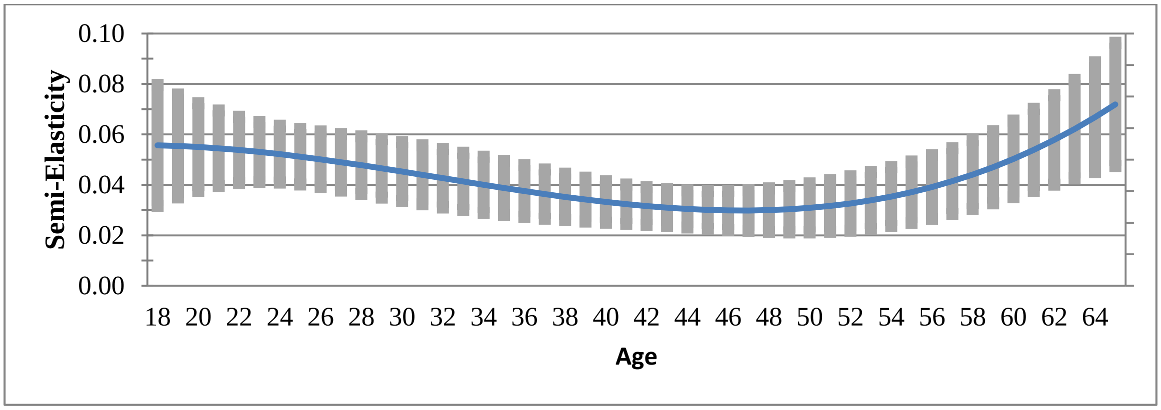
Figure 2.7: Correlation between Normalized State UI Claims & Pop. Growth by Year



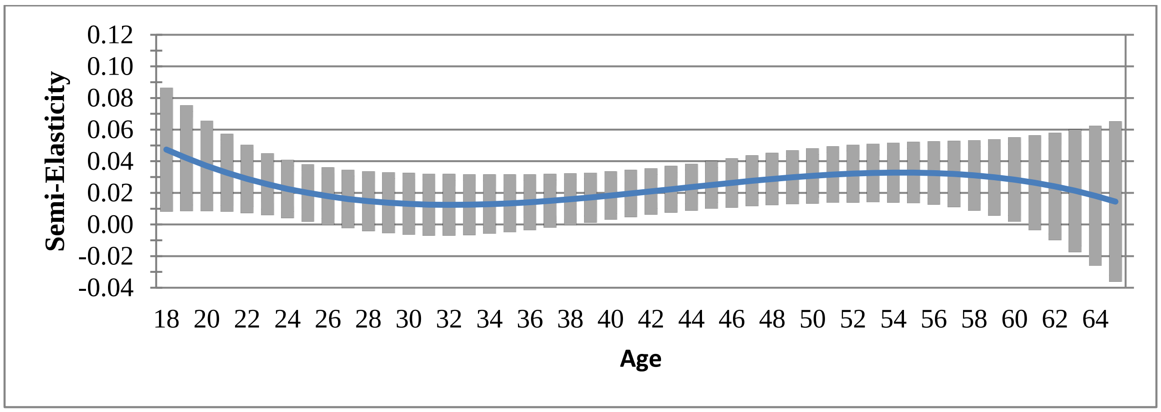
Time series of a simple correlation between two-year average of state's initial unemployment insurance claims rate and state's population growth. State population growth and state UI claims are normalized using that state's average and standard deviation values over the period 1982-2012.

Figure 2.8: Responsiveness of Household Migration to Labor Market Differentials by Age

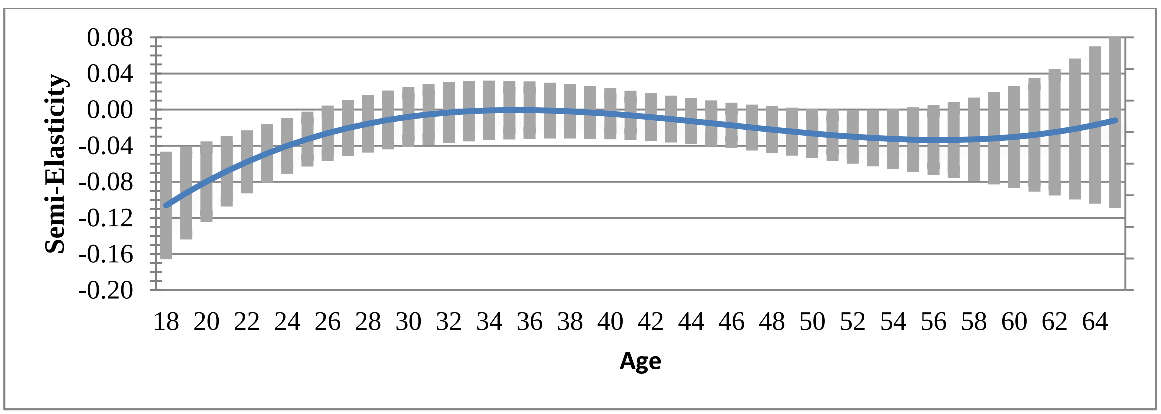
Panel A: Responsiveness of Migration to UI Claims Differentials by Age



Panel B: Responsiveness of Migration to Unemployment Rate Differentials by Age



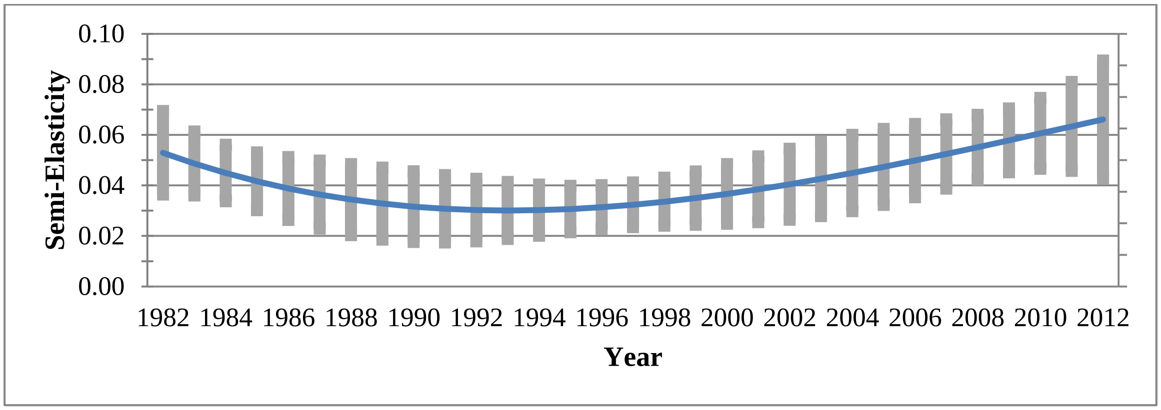
Panel C: Responsiveness of Migration to Employment Growth Differentials by Age



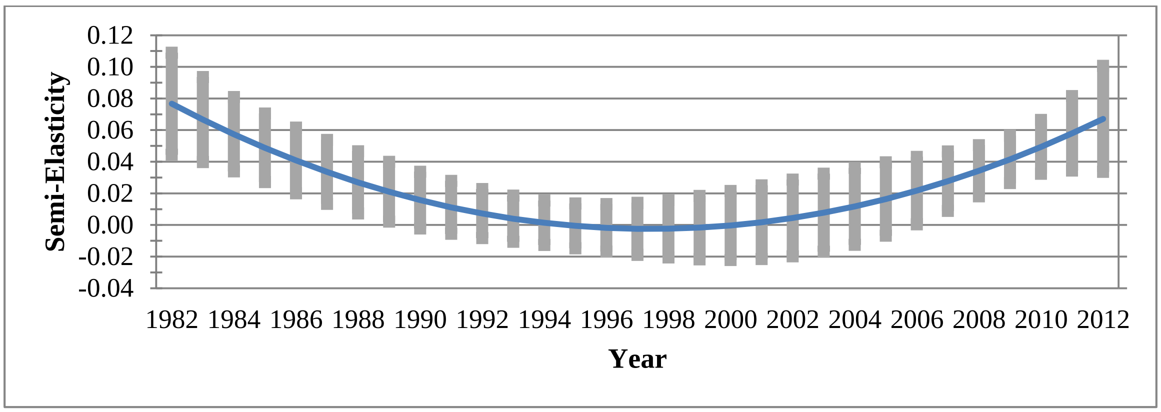
Based on the interactions of the cubic in age with $LMC_{o,t}$ and $LMC_{-o,t}$ in Appendix Table A.3. Semi-elasticities calculated for median/modal characteristics and median LMCs. Gray bars represent 95% confidence intervals for the age cubic.

Figure 2.9: Responsiveness of Household Migration to Labor Market Differentials by Year

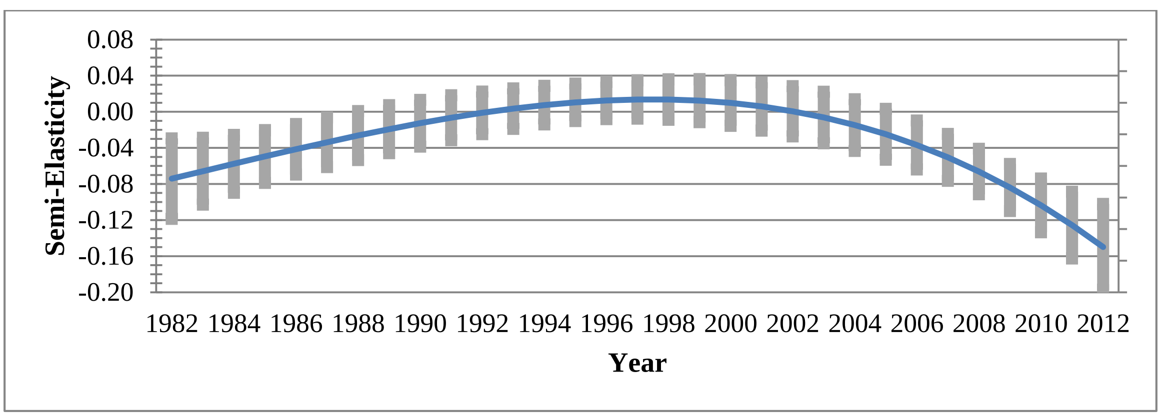
Panel A: Responsiveness of Migration to UI Claims Differentials, 1982-2012



Panel B: Responsiveness of Migration to Unemployment Rate Differentials, 1982-2012



Panel C: Responsiveness of Migration to Employment Growth Differentials, 1982-2012



Based on the interactions of the cubic in age with $LMC_{o,t}$ and $LMC_{-o,t}$ in Appendix Table A.3. Semi-elasticities calculated for median characteristics and median LMCs. Gray bars represent 95% confidence intervals for the time cubic.

3 GIVE ME YOUR MOTIVATED, RICH, EDUCATED MASSES: BRAIN GAIN AND BRAIN DRAIN IN AMERICA

3.1 Introduction

With steady population growth and rising educational attainment, both the number and the share of educated people are rising in almost all areas of the United States. Artz (2003) points out that the share of residents with college degrees declined in only five U.S. counties over the period 1970-2000. In contrast, skilled worker outflows in many developing and less developed countries severely limit their human capital development. In 2000, 44 percent of all working-age (aged 25 and above) individuals with a tertiary education who were born in Melanesia had immigrated to an OECD nation, compared to just 2.5 percent of those with a secondary education or less (Docquier and Marfouk, 2006). If policymakers in Melanesia, the Caribbean, Micronesia, Southeast Asia and much of Africa wish to develop human capital at home, they are fighting an uphill battle thanks to the brain drain.[31] It is unsurprising, then, that the topic of brain gain and brain drain within the United States garners less widespread attention than international brain drain does in these nations. Yet despite almost universal growth in human capital in the U.S., there are substantial differences among local areas in their ability to attract and retain human capital. There are winners and losers from domestic migration and in some pockets of the U.S., business owners, community leaders and policymakers correctly perceive that they are on the wrong end of

[31] Such countries on net may benefit from brain drain through remittances and the educational incentives that arise from higher international and domestic returns to human capital (Beine et al., 2008; Grubel and Scott, 1966). (Brain drain's negative effect on the domestic supply of high skill labor increases the returns to education.)

this exchange, lamenting the loss of the best and brightest from their cities and towns.[32] [33] [34] These cries may spread and grow louder in the future if declining global fertility and increasing global income parity limits the extent to which international flows can plug the areas of brain drain in the United States. Slower national population growth inevitably means that more cities and towns will face population decline, and the inability to attract and retain young educated workers will presage many communities' gradual demise.

This chapter will paint a picture of brain gain and brain drain in America, describing flows of young high school graduates and young to middle-aged college graduates and determining the principal determinants of these flows. I focus on the effect of initial economic conditions and urbanicity (metropolitan status and area density) on three measures: absolute gains in the high school-educated, relative gains in the high school-educated (compared to high school dropouts) and relative gains in the college-educated (compared to non-college-educated). In the previous chapter I showed that the migration of well-educated household heads responds more to short-run labor market conditions, suggesting a role for labor market conditions in area brain gain and brain drain if the response is not transitory. In fact this chapter shows that the strength of initial labor market conditions leads to sizeable positive long-run effects (over a 16 to 20 year period) on an area's stock and share of educated workers. I also find that nonmetropolitan areas struggle to attract and retain educated residents. Both central cities and suburban areas fare well in attracting educated workers, but they apparently

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[32] Rich Lord, "City Hall Hobbled by Brain Drain," *Pittsburgh Post-Gazette*, August 5, 2007. http://www.post-gazette.com/local/city/2007/08/05/City-hall-hobbled-by-brain-drain/stories/200708050100
[33] Jennifer Hemmingsen, "Building Blocks for Reversing the Brain Drain," *The Gazette,* May 30, 2010. http://thegazette.com/2010/05/30/building-blocks-for-reversing-the-brain-drain/
[34] Tom Still, "Brain Gain is what Wisconsin Needs to Work on," *Milwaukee Wisconsin Journal Sentinel*, March 22, 2014. http://www.jsonline.com/business/brain-gain-is-what-wisconsin-needs-to-work-on-b99226633z1-251708091.html

appeal to workers at different points of the lifecycle. Central cities are relatively attractive to young educated migrants while suburban areas are more attractive later in life.

Most economists believe that a concentration of human capital in a place leads to positive externalities. Businesses and individuals benefit from proximity to workers, from improved networking, and from the development and rapid exchange of ideas (Duranton and Puga, 2004). Public coffers expand due to the affluence of a skilled labor force. Families with children may benefit from lower crime rates (Lochner and Moretti, 2004) better public schools, and positive peer effects due to the intergenerational transmission of education (Burke and Sass, 2013; Choy, 2001). Perhaps for any of these reasons, Whisler et al. (2008) discovered that people are almost universally less likely to migrate out of areas with large and growing stocks of human capital. Such migration behavior suggests that the external benefits of human capital are real. Flows of educated workers matter to individuals in both the origin and destination, but perhaps especially to the areas negatively affected by brain drain. For local, state or national policymakers to develop informed policy to deal with brain drain, they first must understand who is affected and why. This chapter is one step towards answering these questions.

3.2 Literature Review

The migration behavior of educated workers is of policy interest in part because economists believe that human capital externalities exist. If neighbors, coworkers, and employers of educated individuals benefit from their human capital, flows of human capital in and out of cities affect the residents of these cities. Moretti (2004) provides a thorough account of the state of economic theory and empirical evidence of human capital externalities. Theories abound explaining why human capital spillovers exist.[35] Economists have suggested that a concentration of educated workers increases the productivity of other workers in an area by facilitating knowledge transfer (Lucas, 1988; Marshall, 1890; Moretti, 2004), by encouraging the development of physical capital and skill-intensive technology (Acemoglu, 1996; Acemoglu, 1998). Others have credited increases in educational attainment with reducing criminal activity (Lochner and Moretti, 2004), encouraging civic involvement (Milligan et al., 2004), and increasing support of free speech (Dee, 2004). Although residents of local areas with high levels of human capital benefit from spillovers in aggregate, in some cases residents of an area might benefit from marginal outmigration of skilled labor because of reductions in congestion. Likewise flows of human capital could lead to net external benefits through improved labor market matches, differences across local areas in the complementarity of types of labor, or by improved Tiebout sorting.

Whatever form human capital externalities take, which local attributes cause an area to attract or repel the human capital that confers these externalities? There is little research directly addressing how area poverty or labor market conditions influence the long-term *growth* of an area's more educated and less educated populations *through migration* (though economists have certainly observed that human capital is more concentrated in places with strong economic conditions). Research identifying higher migration responsiveness to labor market conditions among more educated individuals

[35] Some instead contend that education leads to negative externalities because education increases individuals' wages primarily by signaling to employers that one is a productive worker (rather than *causing* large productivity gains). Because less educated workers lack the positive signal, their labor market outcomes are worse in the presence of a highly educated workforce.

provides suggestive evidence that strong labor market conditions cause relative population gains among college-educated cohorts, but the aggregate effects on local labor markets is unknown. The second chapter of this dissertation shows that the migration of more educated households is particularly responsive to current labor market conditions. Looking over a longer time horizon, Wozniak (2010) has similar findings. Using Census microdata, she finds that a positive labor demand shock in a state at the time of labor market entry (approximated by the year when age is equal to years of education plus six) causes a particularly large increase in college-educated worker's propensity to reside there. While Wozniak convincingly demonstrates the high responsiveness of college-graduates' migration to distant labor market conditions over the medium term, there are several ways that data limitations and methodology cause the results to be poorly-suited for assessing the extent of local area brain gain and brain drain caused by economic conditions. [36]

Given the strong link between educational attainment and income, a positive relationship between initial human capital and growth of human capital would suggest that brain gain is more prevalent where LMCs are (initially) most favorable. Waldorf (2009) observes that the share of a county's initial population that is college-educated positively predicts the share of a county's inmigrants that are college-educated. Note,

[36] First, the use of state of birth as a proxy for potential migrants' initial residence causes moves between birth and labor market entry to be confounded with later moves. Second, since only state-to-state moves can be identified, moves between labor markets within states are not captured *and* heterogeneity of labor market conditions *within* states is ignored. Third, because labor market entry is based on the Mincer formula, any individuals that took time off between high school and college (and any individuals that took longer than four years to complete their degree) are assigned initial state labor market conditions that coincide with when they were still in college or before they started college. This leads to some attenuation of the estimates of the responsiveness of college graduate's migration to *actual* labor market conditions at the time of labor market entry. Fourth, since the unit of observation is the individual, the results reveal causes of heterogeneity in the responsiveness of *individuals* to labor market conditions, but do not reveal how other state characteristics (besides initial labor market conditions) affect brain gain.

however, that this need not imply that migration leads to growing divergence in county educational attainment, since it is probably also true that *outmigrants* from more educated counties are more educated than outmigrants from less educated counties. However, Berry and Glaeser (2005) show that, *ceteris paribus*, metropolitan areas with large proportions of college-educated workers also had higher growth rates of shares of college-educated workers in the 1980s and 1990s.[37] This evidence of divergence in college attainment appears whether shares and growth rates are measured in levels or logarithms. Moretti (2004) shows a similar divergence in city educational attainment in the 1990s. These authors do not seek to explain the initial differences in college attainment, though, so it is unclear whether economically-motivated migration or other factors cause this divergence. For that matter, it isn't clear whether and to what extent migration caused this divergence, as a failure of less educated metropolitan areas to educate young residents would affect human capital growth just as a failure to attract more educated migrants would.

Along a similar vein, some recent economic literature explores the link between where the college-educated received degrees and where they eventually live. Using the NLS72 and the Mellen Foundation's College and Beyond data, Groen (2004) finds only a weak link between where students attended college and where they live and work 15 years later (controlling for where students applied to college). Graduates tend to locate where income opportunities and amenities are maximized (Borjas 1992; Kennan and Walker 2011), which often differs from where they receive their education. Bound et al. (2004) find that at the state level, the elasticity of the stock of BAs with respect to the

[37] Note that any potential time-varying measurement error biases estimates towards finding convergence, not divergence.

number of BAs conferred is less than 0.3 and the number of people with MDs in a state has practically zero relationship with the number of MDs conferred.[38]

If more affluent individuals tend to migrate toward more affluent areas, this would again be suggestive that brain gain would be more likely in areas with strong initial economic conditions. Nord (1998) seeks to determine whether high poverty counties attract more impoverished migrants. He explores this question using five-year county-to-county migration data in the 1990 decennial census. He shows that there was net migration of the poor into high poverty counties and net migration of the "nonpoor" into low poverty counties. There is, however, some concern that an individual's migration influences their poverty status (Nord determined poverty based on income after any moves had already occurred.) The differences in net migration of poor and nonpoor could therefore be explained if moving from rich counties to poor counties causes declines in individual income (perhaps as a tradeoff for better amenities or lower cost of living) while moving from poor counties to rich counties causes increases in individual income. Thus the inmigration of *initially* poor individuals may *not* have been any higher in high poverty counties. By estimating the effect of area poverty on growth of the college-educated, the present paper will similarly address the reinforcement or widening of demographic differences between high and low poverty areas, but because educational attainment is relatively fixed after a certain age, it is less susceptible to endogeneity.

In addition to local economic conditions, I also consider the effect of urbanicity

[38] The authors of this paper note that these results are consistent with the extent of state subsidization of recipients of these degrees. That is, since recipients of bachelor's degrees are apparently more likely to end up where they received that education, states find it worthwhile to subsidize their education to a large degree. However since doctors operate in a national market, states gain little by subsidizing their education (hence states subsidize medical students less.) If the same rationale is applied to primary and secondary educations, one would expect that counties that retain a large proportion of their high school graduates would have somewhat higher education expenditures, *ceteris paribus*.

on the migration of the educated. Waldorf (2008) and others have shown that more educated people are more prevalent in metropolitan areas, particularly central cities, and that this urban-rural gap has been increasing over time. Metropolitan wages are about one-third higher than nonmetropolitan wages, and about two-thirds of this pay gap cannot be explained by differences in skill or cost of living (Glaeser and Mare, 2001). The higher productivity and lower costs possible for firms that locate near a high concentration of other related firms are known as urban agglomeration economies or simply agglomeration economies. Economists have suggested that skilled workers particularly benefit from the spread of ideas in densely populated areas and other advantages of being in close proximity to many firms (Glaeser and Mare, 2001). Adamson et al. (2004) posit instead that the concentration of skilled workers results primarily from their preference for urban amenities. Results presented in this chapter support the contention that labor markets, not urban amenities, are the primary reason educated workers congregate in cities.

Some recent research examines the effect of urbanicity on the relative growth of skilled and unskilled labor. Artz (2003) uses a shift-share analysis of 1970-2000 Census county data to determine the proportion of total population growth (ages 25 and up) over that period that was attributable to growth in the share of the county's college-educated population. Population growth in metropolitan counties, particularly large metropolitan areas, was characterized by particularly high growth of the college-educated. A crucial difference between the present chapter and Artz (2003) is that my data follows specific age cohorts so I can more closely determine the extent that migration (in key periods of the lifecycle) causes this metropolitan human capital growth. Franklin (2003) found markedly higher rates of inmigration to central cities among single, college-educated 25-39 year olds compared to the general population. However, Franklin also found that single, *non*-college-educated 25-39 year olds have a relatively high propensity to migrate into central cities, so the effect of college education on the urban-rural migration decisions of this cohort is not clearly distinguished from the effect of being young and single. Moreover Franklin considers only inmigration and not outmigration, so the effect of urbanicity on net brain gain of young adults remains unclear.

Even if depressed or rural areas suffer from brain drain, does it make sense to attack such a problem, or even to worry about it? Aren't regional losses balanced out by regional gains elsewhere, so wouldn't any policies designed to stop such flows amount to rent-seeking activity? These questions tie into the larger discussion of the merits of "place-based policies." People-based policies are designed to "[improve] the welfare of deserving people as individuals, *regardless of where they live*", while place-based policies are designed to "[improve] the welfare of groups of deserving people defined by their spatial proximity in places," (Bolton 1992). Some economists have argued that place-based policies are at best a zero-sum game, and at worst prolong the structural imbalances in the economy that they are meant to improve (Edel, 1980). Winnick (1966) described place-based policies as "clumsy, expensive, and often inequitable devices" for redistribution. Bartik (1991), for one, disputes this notion. He acknowledges that there are winners and losers from local economic development policies, but argues that well-targeted policies may lead to net societal gains *and* may be progressive in nature.[39]

[39] Since chronically unemployed people tend to have lower reservation wages, the utility gains that they receive from additional employment opportunities are the largest. Therefore Bartik argues that the benefits of regional development policies in depressed regions will greatly outweigh the benefits of similar programs enacted in high employment areas. Because the benefits of place-based policies tend to be largest

Bolton (1992) further makes the case for place-based policies by pointing to economic evidence that people value "sense of place" as evidenced by sacrifices they make to strengthen their local community (e.g. buying local). Additionally, people seem to place either option value or existence value on the sense of place in areas they don't live, as people expend financial and political resources to preserve local landmarks, historical sites and so forth to maintain the character of these places. Bolton thus argues that preventing decline in cities and towns with a unique character is a type of public good, which will tend to be underprovided by private interests.

3.3 Brain Gain Measures

The terms brain gain and brain drain most often refer to the international outmigration of college-educated (or beyond) individuals from developing countries to developed countries, but sometimes they are applied to the growth or loss of educated populations in local areas within a developed nation. International brain drain (gain) is in some ways easier to conceptualize than domestic brain drain (gain). Internationally, educated workers flow fairly consistently out of developing nations and to developed nations. Across local areas within the United States, outflows of educated workers from a given area are often countered by comparable inflows of educated workers with different labor market and life cycle considerations.

Some areas that attract young high school-educated workers may not attract young college-educated workers and some areas that attract young college-educated workers may not attract middle-aged college-educated workers, so it is important to

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in distressed areas, Bartik claims the political pressures to enact such policies should also be greater there. Given these considerations and some "back of the envelope" calculations, he concludes that sensible regional economic development can be simultaneously second-best optimal *and* progressive.

define the type of brain gain or brain drain of interest. I identify three types (and timings) of brain gain in this paper: absolute gain in high school graduates (or "absolute high school gain" for short), relative gain in high school graduates ("relative high school gain"), and relative gain in college graduates ("relative college gain"). I briefly describe these measures and their relevance in this section, but a more thorough explanation of the construction of each of these measures appears in section 3.4. Roughly speaking, absolute high school gain refers to changes in the *level* of high school-educated workers in an area, while relative high school gain and relative college gain refer to changes in the share of educated workers in an area. Changes in *levels* of educated workers and changes in *shares* of educated workers both matter for the residents of affected areas. In light of the literature on human capital externalities, it is more obvious why shares matter. If receiving an education reduces an individual's criminal behavior and increases their civic participation and other pro-social behaviors, then areas with large *shares* of educated workers should have lower crime rates, better voting outcomes, etc. Similarly if a highly educated workforce encourages investment in physical capital, research and development and technology, then the external benefits of education will increase with the share of educated workers.

However, if human capital spillovers occur because interactions with educated individuals in related fields lead to diffusion of knowledge, then both shares and levels matter. Shares matter because the average interaction in a more educated city is with a more educated worker, hence more knowledge should be diffused with a random interaction. Levels matter because interactions are not generally random. A pair of individuals is more likely to interact if they work in related fields or have knowledge that is valuable to one another. Cities with a high *level* of educated workers have more diverse skills and knowledge, so it is more likely that an individual will interact with someone with knowledge pertinent to them. Changes in either the level or share of educated workers also impacts local areas' fiscal situations. An increase in the level of educated workers without an increase in the share of educated workers implies local population growth. Population growth leads to higher housing demand, higher property values and an expansion of the tax base since local revenues are primarily collected through property taxes. Local property owners also benefit from such shocks. Though each property owner bears a larger tax liability their wealth increases with the increase in property values. On the other hand, an increase in the *share* of educated workers improves a locality's fiscal situation by reducing the average citizen's dependence on social services and increasing their ability contribute to local taxes. Thus, both absolute brain gain and relative brain gain in a locality may benefit residents.

I define a locality's absolute high school gain as the percentage growth in the number of high school graduates for a cohort in that locality since the time of that cohort's expected graduation. If $N^H_{r,18}$ describes the total number of high school graduates from a specific class residing in r in the year of their graduation, and $N^H_{r,t2}$ describes the total number of high school graduates in the same age cohort in some subsequent year, then absolute high school gain in locality r for this cohort is defined as:

$$AG^H_{r,18} = \ln(N^H_{r,t2}) - \ln(N^H_{r,18}) \tag{3.1}$$

Note that changes in the population of high school dropouts within a locality do not affect $AG^H_{r,18}$. Absolute high school gain is the only measure used in this paper explicitly affected by population growth (or decline) that occurs proportionally by educational attainment. Indeed area absolute high school gain closely mirrors area population growth.

Second, I define relative high school gain. Relative high school gain measures the percentage growth in the *share* of an area's cohort with a high school diploma or higher since expected graduation, relative to expected growth (expected growth is based on the initial share with a high school diploma.)

$$RG_{r,18}^{H} = \ln\left(\frac{N_{r,t2}^{H}}{N_{r,t2}^{T}}\right) - \ln\left(\frac{N_{r,18}^{H}}{N_{r,18}^{T}}\right) - R^{H^*} \approx \Delta HS\% - R^{H^*} \qquad (3.2)$$

Terms in (3.2) with a T superscript refer to the total number of people of all education levels in the cohort in that period. The term R^{H^*} denotes the expected percentage growth in a cohort's share with a high school diploma. It is determined by performing a simple linear regression of area-cohorts' growth in high school share as a function of their graduation rate, then using the coefficient (and constant) to predict areas' growth in high school population (this is explained in more detail in subsection 3.5.1.) $RG_{r,18}^{H}$ increases with growth in the high school-educated population and decreases with growth in the population of high school dropouts. This measure should be neutral with respect to population growth or decline, but it captures a locality's ability to attract (or retain) the high school-educated relative to its ability to attract (or retain) high school dropouts.

In some cases relative high school drain may be a transient lifecycle phenomenon. The second period in which high school graduates and dropouts are measured ($t2$) occurs when that cohort is in their early to mid-30s. Some localities that are unattractive to young high school graduates (for instance distant suburbs) might be more attractive later in life. The next measure of brain gain considers the relative attractiveness of a locality among the college-educated somewhat later in life.

Relative college gain measures the percentage growth in the share of an area's cohort with a bachelor's degree or higher since the cohort was aged 25-34, relative to expected growth (expected growth is based on initial college graduate share):

$$RG_{r,25}^{C} = \ln\left(\frac{N_{r,t2}^{C}}{N_{r,t2}^{T}}\right) - \ln\left(\frac{N_{r,25}^{C}}{N_{r,25}^{T}}\right) - R^{C^*} \approx \Delta CG\% - R^{C^*} \tag{3.3}$$

This equation is basically analogous to (3.2), except that it measures college graduates (superscript C) instead of high school graduates and the timing of the population measurements differ (the initial measurement of the college-educated in a locality occurs when they are between the ages 25 and 34, the subsequent measurement occurs when most of the cohort is in their late 40s.) Since middle-aged, college-educated people are among the highest earners, relative college drain—if it represents permanent rather than lifecycle changes—may especially harm area productivity.

3.4 Theory and Empirical Model

Unlike Chapter 2, in this chapter the geographical unit of observation is small enough (counties or groups of less populous counties) that many people may live and work in observably different geographic areas. Recent estimates from the Census suggest that 27.4 percent of American workers reside in a different county than their place of employment.[40] Potential migrants must jointly weigh employment prospects in one county with the residential opportunities in that county and in a number of nearby counties. I model the expected utility of an individual residing in r and working in s (r may equal s, but it is not necessary) using a variation on (2.1):

[40] https://www.census.gov/newsroom/releases/pdf/2006-10_commuting_flows_paper.pdf

$$EU_{i,r,s} = E[U\big(Y_{i,s}(LMC_s, X_i) - C_{i,r,s}(X_i), A_{i,r}(LMC_r, X_i)\big)] \quad (3.4)$$

Again, the utility an individual receives in a locale is a function of the income they can receive (less area costs), amenities (amenities are based on the place of residence not the place of employment), and heterogeneous individual preferences for income and various amenities.[41] Area costs, $C_{i,r,s}$, are expanded to include both moving costs and commuting costs, thus they depend on both the place of residence and the place of employment. Equation (3.4) hints at the intricate relationship that exists between local brain gain and surrounding labor markets. On the one hand, strong labor market conditions in nearby counties might reduce net migration of a county's educated population if residents (or potential migrants to the county) are persuaded to move to the thriving nearby counties. On the other hand, since workers in s have the option of residing in r, a thriving metropolitan center's labor market might cause *positive* population spillovers, for instance, in surrounding suburban counties.

The regression models (3.5a-3.5c) estimate growth in a cohort's educated stock (share) as a function of: 1) initial educated stock (share), 2) urbanicity, 3) proximity to a four-year state college, 4) other amenities, 5) initial economic conditions, 6) industrial composition, 7) region, and 8) share of population that is non-native born:

$$\Delta Ln\ HS_{r,t2} = \beta_0 + \beta_1 Ln\ HS_{r,t1} + \beta_2 Urb_{r,t1}$$

[41] Since gross migration between areas within the United States dwarfs net migration, heterogeneous individual preferences and heterogeneity in earnings potential across counties are the factors that drive the most (gross) migration. Without such individual heterogeneity, the wide array of city sizes and characteristics we observe would probably be impossible. However, since the results in this chapter focus on *net* changes in the educated and less educated populations, individual heterogeneity mostly cancels itself out (except for differences between the preferences of educated and less educated labor).

$$+\beta_3 Col\ Prox_r + \beta_4 Amen_r + \beta_5 LMC_{r,t1} \qquad (3.5a)$$

$$+\beta_6 IC_{r,t1} + \beta_7 Region_r + \beta_8 Immig_{r,t2} + \epsilon$$

$$\Delta Ln\ HS\%_{r,t2} = \beta_0 + \beta_1 Ln\ HS\%_{r,t1} + \beta_2 Urb_{r,t1}$$

$$+\beta_3 Col\ Prox_r + \beta_4 Amen_r + \beta_5 LMC_{r,t1} + \beta_6 IC_{r,t1} \qquad (3.5b)$$

$$+\beta_7 Region_r + \beta_8 Immig_{r,t2} + \epsilon$$

$$\Delta Ln\ CG\%_{r,t2} = \beta_0 + \beta_1 Ln\ CG\%_{r,t1} + \beta_2 Urb_{r,t1}$$

$$+\beta_3 Col\ Prox_r + \beta_4 Amen_r + \beta_5 LMC_{r,t1} + \beta_6 IC_{r,t1} \qquad (3.5c)$$

$$+\beta_7 Region_r + \beta_8 Immig_{r,t2} + \epsilon$$

Based on (3.4) any characteristic of a local area that generally increases residents' expected incomes, reduces their costs, or adds to their quality of life should, *ceteris paribus*, encourage inmigration (or deter outmigration) and therefore lead to absolute high school gain. So, clearly greater area amenities and area economic opportunities should lead to more absolute high school gain. Economic opportunity for skilled and unskilled workers is measured with traditional measures in $LMC_{r,t1}$ (unemployment rate and poverty rate), but also with urbanicity ($Urb_{r,t1}$) and industrial composition ($IC_{r,t1}$). Given the agglomeration economies that exist in cities, urbanicity should positively affect absolute high school gain (at least up to a point) by improving economic opportunity. It is generally expected that a concentration of industries with more educated workers (e.g. professional services and information services) will lead to more absolute and relative brain gain while concentration of blue-collar industries like forestry and fishing, mining, and manufacturing will be associated with less brain gain. Some standard area amenities are included in $Amen_r$ (average July high temperature, average January low temperature, an indicator for coastal areas, and the share of compensation in the arts and entertainment industry). *Ceteris paribus* the attraction of nice weather and culture (proxied by arts and entertainment share) should help attract (or retain) high school-educated migrants. $Region_r$ may capture omitted differences in amenities or economic opportunity. College proximity is expected to increase absolute (and relative) high school gain by directly leading to the migration of individuals pursuing college degrees. Although county of residence in the latter period is not measured until long after most people go to college (age 31-37), there is residential inertia for new college graduates (or college dropouts). By attending a college in or near r, they are more likely to live there when they are in their 30s because of the costly nature of migration. The focus of this chapter is domestic migration, so to control for population changes related to immigration, I also include the percentage of local area that is foreign-born (in the latter period).

It is not obvious which direction to expect certain variables to affect relative high school gain or relative college gain. Chapter 2 described how the migration of more educated households (and others at low poverty risk) seems to be more responsive to labor market conditions, at least in the short run. To the extent that local labor market conditions are persistent, it would follow that long run relative brain gain is also more likely to occur where initial labor market conditions are strong. An urban-rural wage gap exists for both educated and uneducated workers, but *ceteris paribus* this wage gap may favor more skilled workers in urban areas because: 1) Their productivity may be especially enhanced by the high level of physical capital and technology and 2) The steep housing costs in urban areas will swallow a larger share of income for the less affluent.[42] There seems to be increasing consensus that amenities are normal goods (Adamson, et al., 2004; Whisler et al., 2008), so it is generally expected that relative brain gain will be higher in areas with higher amenity value. However individuals' valuation of amenities also vary over the lifecycle as the young and single, for example, tend to favor urban amenities, while marriage, middle-age, and kids leads people to prefer suburban amenities (Whisler et al., 2008).

I also extend the model to consider: 1) whether there is heterogeneity in the determinants of brain gain for central cities, suburban areas, and nonmetropolitan areas and 2) whether neighbors' economic conditions affect brain gain. I stratify the sample by central cities, suburban areas and nonmetropolitan areas, adding an average of the initial unemployment rates in adjacent areas as an explanatory variable in (3.5a) - (3.5c). Strong labor demand in one county may lead to absolute or relative brain gain for its neighbors by attracting educated workers who then opt to reside in surrounding counties. Since people are more apt to commute from less densely populated areas to more densely populated areas, I expected that proximity to central cities with strong labor market conditions might cause positive (educated) population spillovers to suburban areas. On the other hand, to the extent that adjacent areas compete with one another over (educated) residents, strong neighboring labor markets may cause brain *drain*.

[42] Likewise, if more educated people have stronger preferences for urban amenities, we should expect more metropolitan areas to experience relative brain gain (Adamson, et al., 2004).

3.5 Data

3.5.1 Data Collection and Construction

I use three different datasets to construct the measures of brain gain: two are used to estimate initial stocks of educational attainment (The National Center for Education Statistics' Common Core of Data and the 1990 decennial Census) and one provides the number and share of people in various age cohorts in the second period with different levels of educational attainment (the 2006-2010 American Community Survey). The most basic measure of brain gain I use is absolute high school gain, the percentage growth of an area-cohort's number of high school graduates in approximately sixteen years following their graduation. Using the number of high school diplomas conferred to estimate an area-cohort's initial stock of high school graduates is the ideal way to measure gains or losses of the high school-educated, because any measurement of the stock of high school graduates in a cohort that isn't made immediately after high school graduation may overlook the many high school graduates who leave their home county within months of graduating. The particular timing of the second measurement (13-19 years after expected graduation) is the result of data availability, but the timing is suitable to identify the areas that benefit from brain gain and those that are harmed by brain drain. I assert this because: 1) It is sufficiently long to allow a great deal of intercounty migration to occur, particularly given the high migration rates of younger adults, 2) It is sufficiently long so that the high school-educated population in the second period are old enough (mid-30s) to be important contributors to local economic production and 3) It is a short enough period to identify movements within a specific stage of life (young adulthood) rather than confounding movements in different stages of life.

The Common Core of Data (CCD) reports annual county high school enrollment numbers by grade and the number of high school diplomas conferred by county, thus providing an estimate of counties' stock of (public) high school graduates and high school dropouts in the graduation year of a given cohort. The number of high school diplomas conferred by schools in a county should fairly accurately measure the number of *public* high school graduates residing in a county upon graduation. This measure will, however, miss any students that graduate from a private high school or from a school in a county other than their county of residence. I estimate the number of high school dropouts from the same cohort based on the difference between the cohort's freshman enrollment and the number of high school diplomas conferred to that cohort. A cohort's estimated number of high school dropouts will fail to capture any students who drop out prior to ninth grade. Estimates of a cohort's number of dropouts will also fail to account for net migration of that cohort between ninth grade and graduation. To reduce some of the noise related to these issues, I use a three-year average of the number of graduates and dropouts in each county for the cohorts in the high school graduating classes of 1991, 1992 and 1993 (I will sometimes refer to these three cohorts as the 1992 cohort for short.)[43]

Then, to determine the extent of absolute high school gain or drain occurring over roughly a 16 year period, I obtain the number of people in a cohort with a high school diploma residing in a geographic area (namely Public Use Microdata Areas or PUMAs) from the American Community Survey's (ACS) 5-year (2006-10) 5% Public Use Microdata Sample (PUMS). Unfortunately because this is a five-year data set, even with

[43] Likewise, using the 1990 Decennial Census I construct the initial level of all measures of educational attainment in 1990.

people's age it is impossible to determine respondents' high school graduating classes precisely. Since about one-fifth of the ACS respondents were surveyed in each year between 2006 and 2010, it is possible to approximate the probability they are members of one of the three cohorts. Table 3.1 illustrates. For an individual who was 18 in their graduating year, this table lists the age they were in each of the ACS survey years. Based on this table, the probability that an individual surveyed in the 2006-10 ACS is in one of the three cohorts is $\frac{1}{5}$ if the individual is 31, $\frac{2}{5}$ if the individual is 32, $\frac{3}{5}$ if the individual is between 33 and 35, $\frac{2}{5}$ if the individual is 36, and $\frac{1}{5}$ if the individual is 37. Then using the 2008 population of the PUMA, the proportion of the PUMA's respondents for each age, and applying weights[44] (based on the above probabilities) to each age between 31 and 37, I estimate the stock of high school graduates and dropouts residing in the PUMA at the time of the ACS survey. Clearly, there is some measurement error in determining the stock of graduates and dropouts in the three cohorts, since about half (by weight) of the individuals used to determine these stocks actually belong to cohorts other than 1991-93. However this measurement error will appear on the left-hand side of the regressions that follow, so it will lead to imprecision but not bias in the estimates of the determinants of brain drain and brain gain.

The second brain gain measure, relative high school gain, is constructed using the same data (CCD and ACS) and the same weights as absolute high school gain, but relative high school gain is based on the percentage change in the *share* of an area's cohort with at least a high school diploma. Relative high school gain (along with other relative brain gain measures) is then adjusted to account for any reversion to the mean.

[44] The weights are $\frac{1}{15}$ for ages 31 and 37, $\frac{2}{15}$ for ages 32 and 36, and $\frac{1}{5}$ for ages 33 to 35.

Panel A of Table 3.2 demonstrates the first step in this process. I perform a simple linear regression of growth in the share of a cohort with a high school diploma as a function of the natural logarithm of the initial share of the cohort with a high school diploma. Then, based on these regression results, I compute predicted growth in high school share as a function of initial share. The difference between an area's actual and predicted growth in high school share is defined as the relative high school gain. The timing of an area's relative high school gain is the same as for absolute high school gain (roughly between age 18 and age 34). Table 3.2 shows that areas with higher observed graduation rates experience substantially smaller gains in their cohorts' share of high school graduates. There is measurement error associated with all of the brain gain measures, so regression to the mean contributes to the negative coefficients in Table 3.2. Also, if high school dropouts are equally likely to obtain a GED regardless of area graduation rates this would cause areas with more dropouts to have more growth in the high school share, *ceteris paribus*.

The third measure of brain gain, relative college gain, is largely analogous to the relative high school gain measure, measuring growth between two periods in an area's share of *college* graduates in a specific cohort. There are some differences, though, in the timing of this growth measure, the cohort being observed, and the data used to measure the initial share. I use the 1990 decennial Census to obtain the initial number of individuals in an area's cohort with and without a college degree. Clearly it would be nonsensical to measure the number of 18 year old college graduates in the initial period; instead I use the cohort of 25-34 year olds at the time of the 1990 Census. I then use the 2006-2010 ACS to determine growth of the college-educated and non-college-educated within cohorts. In the initial period (1990) the cohort is aged 25-34, therefore at the time of the 2006-2010 ACS, such individuals were between the ages 41-54. However, depending on which year of the ACS a respondent was surveyed, some 41-44 year olds and some 51-54 year olds may not have been in the initial 25-34 year old cohort, so I use the number of 45-50 year olds in the 2006-2010 ACS to approximate the share of college-educated individuals in the cohort in the latter period. The timing of the surveys and age of the cohorts are suitable again because: 1) Most people who obtain college degrees do so by age 25 and 2) By the second period (at age 45-50), most college graduates are entering the prime earning years of their career. Otherwise, relative college gain is constructed in the same way as relative high school gain, including the adjustment for predicted growth. Panel B of Table 3.2 shows the regression of the growth in the share of college graduates as a share of initial college graduate shares. Relative college gain is the difference between an area's actual growth in college share and its predicted growth based on Table 3.2. Though it is not a focus of the paper, I also construct relative growth in graduate degrees for the same cohort (Panel C).

One difficulty arising from using the ACS's microdata sample is that its finest geographical unit of measurement is the Public Use Microdata Area (PUMA); the closest geographical unit in the CCD is the county. State governments draw PUMA boundaries so that all PUMAs have sufficiently large populations (100,000 or more persons). Most PUMAs contain one or more undivided counties *or* are contained entirely within a single county (depending on whether county populations in an area tend to be much larger or much smaller than 100,000.) In order to consolidate PUMAs and counties, I reduce both data sets to their lowest common denominator. That is, I construct statistics for the smallest geographic units possible in both data sets. Usually these geographic units are either single counties or single PUMAs.[45] Hereafter I will refer to these as consolidated geographic areas (or CGAs for short). Data exists for a total of 915 of these CGAs in the contiguous United States.[46]

The explanatory variables used in this chapter were obtained from several sources. The county is the unit of observation for all explanatory variables.[47] Each of these variables was then modified to reflect the sum or population-weighted average of all counties within a CGA. 1990 decennial Census data was used to determine counties' initial population and population density of counties.[48] I also use 1990 Census estimates of county poverty rates in the Census of Population and Housing Poverty Statistics.[49] I use Bureau of Labor Statistics estimates of 1991-1993 county unemployment rates.[50] The percentage of a CGA's population that is foreign-born is based on the 2006-10 ACS. Counties' distances from public four-year colleges are based on information in the Integrated Postsecondary Education Data System, made available by the National Center for Education Statistics.[51] Maximum July temperatures and minimum January temperatures are based on 1990-2010 averages in the North America Land Data Assimilation System.[52] The Federal Emergency Management Agency (FEMA) defines a coastal shoreline county as those which are adjacent to an ocean, major estuaries, or the Great Lakes. I create an indicator variable for whether a CGA is coastal based on

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[45] Occasionally because of the way certain PUMA boundaries are drawn, the smallest geographic unit I can construct consists of multiple PUMAs and multiple counties.
[46] Some counties' high school enrollment and graduation statistics were unavailable for pertinent years in the CCD.
[47] In an extension, I test the effect of area wages on brain gain, using PUMA-based wage data.
[48] http://www.census.gov/main/www/cen1990.html
[49] https://usa.ipums.org/usa/voliii/pubdocs/1990/cph-l/cph-l.shtml
[50] http://www.bls.gov/lau/#cntyaa
[51] http://nces.ed.gov/ipeds/datacenter/
[52] http://wonder.cdc.gov/controller/datarequest/D60a

whether FEMA classifies any of the counties within the CGA as coastal shoreline counties.[53] Finally the Bureau of Economic Analysis provides county industrial composition data based on NAICS classifications beginning in 1998.[54] I use 1998 shares of county compensation within two-digit industry codes to describe county industrial composition. In a model extension I also use college graduate and non-college graduate earnings data from the 5% percent sample of Integrated Public Use Microdata Sample of the 1990 Census.[55] [56]

3.5.2 Descriptive Statistics

Table 3.3 displays summary statistics. Absolute high school gain is the first bold variable in the table. Among the 915 CGAs, the average growth in cohorts' number of high school graduates between 1992 and 2008 is 29.5 percent. This is an overestimate of the true average, partly because private high school diplomas conferred between 1991 and 1993 are not captured in the CCD's count of initial high school graduates. The first row shows that cohorts averaged a 24.8 percent decline in high school dropouts, pointing to one factor working to increase the observed absolute high school gain: delayed completion of high school equivalencies (GEDs). On average CGAs experienced 9.9 percent growth in the share of their cohorts with a high school diploma. More growth in cohorts' college shares occurred over the period, with an average 27.5 percent increase across CGAs. Relative high school (college) gain is based on the growth in high school

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[53] http://coastalsocioeconomics.noaa.gov/coast_defined.html
[54] http://www.bea.gov/regional/
[55] https://usa.ipums.org/usa-action/samples
[56] Individuals' wages are calculated as their annual earnings divided by the product of weeks worked last year and typical hours of work per week. I aggregate PUMA wages for college graduates and non-college graduates based on full year workers (at least 40 weeks) who worked between 35 and 50 hours per week.

(college) share, but is adjusted to account for predicted growth based on initial share of high school (college) graduates (see equations 3.2 and 3.3). Thus both of these means equal zero.

Tables 3.4, 3.5, and 3.6 display mean characteristics by quintile of absolute high school gain, relative high school gain, and relative college gain, respectively. These tables put in context the stark differences between the characteristics of CGAs that experience brain gain and those that experience brain drain. CGAs in the bottom quintile of absolute high school gain began the period with 44% more poverty and 40% more unemployment than CGAs in the top quintile. CGAs in the bottom quintile of *relative* high school gain had about 33% more poverty and 36% more unemployment than those in the top quintile. CGAs in the bottom quintile of relative *college* gain had 55% more poverty and 15% more unemployment. High brain gain and high brain drain areas exhibit similarly glaring differences in metropolitan status and density. About 72% of CGAs in the bottom quintile of absolute high school gain are nonmetropolitan and only 7% in the top quintile are nonmetropolitan. Nonmetropolitan CGAs comprise 57% (48%) of the bottom quintile of relative high school (college) gain, but these CGAs comprise only 18% (27%) of the top quintile of relative high school (college) gain. All categories of metropolitan CGAs (high density, medium density, and low density) are noticeably more likely than nonmetropolitan CGAs to experience all types of brain gain. High density metropolitan CGAs (more than 400 people per square mile) are especially likely to experience absolute high school gain, but lag behind less dense metropolitan CGAs in relative college gain.

3.6 Spatial Distribution of Brain Gain in United States

Figure 3.1A illustrates levels of absolute high school gain with a map of 915 CGAs in the United States. Figures 3.2A and 3.2B do the same for relative high school gain and relative college gain, respectively. Each of these maps divides the 915 CGAs into five quintiles ranging from the highest levels of brain gain (dark blue) to the highest level of brain drain (white).[57] (For comparison purposes I also include a map of population density in Figures 3.1B and 3.2C.) While there are some similarities between the maps of brain gain, important differences exist between them, exemplifying various regional issues. In this section I discuss the spatial distribution of these three types of brain gain in turn.

3.6.1 Absolute High School Brain Gain in U.S.

Some regional patterns are immediately apparent in the map of absolute high school gain (Figure 3.1A) coinciding with well-known regional patterns of overall population growth. The highest rates of absolute high school gain are concentrated in the South and also to the west of the Rockies. The CGAs with the lowest levels of absolute high school gain are highly concentrated in the Great Plains. Table 3.7 shows that when CGAs are weighted by population the Mountain, South Atlantic, and Pacific Census Divisions all average about 60 percent absolute high school gain. The Middle Atlantic, West North Central, and East North Central Census Divisions all average less than 30 percent absolute high school gain.[58] With some exceptions, state rankings in absolute high school gain closely align with state rankings in population growth since the early

[57] CGAs in black are missing relevant data (for the relevant years) in the NCES's Common Core of Data.
[58] Note that weighted averages of states' absolute high school gain tend to be higher than unweighted averages because more populous CGAs typically have higher rates of absolute high school gain.

1990s.[59] Since more than 85 percent of adults have a high school diploma or equivalent, it should be unsurprising that gains in cohorts' high school graduates resemble overall population gains. The exceptions are instructive. Several high density states with low population growth rank fairly high in absolute high school gain, including the District of Columbia, Connecticut, Illinois, and Rhode Island. On the other hand, low density states tend to rank lower in absolute high school gain than their population growth rates would suggest, including the Dakotas, Montana, and Wyoming. Figure 3.1A also shows this tendency of high density areas to attain higher absolute high school gain than low density areas; high absolute high school gain is prevalent in eastern and coastal states and low absolute high school gain is common in the Midwest. But a closer look reveals that density is also associated with absolute high school gain at a more local level, as absolute high school gain is typically higher in major metropolitan areas. (This can be seen by comparing Figure 3.1A with the map of CGA population density in Figure 3.1B.) These are the first of several clues suggesting there are sizeable flows of young high school graduates (between graduation and their mid-30s) from low density to high density areas.

The first column of Table 3.8 lists the percentiles of absolute high school gain for the principal counties in the 30 most populous metropolitan areas (as of 1990) for which no data is missing.[60] The next column shows the absolute high school gain percentile of the CGAs adjacent to the principal county ("suburban CGAs" for short).[61] Of the 30

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[59] See https://www.census.gov/prod/2001pubs/c2kbr01-2.pdf for Census estimates of population growth in the 1990s and http://www.census.gov/prod/cen2010/briefs/c2010br-01.pdf for Census estimates of population growth in the 2000s.

[60] Because these are large metropolitan centers, these counties alone compose their CGA. The only exception among these 30 counties is Virginia Beach.

[61] I first determine a weighted average of absolute high school gain for these CGAs. Then treating this weighted average, I determine its percentile relative to the 915 CGAs with available data. The absolute high school gain measure for these areas will be less likely to take extreme values than individuals CGAs since averaging multiple CGAs together tends to push their values toward the mean.

principal counties, 20 are in the top quintile of absolute high school gain. Like the maps of absolute high school, Table 3.8 shows that counties' absolute high school gain largely reflects the counties' overall population growth over the period. The counties encompassing San Jose, San Francisco, Phoenix, and Atlanta are all in the 97th percentile or above of absolute high school gain. The counties including New Orleans, Pittsburgh, Detroit, and Cleveland are the only large metropolitan centers below the 60th percentile. Of the 30 sets of suburban CGAs, only two (the CGAs adjacent to Pittsburgh and Cleveland) were below the median level of absolute high school gain. With a few exceptions, the suburban CGAs have slightly lower (but similar) levels of absolute high school gain relative to the principal counties they surround, again indicative of a tendency of young high school graduates to move to more densely populated CGAs.

The left side of Table 3.9 lists the largest city in the 30 CGAs with the highest absolute high school gain. If the CGA falls within a Census-designated metropolitan statistical area (MSA) the second column lists the MSA, along with the driving distance (in miles) between the CGA's largest city and the MSA's principal city. This table shows that among the areas attracting the most absolute high school gain there is a mix of large metropolitan centers, small metropolitan centers, and suburban CGAs (only the CGA containing Aspen, Colorado is nonmetropolitan.) Each of these 30 areas more than doubled the size of their high school graduate cohorts (see column 3.) The right side of Table 3.9 shows the largest city in the 30 CGAs experiencing the most severe absolute high school *drain*, each of which saw net declines in their high school graduate cohorts of between 27 and 60 percent. In stark contrast with the high brain gain areas, only one of these 30 high brain drain areas (Pine Bluff, AR) is in a metropolitan area. Moreover, only three of the 30 highest absolute high school gain CGAs have population densities below 90 per square mile; all of the 30 highest absolute brain *drain* CGAs have population densities below 90 per square mile. Again, we see evidence of a flow of high school graduates from rural America to urban America. The table also captures the flow of high school graduates out of the Midwest and to the South. Eighteen Midwestern CGAs are among the 30 biggest net senders of high school graduates. Twenty-three Southern CGAs are among the biggest net recipients of high school graduates, including 20 that are either in Florida, Georgia, Texas, or Virginia.

3.6.2 Relative High School Gain and Relative College Gain in U.S.

Patterns of relative high school gain differ considerably from the patterns of absolute high school gain just discussed. The correlation between absolute and relative high school gain is just 0.28. Though there appears to be some positive correlation within states, the broad regional patterns visible in the relative high school gain map (Figure 3.2A) have little in common with the regional patterns in the absolute high school gain map (Figure 3.1A). A number of areas, in fact, look almost the opposite in the two maps. The Southwestern states of California, Nevada and Arizona (and parts of Texas) experienced among the highest rates of absolute high school gain, but these states experienced some of the lowest rates of relative high school gain. Indeed, Table 3.7 shows that the five states with the *lowest* relative high school gain are California (8th in *absolute* high school gain), Nevada (1st), Texas (12th), New Mexico (27th), and Arizona (3rd). On the other hand, many northern states including those in New England and various states stretching from Montana to Iowa are characterized by low absolute high school gain but high relative high school gain. An obvious explanation for this set of observations is that the high rate of immigration to the Southwest increases the size of cohorts of all educational levels, but it causes particularly large increases in the stock of high school dropouts (thus leading to relative high school drain). Northern states which receive fewer immigrants have less absolute growth of the high school-educated, but attract particularly small numbers of high school dropouts.

Figures 3.2A and 3.2B uncover little obvious association between states' relative high school gain and relative college gain; the correlation between the two measures of brain gain is not statistically different than zero (-0.03). In fact, from Figure 3.2B alone few states can be identified as high relative college gain or high relative college drain states because most states contain numerous CGAs experiencing relative college gain and numerous CGAs experiencing relative college drain.[62] Table 3.10 shows states ranked by their relative college gain (it also shows relative "graduate school gain.") This table (contrasted with Table 3.7) illustrates a striking difference between relative high school gain and relative college gain in the West. Whereas the Mountain and Pacific Census divisions experienced among the lowest relative high school gain (ranked seventh and ninth among the nine Census divisions), they experienced the highest relative college gain of any of the Census divisions. As will be further demonstrated, brain gain is not a homogenous phenomenon. Areas or characteristics that tend to attract one group of more educated migrants do not necessarily attract other groups of educated migrants. One exception is that metropolitan areas benefit from all measures of brain gain relative to nonmetropolitan areas. The pattern of metropolitan areas experiencing relative college

[62] One-way analysis of variance (ANOVA) reveals that only 10 percent of variation in relative college gain can be explained by state.

gain can be observed by comparing the map of relative college gain (3.2B) with the map of population density (Figure 3.2C).

The last two columns of Table 3.8 confirm the low relative high school gains in the Southwest, specifically among the major cities. Of the 30 largest CGAs, the most relative high school drain occurred in the counties containing Riverside, Dallas, Houston, Los Angeles, and Phoenix. With the exception of these and other Southwestern cities, the counties containing the 30 largest cities generally experienced high relative high school gain. Fourteen of these 30 counties are in the top quintile of relative high school gain, with the District of Columbia, St. Louis, Baltimore, New Orleans, Atlanta, and Virginia Beach all at or above the 97th percentile. The suburban CGAs adjacent to these 30 principal counties tend to have lower relative high school gain than the populous CGAs they surround. The higher relative high school gain in principal counties compared to the surrounding suburbs may reflect at least two things. First, it may reflect rapid attenuation of the positive human capital spillovers associated with urban agglomerations as distance from urban centers increases (Rosenthal and Strange, 2008). Second, it may reflect life cycle migration of the middle and upper class. Because of the gap in the safety and school quality of suburban areas compared to urban centers, parents of school-age children flock to the suburbs if they have the means to do so, suggesting freshly-minted high school graduates (and dropouts) will be concentrated in suburban areas. However, while quality public schools tend to be located in suburban areas, quality jobs are often concentrated in large cities, attracting young, skilled workers. (Recall that in the second period the cohort is between the ages of 31 and 37, so a large share of educated households will not yet have school-age children of their own.)

Whereas relative high school gain tends to be somewhat higher in principal counties than in suburban CGAs, suburban CGAs have markedly higher relative college gain than principal counties. Table 3.11 lists the relative college gain percentiles for the principal counties of the 30 largest MSAs and the adjacent suburban CGAs. Eighteen of the suburban CGAs rank more than 20 percentiles above their corresponding principal county in relative college gain, including ten suburban CGAs that are more than 50 percentiles higher. No principal counties rank more than 15 percentiles above their suburban CGAs. This apparent outmigration of college-educated people from principal counties to the suburbs is likely the corollary of the migration of young high school-educated people to the principal counties. Relative college gain tracks the movement of the college-educated (initially between the ages of 25-34) over a period of almost two decades, putting most of them in their late 40s in the second period. Just as life-cycle considerations lead many young high school graduates (including future college graduates) from the suburbs to the principal cities, as they enter mid-life they are increasingly drawn to suburban areas (especially those with school age children).

Tables 3.12 and 3.13 show the same pattern of relative high school gain concentrated in large urban centers and relative college gain concentrated in suburban areas. Low density metropolitan centers and nonmetropolitan areas are disproportionately likely to experience the highest rates of relative high school drain and relative college drain. As Table 3.12 shows, many of the 30 CGAs with the most relative high school gain are high and medium density metropolitan centers, including the counties that include Washington, Baltimore, St. Louis, Norfolk, Virginia Beach, New Orleans, Atlanta, and Jacksonville (each of these counties has more than 500 people per square mile.) On the other hand, the 30 CGAs experiencing the most relative high school drain are predominantly less-dense metropolitan centers and rural areas in California and Texas (in bold). Of these 30 areas only Dallas County has a population density above 300 per square mile.[63] As Table 3.13 shows, areas experiencing the most relative *college* gain tend to be suburban. Among the 30 CGAs with the highest relative *college* gain, only four CGAs are nonmetropolitan, and none of them contain the principal city of the MSA. The remaining 26 CGAs are all suburban. On the other hand, only three of the 30 highest relative college *drain* CGAs could be considered suburban.

3.7 Determinants of Brain Gain and Brain Drain

Table 3.14 displays results from ordinary least squares regressions of absolute high school gain over the period 1992-2008. Column 1 displays results of a simple growth regression based on the initial stock of high school graduates. It shows that a large number of high school graduates in a CGA are associated with more absolute high school gain. This result is unsurprising if young adults are more likely to move to large cities. Column 2 adds the additional explanatory variables shown in equations (3.5a)-(3.5c), seeking to determine which local area characteristics contribute to brain gain or to brain drain. Columns 3-5 then estimate the determinants of absolute high school gain separately for metropolitan centers, suburban CGAs and nonmetropolitan CGAs, adding neighbors' labor market conditions as an additional explanatory variable. A CGA is

[63] It is also notable that a number of college towns are among the 30 areas with the most relative high school gain, including Monroe (LA), Gainesville (FL), and Morgantown (WV). Of course one would expect that these places would especially attract the college-educated (or more accurately the soon-to-be college-educated), but the relative *college* gain measure will not capture such gains because it tracks a cohort whose initial age is 25-34 (most of the movement to college towns would occur between the ages 18 and 25.)

classified as a metropolitan center if it contains one or more counties that are included in a MSA and no adjacent CGAs have a higher population density. All other metropolitan CGAs are considered suburban in the regressions described in Tables 3.14, 3.15 and 3.16.

Column 2 of Table 3.14 shows that, *ceteris paribus*, nonmetropolitan CGAs experienced 10.1 percentage points lower growth rates in their high school-educated cohorts than low density CGAs (less than 200 people per square mile). Nonmetropolitan CGAs also experienced 6.4 percentage points lower absolute high school gain than medium density (200-400 people per square mile) metropolitan CGAs. Wages are higher in metropolitan areas, and many young high school-educated individuals can benefit from this and the diversity of urban employment. Contrary to the descriptive evidence presented in Tables 3.4, 3.8 and 3.9, Table 3.14 suggests that high density of a metropolitan CGA *reduces* absolute high school gain relative to less dense metropolitan CGAs, though this particular result seems to arise because the effect of population density is confounded with the effect of the initial (log) number of high school graduates.[64]

As expected, the table also provides evidence that proximity to state universities increases growth of the high school-educated. This seems to be primarily true of nonmetropolitan CGAs where remoteness most severely limits access to higher education (column 5). The amenity variables provide evidence that temperate climates and culture (as proxied by the size of the arts and entertainment industry) attract young high school graduates; these effects are robust to the inclusion and exclusion of alternative amenity

[64] In Appendix Table A.4, I show that removing initial (log) number of high school graduates from the regression causes the coefficient on "Metro > 400 per square mile" to fall from a very highly significant value of -0.147 to a statistically insignificant value of -0.054. Otherwise the results in Appendix Table A.4 differ very little relative to Table 3.14.

variables. Amenity variables, especially the size of the arts and entertainment sector, primarily affect the absolute high school gain of nonmetropolitan CGAs (column 5). Surprisingly coastal CGAs experienced less absolute high school gain, *ceteris paribus*, though this result is not robust to the exclusion of climate or region variables. There are residual regional effects on absolute high school gain, unexplained by the other explanatory variables. Consistent with Table 3.5 and Figure 3.1A, CGAs in the South and West tended to experience the most absolute high school gain, *ceteris paribus*.[65]

Strong local economic conditions, as expected, positively affect growth of high school graduates. Column 2 of Table 3.14 shows that each percentage point increase in the local poverty rate is associated with 1.1 percentage points less growth in the local high school-educated cohort. Likewise each percentage point increase in the local unemployment rate is associated with 2.1 percentage points less growth in the local high school-educated cohort. This is noteworthy since the regression only included *initial* (1991-1993) poverty and unemployment rates, demonstrating either (or both) the persistence of weak local economies or that transient economic downturns negatively affect long-term growth of high school graduates. In either case, local labor market conditions have more than a transient effect on absolute high school gain. CGAs with high concentrations of blue-collar industries like mining and manufacturing experienced somewhat lower growth of high school graduates. Conversely a concentration of professional, scientific, and technical services positively affects absolute high school gain in metropolitan centers (column 3). Column 4 shows that unemployment in neighboring CGAs negatively affects absolute high school gain in suburban CGAs. Given the extent

[65] Unlike the descriptive analysis, the regression shows that, *ceteris paribus*, CGAs in the South experience significantly more absolute high school gain than CGAs in the West.

that suburban areas depend on the labor markets of the central cities they surround, this result is unsurprising.

Table 3.15 shows how the same explanatory variables affect the relative growth of the young high school-educated population compared to young high school dropouts (i.e. relative high school gain). This table displays results from Ordinary Least Squares regressions of the growth in the high school-educated population as a *share* of a cohort's population. Recall that relative high school gain is the difference between a CGA's actual growth in the share with a high school diploma and their predicted growth based on column 1 of this table (equivalent to Panel A of Table 3.2). When the additional covariates in columns 2-4 are added, we explain the deviations between actual and predicted high school share growth that I have been referring to as relative high school gain. For a CGA with a high school graduation rate of 80 percent, a coefficient of 0.01 would imply that each unit change results in 0.8 percent more of the cohort being high school-educated in the second period. Likewise, Table 3.16 shows the effect of the explanatory variables on the growth of those with a bachelor's degree or higher relative to the growth of those without a bachelor's degree (between ages 25-34 and 45-50). For a CGA in which 20 percent of a cohort initially has a college degree, a coefficient of 0.01 in Table 3.16 would imply that each unit change results in a 0.2 percent higher share of the population having a college degree in the latter period.

In subsection 3.6.2 I noted that relative high school gain appeared to be higher among high density counties and relative college gain appeared to be lower among high density counties. I suggested crime, school quality and the prevalence of high-paying jobs might explain these stylized facts; as the young and high school-educated set off on their own, the high wages and diverse labor markets of densely populated cities attracts them, but as they approach middle age the quality schools, comfort and safety of the suburbs attract college-educated individuals with children (less educated individuals tend to be less mobile.) Table 3.15 shows that, *ceteris paribus*, metropolitan CGAs attract relatively more growth of high school-educated workers than nonmetropolitan CGAs. Moreover within metropolitan areas, high population density is associated with more relative high school gain. Table 3.16, meanwhile, suggests that a CGA with an initial college share of 20 percent would have about one percentage point more expected growth in its college share if it was either a low density or medium density CGA (compared to either high density CGAs or nonmetropolitan CGAs).

Tables 3.15 and 3.16 demonstrate some residual regional differences in relative high school gain and relative college gain. *Ceteris paribus*, CGAs in the West experience more relative high school *drain* and more relative college *gain* than CGAs in other regions. This could indicate either that the West Region: 1) offers unobserved amenities or labor market opportunities that benefit college graduates over those with only a high school diploma, 2) offers unobserved amenities or labor market opportunities that especially benefit 30 and 40-somethings over younger adults, or 3) offers some combination of 1) and 2). It seems likely, though, that some of the observed relative high school drain in the West results from unexplained differences in their propensity to attract less educated immigrants. The share of the population that is foreign-born negatively affects relative high school gain, as immigrants are disproportionately likely to have less than a high school diploma. The share of the foreign-born population is, however, an imperfect proxy for the effect of immigration on brain gain, as local areas differ in the share of recent immigrants and in the distribution of immigrants' country of origin, age and education level. The West region dummy likely captures some of these unobserved differences, which may partially account for the West region's observed negative effect on relative high school gain. Nonetheless the size of the West region effect on relative high school gain (equivalent to the effect of a 4-5 percentage point increase in the share of the population that is foreign-born) suggests that immigration alone does not fully account for the relative high school drain in the West. The reason for the relative college gain in the West is not obvious. [66]

With the possible exception of the arts and entertainment industry in nonmetropolitan areas, the amenities included in these regressions do not apparently attract disproportionately high net migration of more educated individuals (relative to their effect on the migration of less educated individuals). In fact there is more relative high school gain, *ceteris paribus* in colder climates (though this result, too, may indirectly stem from unobserved differences in immigration in hot climates). There is also some evidence that proximity to a four year state college positively affects relative high school gain, but not relative college gain. Given the ages of the high school and college cohorts, this result is logical, as proximity to colleges should primarily attract young migrants who are *seeking* college degrees, not those who already have them.

Strong initial economic conditions increase all measures of brain gain (unlike the effects of density, amenities, region, and state college proximity). Consistent with

[66] Kodrzycki (2001) similarly finds that Western states experience high rates of domestic net migration of young college graduates, though she uses high school location for the state of origin, so it also encompasses moves for college. She argues the domestic migration of college graduates to the West is partly the result of the extensive, low-cost state college system of states in the West. Only 13 percent of young people from the West went out of state for college compared to over 35 percent of young people from the Northeast in the National Longitudinal Survey of Youth data used by Kodrzycki.

Chapter 2, CGAs with strong economies tend to attract disproportionately high growth among more educated populations (in addition to the higher absolute high school gain discussed above). Both initial poverty rates and initial unemployment rates negatively impact relative high school gain and relative college gain. Consider a CGA with a 1992 high school graduation rate of 80% in which 20% of 25-34 year olds had a bachelor's degree or higher in 1990. *Ceteris paribus*, if the initial poverty rate and unemployment rate in that CGA were each one percentage point higher, by 2008 the expected share of the 31-37 year old cohort with a high school diploma would be about 0.4 percentage points lower and the expected share of the 45-50 year old cohort with a college degree would also be about 0.4 percentage points lower. Unsurprisingly, like absolute high school gain, relative high school gain and relative college gain seem to be more (less) prevalent in CGAs whose economies are concentrated in white (blue)-collar industries. CGAs with large shares of total compensation for military jobs experience somewhat higher relative high school gain, but somewhat lower relative college gain, while other public sector employment has an insignificant effect on relative growth of the high school or college-educated.

I consider the effects of labor market conditions in adjacent CGAs on relative high school gain and relative college gain in the last three columns of Tables 3.15 and 3.16. Recall that strong adjacent labor market conditions led to positive *absolute* high school-educated population spillovers within metropolitan areas (Table 3.14). Adjacent area labor market conditions do not significantly affect *relative* high school gain (Table 3.15). Column 3 of Table 3.16 shows that central metropolitan CGAs experience more relative college gain when surrounding CGAs have high unemployment. On the other hand, neighbors' unemployment does not significantly affect relative college gain in suburban or nonmetropolitan CGAs. This suggests that central metropolitan CGAs largely compete with surrounding CGAs to retain 25-50 year old college graduates rather than benefitting from positive spillovers from these areas.

Finally in Table 3.17, I estimate an alternative specification which includes average log wages of college graduates and average log wages of non-college graduates as additional explanatory variables. Because average wages by educational attainment are not available at the county level, and because many PUMA boundaries changed between the 1990 decennial Census and the 2006-10 ACS, the geographic unit used for the regressions in Table 3.17 is based on Census-defined "Consistent PUMAs" which consolidate the two sets of PUMA definitions. By using broader geographic areas—these regressions include 312 observations instead of 915—this table also acts as a sensitivity check of the earlier regressions. Column 1 of Table 3.17 replicates the earlier regression of absolute high school gain (column 2 of Table 3.14) using this alternative unit of observation. Likewise columns 3 and 5 replicate the regressions explaining relative high school gain and relative college gain (column 2 of Table 3.15 and 3.16, respectively). Bold coefficients indicate that the value differs by more than 1.5 standard errors relative to the corresponding value in Tables 3.14-3.16. Italics are used to denote coefficients that lose statistical significance when the alternative geographic units are used (from significant at the 5% level to insignificant at the 10% level) *or* coefficients that gain statistical significance.

The results in Table 3.17 largely support the qualitative findings of the previous regressions. Only the regression of absolute high school gain (column 1) shows much sensitivity to using Consistent PUMAs as the unit of analysis. Most notably, using the broader geographic units has large effects on the coefficients on the initial stock of high school graduates and on the indicators for high and medium-density metropolitan areas. There are two factors that seem to lead to this sensitivity. First, by combining low density and high density PUMAs to form Consistent PUMAs, many areas switch metropolitan type (e.g. high density to medium density). Second, metropolitan density in the absolute high school regression—as mentioned earlier—is confounded with the initial stock of high school graduates. (Comparison of Appendix Tables A.4 and A.5 shows that the metropolitan density indicators are less sensitive to the change in geographic unit when the initial stock of high school graduates is omitted.)

Given that the change in geographic unit has modest effects, what effect do college and non-college wages have on brain gain? Columns 2 and 4 show that each percent increase in (initial) non-college wages leads to 0.5 percent more absolute growth in the high school-educated cohort, and 0.15 percent more of the cohort being college-educated in the latter period.[67] College wages have an insignificant effect in both regressions.[68] The high school-educated cohorts may be more likely to migrate to areas with high wages for *unskilled* labor—even though a subset of this group is highly educated—because the group is also young and relatively unskilled due to their lack of work experience. Inclusion of the wage variables eliminates the effect of the poverty rate on each of the brain gain measures, but it *strengthens* the effect of the unemployment rate.

[67] This assumes an 80 percent graduation rate.
[68] College wages have a significant positive effect on both absolute high school gain and relative high school gain when non-college wages are omitted.

Higher college wages lead to higher growth of the share of college-educated in a cohort, but higher non-college wages do not reduce the share of college-educated individuals. One percent higher initial college wages are associated with 0.1 percentage points higher growth in the college share,[69] again demonstrating the high responsiveness of college-educated migration to labor market stimuli.

Finally note that the effect of nonmetropolitan status on relative high school gain and relative college disappears with the inclusion of the wage variables. In fact, when wages are included, nonmetropolitan areas and less dense metropolitan areas *outperform* medium density and high density metropolitan areas in terms of relative college gain. Since specifically urban and rural amenities are not included in these regressions, this result strongly suggests that metropolitan areas' advantage in attracting educated migrants stems primarily from the strength of labor market opportunities, *not* from educated workers having stronger preferences for urban amenities.

3.8 Conclusion

In this chapter I describe three measures of growth or decline of local educational attainment and estimate these measures and their determinants in localities across the United States. Gains in any of these measures potentially benefit public finances, local industry, business owners, and others through the positive externalities of human capital. Absolute high school gain describes the total growth of the population of the high school-educated after (expected) graduation. Rising property values in cities and counties experiencing this type of growth strengthens the fiscal position of these localities. Relative high school gain and relative college gain—rapid growth of the high school-

[69] This assumes that 20 percent of the cohort had a bachelor's degree at the beginning of the period.

educated and college-educated *compared* to the growth of less educated people—similarly expand local tax bases because of education's positive effect on earnings.

Unlike brain gain and brain drain between countries, many places are neither clear winners nor clear losers as a result of brain gain and brain drain within the United States. Warmer localities tend to attract more absolute high school gain but experience less *relative* high school gain. Localities in the West attract disproportionate shares of high school dropouts, but also attract disproportionate shares of college graduates. Immigration explains at least some of this difference as Border States attract more population growth because of immigration, but this population growth tends to be less educated than the native population. Some regional brain gain differences, then, partly stem from the familiar issue of immigration to the Southwest.

Within metropolitan areas, this chapter yields mixed evidence about whether high density is associated with more brain gain. Some descriptive evidence suggests that more dense metropolitan areas attract more absolute growth of young high school graduates, but the regression results suggest that, *all else being equal*, low density metropolitan areas experience at least as much absolute high school gain as high density metropolitan areas. As a share of (25-50 year old) cohort populations, low density metropolitan areas experience *more* growth of *college* graduates than high density metropolitan areas. This finding partially reflects the lifecycle pattern where more educated (and more mobile) populations are especially likely to migrate to more urban areas early in their working life, but then flow to suburbs later in life. No obvious policy implications emerge from this type of life-cycle migration, as these differences in migration patterns between young and old educated workers reveal differences in preferences and not obvious inefficiencies or major equity concerns between high density and low density metropolitan areas (since the flows of educated workers often balance each other).

There are, however, two area characteristics that cause unambiguously negative effects on brain gain: nonmetropolitan status and poor initial labor market conditions. Nonmetropolitan areas attract less absolute growth of the high school-educated population and the growth they do experience is disproportionately high among young high school dropouts and is disproportionately low among young to middle-aged college graduates. The same bleak story is true of localities which began the period with high unemployment rates, high poverty rates, or low wages. Such areas experience lower absolute high school gain, lower relative high school gain and lower relative college gain.

The absolute and relative decline in educated individuals from these areas is large enough to be a concern for areas that are rural or economically depressed, but the solution to the problem is less obvious. Informing policy makers of a city with high unemployment and poverty that poor economic conditions will have detrimental long-term effects on their ability to attract educated workers is not particularly helpful, except perhaps to add to the urgency to find a solution. From a federal or state standpoint, it is debatable whether lack of growth of educated populations in nonmetropolitan and economically depressed areas warrants any action, and if it does, what kind of actions it warrants. Combined with the previous chapter, the results in this essay have some bearing on the use of place-based policies in areas with poor labor market conditions. Current general economic conditions lead to particularly large changes in the propensity of educated individuals to move in or out of an area, and such spatial differences in labor market conditions give rise to important differences in net flows of skilled labor.

Therefore, depending on the specific nature of a place-based policy (for example the extent that development is targeted to blue-collar industries or that the policy targets general development), it may lead to substantial net changes in the amount of skilled labor, but smaller effects on unskilled labor. Stanching the outflows of skilled labor from depressed areas may limit the demographic shifts that exacerbate economic problems in these areas. The welfare implications of such changes depend on the complementarity of skilled and unskilled labor and the nature of human capital spillovers, among other things. Note also that a failure to retain high school graduates in these places causes a larger share of the benefits of that education to accrue elsewhere, potentially leading to an underinvestment in education. Therefore a case can also be made for larger subsidies for primary and secondary education in nonmetropolitan areas and economically depressed areas on both equity and efficiency grounds.

Tables

Table 3.1 Age at Time of ACS Survey, Based on High School Class and Survey Year

HS Class | Survey Year	2006	2007	2008	2009	2010
Class of 1991	33	34	35	36	37
Class of 1992	32	33	34	35	36
Class of 1993	31	32	33	34	35

Age assumes someone was 18 in their expected high school graduating year.

Table 3.2 Basic Educational Attainment Growth Regressions

Panel A		
Growth High School Share	Coefficient	Standard Error
Ln(High School Share 1992)	-0.720**	(0.016)
Constant	-0.071**	(0.004)
R-squared = 0.696		
Panel B		
Growth College Share	Coefficient	Standard Error
Ln(College Share 1990)	-0.176**	(0.013)
Constant	-0.050*	(0.024)
R-squared = 0.176		
Panel C		
Growth Graduate School Share	Coefficient	Standard Error
Ln(Grad School Share 1990)	-0.256**	(0.016)
Constant	-0.141*	(0.055)
R-squared = 0.222		

Initial (1992) high school share is estimated based on an area's 1991-1993 high school graduates and 1988-1991 freshmen enrollment, based on the National Center of Education Statistics' Common Core of Data. Initial (1990) college and graduate school shares are based on 1990 decennial Census estimates of the population of 25-34 year olds by educational attainment. Growth of high school share subtracts the initial high school share from a weighted average of the share of 31-37 year old high school graduates in the 5% Public Use Microdata Sample of the 2006-2010 American Community Survey. Growth of college (graduate school) shares subtracts the initial shares from an average of the share of 45-50 year old college (graduate school) graduates in the 5% Public Use Microdata Sample of the 2006-2010 American Community Survey. Regressions employ Hubert-White robust standard error corrections.

** Significant at the 1% level

* Significant at the 5% level

Table 3.3 Summary Statistics

VARIABLES	Mean	Standard Deviation	Minimum	Maximum	Observs.
Absolute growth dropouts ('92-'08)	-0.248	0.631	-2.633	1.653	915
Abs. high school gain ('92-'08)	**0.295**	**0.366**	**-0.596**	**1.800**	**915**
Growth high school share ('92-'08)	0.099	0.113	-0.260	0.700	915
Relative high school gain ('92-'08)	**0.000**	**0.062**	**-0.361**	**0.207**	**915**
Abs. college gain ('90-'08)	0.433	0.372	-1.634	2.803	915
Growth college share ('90-'08)	0.275	0.186	-0.494	1.108	915
Relative college gain ('90-'08)	**0.000**	**0.169**	**-0.670**	**0.753**	**915**
Abs. grad school gain ('90-'08)	0.894	0.450	-1.116	3.496	915
Growth grad school share ('90-'08)	0.737	0.300	-0.230	1.942	915
Relative grad school gain ('90-'08)	0.000	0.264	-0.943	0.826	915
Population 1990	246,012	436,129	57,508	8,863,164	915
Population 2008	301,559	515,610	92,274	9,862,049	915
Pop. density (/sq. mile) 1990	404.6	1521.3	1.2	32,633.5	915
High school grad. rate 1991-93 %	79.6	10.0	42.9	96.0	915
College enrollment per 100	6.1	5.5	0	36.6	915
Dist. to four-year state college (miles)	35.4	32.7	0	193.3	915
Non-native born %	7.1	6.8	44.6	0.5	915
July average temperature (F)	85.5	6.0	56.8	106.9	915
January avg. temperature (F)	27.1	11.5	-2.9	59.4	915
Industry Herfindahl Index	0.134	0.044	0.067	0.373	915
Poverty Rate (1990) %	14.4	6.6	2.6	44.1	915
Unemployment Rate (1991-93)	6.7	2.6	2.1	28.4	915
Forestry and fishing %	0.44	0.93	0	13.36	915
Mining %	1.18	3.21	0	29.80	915
Utilities %	9.77	1.36	0	17.92	915
Construction %	5.78	2.26	0	19.99	915
Manufacturing %	19.53	10.95	0.58	59.42	915
Wholesale %	4.31	2.46	0	42.21	915
Retail %	8.22	1.90	1.16	20.24	915
Transportation %	3.39	2.94	0	45.87	915
Information services %	2.10	1.89	0.23	33.65	915
Finance services %	4.05	2.82	0.78	24.98	915
Real Estate %	0.89	0.60	0.17	5.81	915
Professional %	4.08	3.31	0	27.38	915
Management %	1.36	2.02	0	27.74	915
Educational services %	0.85	1.04	0	10.66	915
Administrative %	2.74	1.73	0.45	33.08	915
Health care services %	9.35	3.74	0	40.26	915
Arts and entertainment %	0.74	0.90	0.01	9.98	915
Accommodation services %	3.22	2.33	1.04	33.72	915
Other services %	3.29	0.79	1.23	10.51	915
Federal government %	3.04	3.46	0.30	33.76	915
Military %	1.59	4.69	0.07	54.87	915
State and local government %	18.88	7.60	4.50	48.82	915

Initial (1992) high school share is estimated based on an area's 1991-1993 high school graduates and 1988-1991 freshmen enrollment, based on the National Center of Education Statistics' Common Core of Data. Initial (1990) college and graduate school shares are based on 1990 decennial Census estimates of the population of 25-34 year olds by educational attainment. Growth of high school share subtracts the initial high school share from a weighted average of the share of 31-37 year old high school graduates in the 5% Public Use Microdata Sample of the 2006-2010 American Community Survey. Growth of college (graduate school) shares subtracts the initial shares from an average of the share of 45-50 year old college (graduate school) graduates in the 5% Public Use Microdata Sample of the 2006-2010 American Community Survey. See Section 2.5.1 for sources of explanatory variables.

Table 3.4 Mean Characteristics by Quintile of Absolute HS Gain (1992-2008)

VARIABLES	Brain Gain Quintile 1	Brain Gain Quintile 2	Brain Gain Quintile 3	Brain Gain Quintile 4	Brain Gain Quintile 5
Abs. high school brain gain ('92-'08) %	-15.5	7.8	25.5	45.2	84.8
Rel. high school brain gain ('92-'08) %	-1.7	-0.7	0.3	-0.4	2.4
Absolute college brain gain ('90-'08) %	33.9	39.9	39.8	44.1	58.7
Relative college brain gain ('90-'08) %	-5.9	-3.4	-1.1	2.6	7.8
Rel. grad school brain gain ('90-'08) %	-8.6	-5.8	0.3	3.7	10.4
Population 1990	133,626	176,786	210,356	276,670	434,025
Population 2008	135,384	194,702	237,811	341,770	600,344
Pop. density (/sq. mile) 1990	63.7	324.4	295.0	437.9	905.1
Metro > 400 per square mile (dummy)	0.011	0.060	0.153	0.268	0.330
Metro 200-400 per square mile (dummy)	0.033	0.120	0.180	0.224	0.181
Metro < 200 per square mile (dummy)	0.240	0.293	0.339	0.339	0.418
Non-metro (dummy)	0.716	0.527	0.328	0.169	0.071
College enrollment per 100	5.3	5.4	6.4	6.5	7.0
Dist. to four-year state college (miles)	54.4	47.6	30.2	23.9	20.9
Non-native born %	3.5	4.8	6.0	9.2	12.2
July average temperature (F)	84.3	84.8	85.4	85.5	87.4
January avg. temperature (F)	20.4	25.7	27.3	29.0	33.0
Coast (dummy)	0.142	0.174	0.251	0.284	0.324
Poverty Rate (1990) %	16.8	16.7	14.2	12.7	11.7
Unemployment Rate (1991-93) %	7.4	7.6	6.6	6.4	5.3
Industry Herfindahl Index	0.150	0.143	0.133	0.130	0.114
Forestry and fishing %	0.62	0.59	0.36	0.47	0.19
Mining %	2.28	1.73	1.01	0.49	0.41
Utilities %	1.37	1.11	0.73	0.91	0.76
Construction %	4.68	5.54	5.75	5.92	7.01
Manufacturing %	22.58	21.90	20.25	18.94	13.94
Wholesale %	3.94	3.72	4.02	4.47	5.41
Retail %	8.31	8.21	8.33	8.17	8.06
Transportation %	3.90	3.39	3.16	3.20	3.29
Information services %	1.51	1.63	1.89	2.23	3.22
Finance services %	3.27	3.32	3.64	4.49	5.57
Real Estate %	0.53	0.74	0.88	0.99	1.31
Professional %	2.24	2.91	4.09	4.60	6.60
Management %	0.79	0.90	1.28	1.80	2.03
Educational services %	1.85	2.25	2.80	3.01	3.79
Administrative %	0.68	0.77	0.91	0.88	1.00
Health care services %	9.72	9.35	9.80	9.29	8.55
Arts and entertainment %	0.51	0.58	0.77	0.75	1.07
Accommodation services %	2.84	3.20	3.19	3.32	3.58
Other services %	3.32	3.29	3.33	3.19	3.33
Federal government %	2.81	3.16	3.07	3.18	2.98
Military %	0.72	1.40	2.02	1.79	2.03
State and local government %	21.55	20.33	18.72	17.92	15.88
Northeast	0.137	0.158	0.180	0.153	0.033
Midwest	0.546	0.288	0.230	0.219	0.137
South	0.257	0.418	0.492	0.475	0.665
West	0.060	0.136	0.098	0.153	0.165

Initial stock of high school graduates is based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduate stock is then based on 31-37 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures. See Section 3.5.1 for sources of explanatory variables.

Table 3.5 Mean Characteristics by Quintile of Relative High School Gain (1992-2008)

VARIABLES	Brain Gain Quintile 1	Brain Gain Quintile 2	Brain Gain Quintile 3	Brain Gain Quintile 4	Brain Gain Quintile 5
Abs. high school brain gain ('92-'08) %	19.9	22.0	26.9	33.4	45.1
Rel. high school brain gain ('92-'08) %	-9.3	-2.0	1.0	3.3	7.0
Absolute college brain gain ('90-'08) %	44.4	45.7	42.6	44.3	39.4
Relative college brain gain ('90-'08) %	-3.8	-1.0	-0.6	1.9	3.4
Rel. grad school brain gain ('90-'08) %	-6.7	-3.1	0.1	3.0	6.5
Population 1990	273,603	207,699	265,042	228,060	255,544
Population 2008	350,731	257,084	323,223	272,026	304,649
Pop. density (/sq. mile) 1990	205.1	255.8	353.9	350.5	857.1
Metro > 400 per square mile (dummy)	0.098	0.110	0.180	0.196	0.235
Metro 200-400 per square mile (dummy)	0.082	0.132	0.126	0.179	0.219
Metro < 200 per square mile (dummy)	0.251	0.297	0.361	0.348	0.372
Non-metro (dummy)	0.568	0.462	0.333	0.277	0.175
College enrollment per 100	5.1	5.6	5.9	6.1	7.8
Dist. to four-year state college (miles)	47.3	41.8	33.5	30.2	24.4
Non-native born %	10.6	6.1	6.6	5.7	6.7
July average temperature (F)	88.4	85.8	85.0	84.3	84.1
January avg. temperature (F)	32.0	27.9	25.6	24.2	25.6
Coast (dummy)	0.219	0.209	0.219	0.239	0.290
Poverty Rate (1990) %	17.1	15.6	13.5	13.0	12.9
Unemployment Rate (1991-93) %	8.0	6.9	6.4	6.1	5.9
Industry Herfindahl Index	0.141	0.143	0.137	0.130	0.119
Forestry and fishing %	1.02	0.40	0.31	0.25	0.25
Mining %	1.70	1.33	1.06	0.88	0.95
Utilities %	1.10	0.92	0.86	1.07	0.94
Construction %	5.63	5.46	5.49	6.28	6.03
Manufacturing %	19.32	21.86	20.86	20.34	15.26
Wholesale %	4.02	3.92	4.26	4.60	4.73
Retail %	8.39	8.26	8.18	8.18	8.07
Transportation %	3.51	3.75	3.23	3.24	3.23
Information services %	1.74	1.83	2.03	2.17	2.70
Finance services %	3.42	3.47	4.27	4.32	4.79
Real Estate %	0.85	0.84	0.83	0.89	1.02
Professional %	3.06	3.56	4.05	4.45	5.30
Management %	1.04	1.32	1.33	1.38	1.72
Educational services %	2.50	2.60	2.71	2.94	2.95
Administrative %	0.56	0.83	0.93	0.82	1.12
Health care services %	8.71	9.09	9.62	9.58	9.71
Arts and entertainment %	0.64	0.62	0.79	0.77	0.86
Accommodation services %	3.25	3.25	3.36	2.97	3.29
Other services %	3.33	3.32	3.26	3.30	3.26
Federal government %	3.15	2.87	2.80	2.54	3.83
Military %	1.45	0.86	1.53	1.51	2.61
State and local government %	21.61	19.64	18.23	17.53	17.40
Northeast	0.033	0.143	0.142	0.152	0.191
Midwest	0.208	0.231	0.344	0.348	0.290
South	0.481	0.527	0.443	0.429	0.426
West	0.279	0.099	0.071	0.071	0.093

Initial share of high school graduates is based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduate share is then based on 31-37 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures. See Section 3.5.1 for sources of explanatory variables.

Table 3.6 Mean Characteristics by Quintile of Relative College Gain (1990-2008)

VARIABLES	Brain Gain Quintile 1	Brain Gain Quintile 2	Brain Gain Quintile 3	Brain Gain Quintile 4	Brain Gain Quintile 5
Abs. high school brain gain ('92-'08) %	18.6	20.0	26.2	35.0	47.9
Rel. high school brain gain ('92-'08) %	-1.3	-0.9	0.9	0.6	0.7
Absolute college brain gain ('90-'08) %	9.9	28.3	39.1	49.9	89.6
Relative college brain gain ('90-'08) %	-22.9	-8.0	-0.2	7.3	23.9
Rel. grad school brain gain ('90-'08) %	-27.4	-10.5	0.0	12.4	25.8
Population 1990	176,564	288,493	280,117	268,890	215,301
Population 2008	196,372	324,842	329,414	352,014	304,785
Pop. density (/sq. mile) 1990	413.8	648.1	320.3	383.1	254.7
Metro > 400 per square mile (dummy)	0.120	0.201	0.164	0.223	0.110
Metro 200-400 per square mile (dummy)	0.109	0.109	0.169	0.163	0.188
Metro < 200 per square mile (dummy)	0.290	0.288	0.339	0.277	0.436
Non-metro (dummy)	0.481	0.402	0.328	0.337	0.265
College enrollment per 100	8.0	6.5	6.5	5.9	3.6
Dist. to four-year state college (miles)	36.9	34.8	30.5	34.5	40.5
Non-native born %	5.9	7.0	6.2	8.4	8.2
July average temperature (F)	87.1	85.4	85.1	85.3	84.6
January avg. temperature (F)	28.5	26.5	23.8	26.9	29.5
Coast (dummy)	0.164	0.207	0.191	0.293	0.320
Poverty Rate (1990) %	18.8	15.2	13.6	12.5	12.1
Unemployment Rate (1991-93)	7.5	6.9	6.3	6.1	6.5
Industry Herfindahl Index	0.144	0.138	0.130	0.131	0.126
Forestry and fishing %	0.64	0.51	0.35	0.27	0.46
Mining %	1.85	0.90	1.11	1.13	0.93
Utilities %	0.94	1.15	0.86	0.83	1.11
Construction %	5.00	5.15	5.79	5.84	7.14
Manufacturing %	19.73	20.95	19.55	19.83	17.55
Wholesale %	3.89	4.19	4.41	4.90	4.14
Retail %	7.88	7.81	8.21	8.27	8.91
Transportation %	3.99	3.33	3.36	3.15	3.12
Information services %	1.82	2.00	2.08	2.41	2.17
Finance services %	3.50	4.27	4.32	4.24	3.94
Real Estate %	0.76	0.82	0.86	1.01	0.99
Professional %	3.00	3.90	3.91	4.86	4.76
Management %	1.00	1.31	1.50	1.51	1.48
Educational services %	2.31	2.51	2.77	3.07	3.03
Administrative %	0.78	0.90	0.90	0.83	0.85
Health care services %	9.66	9.68	9.37	9.22	8.78
Arts and entertainment %	0.50	0.72	0.69	0.82	0.95
Accommodation services %	2.91	2.87	3.44	3.25	3.66
Other services %	3.29	3.25	3.26	3.22	3.44
Federal government %	3.14	2.90	3.10	2.65	3.42
Military %	1.78	1.29	1.54	2.11	1.23
State and local government %	21.64	19.60	18.63	16.61	17.93
Northeast	0.104	0.196	0.148	0.152	0.061
Midwest	0.262	0.299	0.350	0.293	0.215
South	0.579	0.435	0.388	0.435	0.470
West	0.055	0.071	0.115	0.120	0.254

Initial share of college graduates is based on 25-34 year olds in the 1990 decennial Census. Growth of college graduate share is then based on 45-50 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures. See Section 3.5.1 for sources of explanatory variables.

Table 3.7 State Absolute HS and Dropout Gain 1992-2008 (Graduation to Age 31-37)

State	Rank Abs. High School Gain	Abs. High School Gain	Rank Abs. HS Dropout Gain	Abs. HS Dropout Gain	Rank Rel. High School Gain	Rel. High School Gain
Nevada	1	1.113	1	1.172	46	-0.07
District of Columbia	2	1.043	43	-1.045	1	0.137
Arizona	3	0.878	5	0.297	43	-0.026
Florida	4	0.775	18	-0.183	15	0.025
Colorado	5	0.705	12	-0.015	24	0.014
Georgia	6	0.66	19	-0.199	32	0.005
Delaware	7	0.598	14	-0.056	31	0.007
California	8	0.563	3	0.453	47	-0.083
Oregon	9	0.559	23	-0.239	27	0.010
Maryland	10	0.552	6	0.229	19	0.022
North Carolina	11	0.55	20	-0.207	40	-0.006
Texas	12	0.518	15	-0.063	45	-0.056
Virginia	13	0.50	17	-0.173	13	0.027
Tennessee	14	0.489	32	-0.431	20	0.020
Connecticut	15	0.468	35	-0.526	6	0.047
New Jersey	16	0.459	34	-0.505	35	0.003
South Carolina	17	0.448	37	-0.653	9	0.033
Illinois	18	0.43	7	0.088	39	-0.004
Utah	19	0.406	8	0.04	29	0.010
Rhode Island	20	0.388	30	-0.41	26	0.012
Missouri	21	0.383	29	-0.358	18	0.023
Kentucky	22	0.36	31	-0.422	23	0.016
Minnesota	23	0.31	11	-0.011	12	0.028
Louisiana	24	0.306	42	-0.903	8	0.036
New Hampshire	25	0.306	4	0.383	17	0.024
Idaho	26	0.303	25	-0.282	38	-0.002
New Mexico	27	0.303	13	-0.029	44	-0.043
Pennsylvania	28	0.301	16	-0.141	14	0.027
Alabama	29	0.288	38	-0.698	22	0.010
Wisconsin	30	0.288	2	0.494	28	0.018
Mississippi	31	0.263	40	-0.783	33	0.005
Indiana	32	0.247	24	-0.258	34	0.003
Michigan	33	0.231	27	-0.349	11	0.028
Kansas	34	0.224	21	-0.225	36	0.0
Ohio	35	0.221	36	-0.618	10	0.032
Oklahoma	36	0.22	26	-0.292	41	-0.008
Arkansas	37	0.177	33	-0.46	42	-0.008
Maine	38	0.164	46	-1.329	2	0.081
Wyoming	39	0.137	45	-1.319	4	0.008
Vermont	40	0.128	44	-1.245	5	0.075
New York	41	0.12	22	-0.239	30	0.010
Nebraska	42	0.119	9	0.003	37	-0.001
Iowa	43	0.111	10	0.0	25	0.013
South Dakota	44	0.085	28	-0.35	16	0.024
Montana	45	0.074	41	-0.845	7	0.046
West Virginia	46	-0.021	39	-0.709	21	0.020
North Dakota	47	-0.043	47	-1.459	3	0.079
New England	**6**	**0.351**	**9**	**-0.564**	**1**	**0.046**
Middle Atlantic	**8**	**0.262**	**3**	**-0.040**	**5**	**0.015**
East North Central	**7**	**0.289**	**4**	**-0.195**	**6**	**0.015**
West North Central	**9**	**0.25**	**5**	**-0.202**	**2**	**0.019**
South Atlantic	**2**	**0.593**	**6**	**-0.213**	**2**	**0.019**
East South Central	**5**	**0.367**	**8**	**-0.559**	**4**	**0.016**
West South Central	**4**	**0.419**	**7**	**-0.258**	**8**	**-0.031**
Mountain	**1**	**0.623**	**2**	**0.068**	**7**	**-0.008**
Pacific	**3**	**0.563**	**1**	**0.393**	**9**	**-0.075**

State and Census division brain gain based on population-weighted averages of CGAs. See Table 3.2 and text for details.

Table 3.8 High School Gain Percentile for Counties Containing Largest U.S. MSA Centers (as of 1990) and Adjacent Areas

County (City)	Abs. High School Gain Percentile (MSA Center)	Abs. High School Gain Percentile (Suburban)	Rel. High School Gain Percentile (MSA Center)	Rel. High School Gain Percentile (Suburban)
Los Angeles (Los Angeles, CA)	81	70	8	4
Cook (Chicago, IL)	82	70	40	23
Philadelphia (Philadelphia, PA)	89	67	85	64
Wayne (Detroit, MI)	58	63	76	73
District of Columbia (Washington, DC)	95	88	99	27
Dallas (Dallas, TX)	84	95	3	38
Harris (Houston, TX)	88	87	7	56
San Francisco (San Francisco, CA)	99	84	89	29
Fulton (Atlanta, GA)	97	95	98	43
Riverside (Riverside, CA)	91	74	2	4
St. Louis (city), MO	98	48	99	79
Hennepin (Minneapolis, MN)	85	76	60	63
San Diego (San Diego, CA)	83	69	28	4
Allegheny (Pittsburgh, PA)	49	16	81	76
Baltimore (city), MD	98	80	99	75
Maricopa (Phoenix, AZ)	96	91	20	38
Cuyahoga (Cleveland, OH)	59	42	70	78
Hillsborough (Tampa, FL)	93	86	82	57
Hamilton (Cincinnai, OH)	68	73	92	72
Jackson (Kansas City, MO)	72	74	80	66
Santa Clara (San Jose, CA)	99	81	89	10
Multnomah (Portland, OR)	94	90	71	63
Providence (Providence, RI)	71	53	24	87
Sacramento (Sacramento, CA)	86	72	27	13
Virginia Beach (city), VA	71	90	97	99
Milwaukee (Milwaukee, WI)	74	51	44	68
Bexar (San Antonio, TX)	79	57	52	21
Franklin (Columbus, OH)	87	74	87	63
Marion (Indianapolis, IN)	82	74	53	74
Orleans (New Orleans, LA)	40	78	99	71

Suburbs defined as CGAs that contain at least one county that is adjacent to the central county. Initial high school graduation rate data is unavailable for New York County (New York City), Suffolk County (Boston), King County (Seattle), Denver County (Denver), and Miami-Dade County (Miami). See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures.

Table 3.9 Thirty Areas with Highest and Lowest Absolute High School Gain

Brain Gain: Area's Largest City	MSA (Distance to Central City)	Absolute Brain Gain	Pop. Density	**Brain Drain**: Area's Largest City	Absolute Brain Gain	Pop. Density
Stockbridge, GA	Atlanta (21)	1.80	182.0	Andrews, TX	-0.60	3.1
Newport News, VA	Va. Beach (40)	1.69	7,266.9	Great Falls, MT	-0.56	2.0
Arlington, VA	Washington (6)	1.61	6599.8	Scottsbluff, NE	-0.47	4.6
Denton, TX	Dallas (39)	1.54	307.9	Woodward, OK	-0.42	7.0
Cumming, GA	Atlanta (39)	1.53	101.6	Caro, MI	-0.42	49.9
Amarillo, TX	Amarillo (0)	1.45	98.1	Salina, KS	-0.42	6.2
San Francisco, CA	San Francisco (0)	1.45	15,502	Levelland, TX	-0.41	11.0
Woodstock, GA	Atlanta (30)	1.44	212.9	Marshall, MN	-0.41	22.6
Las Vegas, NV	Las Vegas (0)	1.41	93.7	Aberdeen, SD	-0.39	7.7
Plano, TX	Dallas (19)	1.39	311.5	Marquette, MI	-0.38	24.1
Leesburg, VA	Washington (40)	1.37	110.9	Jamestown, ND	-0.38	6.4
Delaware, OH	Columbus (29)	1.36	151.3	Gladwin, MI	-0.37	42.1
Cartersville, GA	Atlanta (43)	1.35	126.1	Presque Isle, ME	-0.36	13.2
San Marcos, TX	Austin (31)	1.34	385.1	Forest City, AR	-0.35	34.6
St. Louis, MO	St. Louis (0)	1.31	6,408.5	Oil City, PA	-0.35	62.1
Kissimmee, FL	Orlando (22)	1.31	81.5	Bluefield, WV	-0.35	88.7
Raleigh, NC	Raleigh (0)	1.30	507.7	Houghton, MI	-0.35	17.6
Alabaster, AL	Birmingham (24)	1.25	125.0	Fergus Falls, MN	-0.35	17.0
*Ponte Vedra Beach, FL	Jacksonville (22)	1.23	137.7	Fremont, NE	-0.34	19.8
Charlotte, NC	Charlotte (0)	1.22	969.7	North Platte, NE	-0.33	6.4
Aspen, CO	-------	1.21	6.7	Macomb, IL	-0.32	38.5
Round Rock, TX	Austin (19)	1.20	124.1	Beatrice, NE	-0.32	18.4
Casa Grande, AZ	Phoenix (48)	1.18	15.4	Worthington, MN	-0.29	22.6
Atlanta, GA	Atlanta (0)	1.16	1227.4	Pampa, TX	-0.29	7.7
Winder, GA	Atlanta (50)	1.14	139.0	Carroll, IA	-0.29	22.4
Orlando, FL	Orlando (0)	1.13	746.5	Pine Bluff, AR	-0.29	48.3
Port. St. Lucie, FL	Port St. Lucie (0)	1.13	262.3	Williamson, WV	-0.28	76.8
New Port Richey, FL	Tampa (38)	1.12	377.4	Waverly, IA	-0.28	28.8
Peachtree Corners, GA	Atlanta (20)	1.12	815.2	Sayre, PA	-0.28	39.6
Shakopee, MN	Minneapolis (27)	1.09	148.1	Alpena, MI	-0.28	25.5

Initial stock of high school graduates is based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduate stock is then based on 31-37 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures.

*Unincorporated community

Table 3.10 State Relative College Gain (1990-2008), (Between Age 25-34 and 45-50)

State	Rank Rel. Brain Gain Some College	Rel. Brain Gain Some Coll.	Rank Rel. Brain Gain Bachelor's	Rel. Brain Gain Bachelor's	Rank Rel. Brain Gain Graduate School	Rel. Brain Gain Grad School
Vermont	1	0.079	1	0.136	2	0.222
Colorado	10	0.028	2	0.118	3	0.199
Utah	18	0.009	3	0.113	1	0.278
Oregon	2	0.057	4	0.107	4	0.174
Nevada	25	-0.010	5	0.105	19	0.049
New Mexico	4	0.042	6	0.100	13	0.093
Florida	12	0.021	7	0.087	15	0.091
Montana	3	0.050	8	0.078	10	0.110
California	24	-0.009	9	0.073	18	0.053
Arizona	20	0.001	10	0.057	12	0.094
Idaho	13	0.020	11	0.050	22	0.030
Virginia	11	0.021	12	0.049	6	0.154
Georgia	5	0.041	13	0.045	16	0.087
Minnesota	6	0.035	14	0.045	5	0.156
New Hampshire	9	0.029	15	0.041	7	0.149
Nebraska	26	-0.011	16	0.024	23	0.025
Maryland	16	0.010	17	0.023	8	0.126
Maine	8	0.034	18	0.020	11	0.105
Michigan	23	-0.007	19	0.020	20	0.045
North Carolina	7	0.034	20	0.013	26	-0.011
South Carolina	15	0.013	21	0.007	34	-0.027
North Dakota	41	-0.044	22	0.004	45	-0.147
District of Columbia	43	-0.047	23	-0.008	30	-0.020
Kentucky	21	-0.001	24	-0.013	38	-0.073
Connecticut	28	-0.015	25	-0.015	17	0.079
New York	38	-0.036	26	-0.018	33	-0.026
New Jersey	35	-0.027	27	-0.021	30	-0.020
Kansas	22	-0.002	28	-0.022	27	-0.011
Wyoming	14	0.014	29	-0.025	14	0.092
South Dakota	30	-0.020	30	-0.026	24	0.018
Ohio	32	-0.023	31	-0.027	28	-0.012
Wisconsin	32	-0.023	32	-0.027	28	-0.012
Missouri	19	0.005	33	-0.029	21	0.040
Delaware	17	0.010	34	-0.032	9	0.114
Texas	46	-0.058	35	-0.038	36	-0.058
Tennessee	31	-0.021	36	-0.046	39	-0.074
Illinois	34	-0.025	37	-0.048	25	-0.008
Indiana	36	-0.029	38	-0.051	43	-0.128
Oklahoma	40	-0.043	39	-0.062	42	-0.126
Arkansas	27	-0.013	40	-0.063	44	-0.144
Iowa	29	-0.019	41	-0.064	32	-0.022
Rhode Island	37	-0.030	42	-0.072	35	-0.041
Alabama	39	-0.042	43	-0.072	37	-0.063
Louisiana	47	-0.075	44	-0.075	47	-0.179
West Virginia	45	-0.056	45	-0.081	46	-0.167
Pennsylvania	44	-0.048	46	-0.101	40	-0.111
Mississippi	42	-0.046	47	-0.110	41	-0.112
New England	**3**	**0.006**	**4**	**0.004**	**2**	**0.089**
Middle Atlantic	**8**	**-0.038**	**8**	**-0.050**	**7**	**-0.057**
East North Central	**6**	**-0.014**	**6**	**-0.020**	**6**	**0.002**
West North Central	**4**	**0.003**	**5**	**-0.009**	**5**	**0.043**
South Atlantic	**1**	**0.019**	**3**	**0.037**	**3**	**0.065**
East South Central	**7**	**-0.026**	**9**	**-0.056**	**8**	**-0.077**
West South Central	**9**	**-0.055**	**7**	**-0.049**	**9**	**-0.093**
Mountain	**2**	**0.016**	**1**	**0.086**	**1**	**0.135**
Pacific	**5**	**-0.003**	**2**	**0.076**	**4**	**0.064**

State and Census division brain gain based on population-weighted averages of CGAs. See Table 3.2 and text for details.

Table 3.11 Relative College and Graduate School Gain Percentile for Counties Containing Largest U.S. MSA Centers (as of 1990) and Adjacent Areas

County (City)	Rel. College Gain Percentile (MSA Center)	Rel. College Gain Percentile (Suburban)	Rel. Grad School Gain Percentile (MSA Center)	Rel. Grad School Gain Percentile (Suburban)
Los Angeles (Los Angeles, CA)	53	78	28	62
Cook (Chicago, IL)	24	83	34	74
Philadelphia (Philadelphia, PA)	0	51	2	63
Wayne (Detroit, MI)	46	61	35	72
District of Columbia (Washington, DC)	28	52	45	72
Dallas (Dallas, TX)	15	59	21	62
Harris (Houston, TX)	24	87	27	69
San Francisco (San Francisco, CA)	28	82	61	73
Fulton (Atlanta, GA)	88	78	81	70
Riverside (Riverside, CA)	80	72	63	56
St. Louis (city), MO	0	92	4	84
Hennepin (Minneapolis, MN)	65	66	75	77
San Diego (San Diego, CA)	82	83	79	70
Allegheny (Pittsburgh, PA)	31	59	36	44
Baltimore (city), MD	0	72	4	78
Maricopa (Phoenix, AZ)	62	69	62	60
Cuyahoga (Cleveland, OH)	26	78	43	73
Hillsborough (Tampa, FL)	70	87	58	69
Hamilton (Cincinnai, OH)	46	47	40	47
Jackson (Kansas City, MO)	22	37	50	50
Santa Clara (San Jose, CA)	28	70	61	59
Multnomah (Portland, OR)	80	81	84	83
Providence (Providence, RI)	12	71	22	60
Sacramento (Sacramento, CA)	39	78	39	63
Virginia Beach (city), VA	80	70	90	72
Milwaukee (Milwaukee, WI)	42	77	66	78
Bexar (San Antonio, TX)	57	92	57	95
Franklin (Columbus, OH)	24	94	31	83
Marion (Indianapolis, IN)	5	78	16	51
Orleans (New Orleans, LA)	50	53	52	47

Suburbs defined as CGAs that contain at least one county that is adjacent to the central county. Initial high school graduation rate data is unavailable for New York County (New York City), Suffolk County (Boston), King County (Seattle), Denver County (Denver), and Miami-Dade County (Miami). Initial share of college graduates is based on 25-34 year olds in the 1990 decennial Census. Growth of college graduate share is then based on 45-50 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures.

Table 3.12 Thirty Areas with Highest and Lowest Relative High School Gain

Brain Gain: Area's Largest City	MSA (Distance to Central City)	Rel. Brain Gain	Area Pop. Dens.	**Brain Drain:** Area's Largest City	MSA (Distance to Central City)	Rel. Brain Gain	Area Pop. Dens.
St. Marys, PA	-------	0.207	24.9	**Madera, CA**	Madera (0)	-0.361	41.2
Van Wert, OH	-------	0.184	64.7	Garden City, KS	-------	-0.339	8.7
St. Louis, MO	St. Louis (0)	0.161	6,409	**El Centro, CA**	El Centro (0)	-0.264	26.2
Washington, DC	Washington (0)	0.137	9,884	**Visalia, CA**	Visalia (0)	-0.263	64.7
Charleston, SC	Charleston (0)	0.132	321.6	**Merced, CA**	Merced (0)	-0.260	92.5
Norfolk, VA	Va. Beach (18)	0.128	4,856	**Kingsville, TX**	-------	-0.252	15.4
New Orleans, LA	New Orleans (0)	0.119	2,752	**Hanford, CA**	Hanford (0)	-0.236	73.0
Jamestown, ND	-------	0.114	6.4	**Salinas, CA**	Salinas (0)	-0.231	83.3
Jacksonville, FL	Jacksonville (0)	0.111	502.9	**Bakersfield, CA**	Bakersfield (0)	-0.226	66.8
Chesapeake, VA	Chesapeake (0)	0.110	446.1	**Colusa, CA**	-------	-0.204	12.1
Norwich, CT	Norwich (0)	0.108	382.8	**Fresno, CA**	Fresno (0)	-0.186	111.9
Baltimore, MD	Baltimore (0)	0.107	9,109	Clinton, NC	-------	-0.186	49.5
Pearl, MS	Jackson (6)	0.104	112.5	McAllen, TX	McAllen (0)	-0.181	244.4
Vernon, CT	Hartford (14)	0.101	313.8	**Santa Maria, CA**	Santa Maria (0)	-0.181	135.0
Gainesville, FL	Gainesville (0)	0.101	207.7	**Clearlake, CA**	-------	-0.180	27.5
Atlanta, GA	Atlanta (0)	0.101	1,227	**Lamesa, TX**	-------	-0.179	5.3
Fargo, ND	Fargo (0)	0.099	17.1	Sebring, FL	-------	-0.177	34.3
Skowhegan, ME	-------	0.099	17.1	Lumberton, NC	-------	-0.175	110.8
Va. Beach, VA	Va. Beach (0)	0.098	1,583	Gallup, NM	-------	-0.169	8.5
Morgantown, WV	Morgantown (0)	0.097	103.6	Woodward, OK	-------	-0.169	7.0
Portsmouth, VA	Va. Beach (21)	0.096	241.8	**Napa, CA**	Napa (0)	-0.157	146.9
*Ponte Vedra Beach, FL	Jacksonville (22)	0.095	137.7	**Andrews, TX**	-------	-0.157	3.1
Burlington, VT	Burlington (0)	0.094	140.7	De Queen, AR	-------	-0.154	21.4
Portland, ME	Portland (0)	0.093	186.0	Modesto, CA	Modesto (0)	-0.153	247.9
Brunswick, OH	Cleveland (32)	0.092	290.2	**Riverside, CA**	Riverside (0)	-0.152	162.4
Bangor, ME	Bangor (0)	0.092	22.4	Dalton, GA	Dalton (0)	-0.151	135.1
Lakeside, FL	Jacksonville (28)	0.091	176.3	Mt. Vernon, OH	-------	-0.147	76.4
Huntington, WV	Huntington (0)	0.091	171.0	Brownsville, TX	Brownsville (0)	-0.145	287.2
Davenport, IA	Davenport (0)	0.087	329.7	Dallas, TX	Dallas (0)	-0.141	2,106
S. Kingstown, RI	Providence (32)	0.087	330.4	**Bay City, TX**	-------	-0.141	27.5

Initial stock and share of high school graduates are based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduate stock and share are then based on 31-37 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures.
*Unincorporated community

Table 3.13 Thirty Areas with Highest and Lowest Relative College Gain

Brain Gain: Area's Largest City	MSA (Distance to Central City)	Rel. Brain Gain	Pop. Dens.	**Brain Drain:** Area's Largest City	MSA (Distance to Central City)	Rel. Brain Gain	Pop. Dens.
Cumming, GA	Atlanta (39)	0.753	101.6	Colonial Beach, VA	-------	-0.670	48.9
Casa Grande, AZ	Phoenix (48)	0.718	15.4	St. Louis, MO	St. Louis (0)	-0.606	6,408
Monroe, NC	Charlotte (25)	0.622	132.1	Emporia, VA	-------	-0.596	34.1
Hollins, VA	Roanoke (5)	0.611	131.5	Clarksdale, MS	-------	-0.549	40.7
New Port Richey, FL	Tampa (38)	0.476	377.4	Columbus, MS	-------	-0.546	55.3
Las Vegas, NM	-------	0.438	5.2	Philadelphia, PA	Philadelphia (0)	-0.522	11,736
Delaware, OH	Columbus (29)	0.435	151.3	Anniston, AL	Anniston (0)	-0.495	190.7
Pt. Charlotte, FL	Punta Gorda (4)	0.434	160	Athens, OH	-------	-0.488	67.2
Manassas, VA	Washington (33)	0.428	715	Jacksonville, TX	-------	-0.445	38.5
Heber City, UT	-------	0.426	3.9	Greeneville, TN	-------	-0.436	95.1
Monroe, GA	Atlanta (46)	0.394	55.6	Alice, TX	-------	-0.432	16.7
Kenosha, WI	Chicago (64)	0.393	469.9	Enid, OK	-------	-0.411	42.8
Peachtree City, GA	Atlanta (32)	0.392	203.6	Blacksburg, VA	Blacksburg (0)	-0.405	104.7
Fairfax, VA	Washington (20)	0.378	110.9	Greenville, MS	-------	-0.384	68.6
Waxahachie, TX	Dallas (30)	0.372	90.6	Aberdeen, SD	-------	-0.382	7.7
Stockbridge, GA	Atlanta (21)	0.366	182.0	Kirksville, MO	-------	-0.375	17.5
Shakopee, MN	Minneapolis (27)	0.364	148.1	Bastrop, LA	-------	-0.367	27.3
Bentonville, AR	Fayetteville (27)	0.363	115.6	Troy, NY	Albany (8)	-0.364	236.1
Port Huron, MI	Detroit (63)	0.356	159.8	Huntsville, TX	-------	-0.355	30.1
Washington, MO	St. Louis (51)	0.354	65.0	Kingsville, TX	-------	-0.347	15.4
Kalispell, MT	-------	0.352	8.2	Richmond, VA	Richmond (0)	-0.342	3,379
Shelbyville, KY	Louisville (32)	0.352	87.8	Oil City, PA	-------	-0.341	62.1
Denham Springs, LA	Baton Rouge (13)	0.350	137.0	Sioux City, IA	Sioux City (0)	-0.337	112.6
Richmond, KY	Lexington (26)	0.349	85.4	Indiana, PA	Pittsburgh (58)	-0.334	110.2
Florissant, MO	St. Louis (18)	0.347	1,957	Greenville, NC	Greenville (0)	-0.319	165.6
*Ponte Vedra Beach, FL	Jacksonville (23)	0.343	137.7	Danville, IL	Danville (0)	-0.316	48.7
Palm City, FL	Port St. Lucie (13)	0.343	181.6	Sweetwater, TX	-------	-0.311	10.4
Ashland, VA	Richmond (19)	0.325	91.1	Live Oak, FL	-------	-0.309	22.8
McMinnville, OR	Portland (38)	0.320	79.0	Bardstown, KY	Louisville (41)	-0.307	43.9
Barre, VT	-------	0.317	42.0	Lafayette, IN	Lafayette (0)	-0.303	178.6

Initial share of college graduates is based on 25-34 year olds in the 1990 decennial Census. Growth of college graduate share is then based on 45-50 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 or Section 3.5.1 of the text for details of the construction of brain gain measures.
*Unincorporated community

Table 3.14 Absolute High School Gain, 1992-2008 (Ordinary Least Squares)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Ln (HS grads (1991-93))	0.270**	0.144**	0.051	0.164**	0.379**
(SD)	(0.016)	(0.021)	(0.031)	(0.031)	(0.042)
Metro > 400 per square mile		-0.147**	-0.068	-0.207**	--
(SD)		(0.034)	(0.058)	(0.046)	--
Metro 200-400 per square mile		-0.037	0.007	-0.051	--
(SD)		(0.025)	(0.043)	(0.033)	--
Non-Metro		-0.101**	--	--	--
(SD)		(0.020)	--	--	--
Ln (dist. to four-year state coll.)		-0.015*	-0.011	-0.006	-0.047**
(SD)		(0.007)	(0.012)	(0.010)	(0.012)
July average high temperature (F)		-0.005*	-0.004	0.007	-0.012**
(SD)		(0.002)	(0.004)	(0.004)	(0.003)
January avg. low temperature (F)		0.005**	0.005	0.006*	0.012**
(SD)		(0.001)	(0.003)	(0.002)	(0.002)
Coast dummy		-0.080**	-0.043	-0.044	-0.090*
(SD)		(0.020)	(0.053)	(0.030)	(0.035)
Poverty rate (1990) %		-0.011**	-0.006	-0.016**	-0.004
(SD)		(0.002)	(0.007)	(0.004)	(0.003)
Unemployment rate (1991-93) %		-0.021**	-0.032	-0.023**	-0.017**
(SD)		(0.004)	(0.019)	(0.007)	(0.006)
Neighbors' unemployment %			-0.017	-0.024*	0.003
(SD)			(0.015)	(0.010)	(0.008)
Mining %		-0.015**	-0.019*	-0.016**	-0.009**
(SD)		(0.003)	(0.009)	(0.005)	(0.003)
Manufacturing %		-0.004**	-0.006*	-0.005**	0.000
(SD)		(0.001)	(0.003)	(0.002)	(0.002)
Information services %		0.006	-0.012	0.008*	0.030
(SD)		(0.005)	(0.013)	(0.004)	(0.018)
Professional %		0.006	0.027**	-0.004	0.003
(SD)		(0.005)	(0.009)	(0.005)	(0.009)
Arts and entertainment %		0.036**	0.007	0.016	0.081**
(SD)		(0.012)	(0.025)	(0.013)	(0.019)
Federal government %		-0.002	-0.001	-0.008*	-0.002
(SD)		(0.003)	(0.006)	(0.004)	(0.004)
Military %		0.001	-0.002	-0.001	0.007*
(SD)		(0.002)	(0.005)	(0.003)	(0.003)
State and local government %		0.001	-0.001	0.001	0.001
(SD)		(0.001)	(0.003)	(0.002)	(0.002)
Midwest		0.099**	0.171**	0.068	0.100*
(SD)		(0.027)	(0.065)	(0.038)	(0.043)
South		0.305**	0.306**	0.218**	0.165**
(SD)		(0.036)	(0.086)	(0.056)	(0.047)
West		0.159**	0.203*	0.093	0.145**
(SD)		(0.037)	(0.087)	(0.051)	(0.047)
Non-Native %		0.008**	0.013**	0.008*	0.004
(SD)		(0.002)	(0.004)	(0.003)	(0.004)
Constant	-1.788**	-0.349	0.351	-1.156**	-1.865**
(SD)	(0.118)	(0.229)	(0.312)	(0.376)	(0.409)
Sample	All CGAs	All CGAs	Metro Center	Suburb	Non-Metro
Observations	915	915	203	380	332
R-squared	0.324	0.614	0.589	0.583	0.646

Regressions employ Hubert-White robust standard error corrections. Initial stock of high school graduates is based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduates is then based on the 2006-2010 5% Public Use Microdata Sample of the ACS. See Table 3.2 for details.

** Significant at the 1% level * Significant at the 5% level

Table 3.15 Growth in High School Share, 1992-2008 (Ordinary Least Squares)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Ln(HS grad % (1991-93))	-0.720**	-0.864**	-0.904**	-0.849**	-0.871**
(SD)	(0.018)	(0.022)	(0.029)	(0.031)	(0.045)
Metro > 400 per square mile		0.011*	-0.005	0.017*	--
(SD)		(0.005)	(0.008)	(0.008)	--
Metro 200-400 per square mile		0.003	-0.001	0.006	--
(SD)		(0.004)	(0.008)	(0.006)	--
Non-Metro		-0.019**	--	--	--
(SD)		(0.004)	--	--	--
Ln (dist. to four-year state coll.)		-0.003*	0.000	-0.002	-0.008
(SD)		(0.001)	(0.002)	(0.002)	(0.005)
July average high temperature (F)		-0.0018**	-0.0036**	0.0000	0.0005
(SD)		(0.0005)	(0.0006)	(0.0007)	(0.0008)
January avg. low temperature (F)		-0.0006*	-0.0001	-0.0005	-0.0018**
(SD)		(0.0003)	(0.0005)	(0.0005)	(0.0006)
Coast dummy		0.005	0.002	0.007	0.008
(SD)		(0.004)	(0.008)	(0.006)	(0.008)
Poverty rate (1990) %		-0.0013**	-0.0011	-0.0010	-0.0028**
(SD)		(0.0005)	(0.0009)	(0.0008)	(0.0009)
Unemployment rate (1991-93) %		-0.0035**	-0.0034**	-0.0066**	0.0025
(SD)		(0.0011)	(0.0025)	(0.0024)	(0.0019)
Neighbors' unemployment %			-0.0001	-0.0002	-0.0011
(SD)			(0.0019)	(0.0027)	(0.0023)
Mining %		-0.0006	-0.0023*	-0.0006	-0.0001
(SD)		(0.0006)	(0.0011)	(0.0008)	(0.0006)
Manufacturing %		-0.0010**	-0.0013**	-0.0010**	-0.0006
(SD)		(0.0002)	(0.0005)	(0.0003)	(0.0004)
Information services %		0.0036**	0.0029	0.0025**	0.0083**
(SD)		(0.0010)	(0.0021)	(0.0008)	(0.0030)
Professional %		0.0023**	0.0011	0.0026**	0.0027
(SD)		(0.0007)	(0.0013)	(0.0010)	(0.0016)
Arts and entertainment %		0.0040	0.0021	0.0050	0.0050
(SD)		(0.0024)	(0.0043)	(0.0029)	(0.0035)
Federal government %		0.0000	0.0004	-0.0004	0.0009
(SD)		(0.0005)	(0.0011)	(0.0007)	(0.0012)
Military %		0.0011**	0.0008	0.0010	0.0019*
(SD)		(0.0004)	(0.0005)	(0.0006)	(0.0009)
State and local government %		-0.0004	0.0003	-0.0001	-0.0007
(SD)		(0.0003)	(0.0005)	(0.0004)	(0.0005)
Midwest		-0.004	-0.001	-0.004	0.018
(SD)		(0.005)	(0.010)	(0.007)	(0.011)
South		-0.007	-0.007	-0.017	-0.007
(SD)		(0.006)	(0.012)	(0.009)	(0.012)
West		-0.024**	-0.026*	-0.040**	0.002
(SD)		(0.008)	(0.013)	(0.011)	(0.013)
Non-Native		-0.0047**	-0.0032**	-0.0042**	-0.0101**
(SD)		(0.0006)	(0.0007)	(0.0006)	(0.0012)
Constant	-0.071**	0.167**	0.293**	0.028	-0.001
(SD)	(0.004)	(0.039)	(0.058)	(0.059)	(0.064)
Sample	All CGAs	All CGAs	Metro Center	Suburb	Non-Metro
Observations	915	915	203	380	332
R-squared	0.696	0.846	0.914	0.833	0.853

Regressions employ Hubert-White robust standard error corrections. Initial share of high school graduates is based on NCES Common Core of Data, 1991-93. Growth of high school graduate share is then based on 31-37 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 for details.

** Significant at the 1% level * Significant at the 5% level

Table 3.16 Growth in College Share, 1990-2008 (Ordinary Least Squares)

VARIABLES	(1)	(2)	(3)	(4)	(5)
Ln (college grad % (1990))	-0.176**	-0.358**	-0.331**	-0.383**	-0.358**
(SD)	(0.013)	(0.023)	(0.050)	(0.035)	(0.045)
Metro > 400 per square mile		-0.048**	-0.035	-0.037	--
(SD)		(0.017)	(0.024)	(0.025)	--
Metro 200-400 per square mile		0.007	0.005	-0.001	--
(SD)		(0.014)	(0.022)	(0.021)	--
Non-Metro		-0.044**	--	--	--
(SD)		(0.013)	--	--	--
Ln (dist. to four-year state coll.)		0.005	-0.002	-0.001	0.001
(SD)		(0.004)	(0.006)	(0.005)	(0.012)
July average high temperature (F)		-0.004*	-0.001	-0.001	-0.005*
(SD)		(0.001)	(0.002)	(0.002)	(0.003)
January avg. low temperature (F)		0.000	-0.001	0.002	0.000
(SD)		(0.001)	(0.001)	(0.001)	(0.002)
Coast dummy		0.014	-0.030	0.027	-0.028
(SD)		(0.014)	(0.025)	(0.018)	(0.033)
Poverty rate (1990) %		-0.009**	-0.007**	-0.010**	-0.006*
(SD)		(0.001)	(0.003)	(0.002)	(0.002)
Unemployment rate (1991-93) %		-0.013**	-0.034**	-0.020**	-0.006*
(SD)		(0.003)	(0.009)	(0.005)	(0.006)
Neighbors' unemployment %			0.024**	0.000	-0.004
(SD)			(0.006)	(0.005)	(0.008)
Mining %		-0.004	-0.001	-0.009**	-0.002
(SD)		(0.002)	(0.003)	(0.003)	(0.003)
Manufacturing %		-0.003**	0.000	-0.003**	-0.002
(SD)		(0.001)	(0.001)	(0.001)	(0.001)
Information services %		0.002	-0.002	0.003	0.000
(SD)		(0.003)	(0.007)	(0.003)	(0.010)
Professional %		0.008**	0.005	0.009**	0.006
(SD)		(0.002)	(0.004)	(0.002)	(0.006)
Arts and entertainment %		0.008	-0.011	0.000	0.029
(SD)		(0.007)	(0.010)	(0.008)	(0.015)
Federal government %		0.000	0.000	0.001	0.001
(SD)		(0.002)	(0.003)	(0.002)	(0.003)
Military %		-0.002*	0.001	-0.004**	-0.001
(SD)		(0.001)	(0.002)	(0.001)	(0.002)
State and local government %		-0.001	-0.002*	-0.003*	-0.001
(SD)		(0.001)	(0.002)	(0.001)	(0.002)
Midwest		0.037*	0.050	0.051*	0.036
(SD)		(0.018)	(0.031)	(0.025)	(0.039)
South		0.065**	0.074	0.044	0.056
(SD)		(0.022)	(0.042)	(0.034)	(0.042)
West		0.118**	0.122**	0.086**	0.131**
(SD)		(0.022)	(0.041)	(0.029)	(0.044)
Non-Native		0.002	0.004*	0.001	0.003
(SD)		(0.001)	(0.002)	(0.002)	(0.003)
Constant	-0.050	0.102	-0.105	-0.052	-0.150
(SD)	(0.023)	(0.119)	(0.182)	(0.199)	(0.236)
Sample	All CGAs	All CGAs	Metro Center	Suburb	Non-Metro
Observations	915	915	203	380	332
R-squared	0.176	0.433	0.552	0.501	0.331

Regressions employ Hubert-White robust standard error corrections. Initial share of college graduates is based on 25-34 year olds in the 1990 decennial Census. Growth of college graduate share is then based on 45-50 year olds in the 2006-2010 5% Public Use Microdata Sample of the American Community Survey. See Table 3.2 for details.

** Significant at the 1% level * Significant at the 5% level

Table 3.17 Brain Gain, “Consistent PUMAs” (Ordinary Least Squares)

VARIABLES	Abs. HS Gain	Abs. HS Gain	Rel. HS Gain	Rel. HS Gain	Rel. Coll. Gain	Rel. Coll. Gain
Ln (Initial Stock or Share)	**0.045***	0.045*	-0.834**	-0.852**	**-0.462****	-0.478**
(SD)	(0.019)	(0.019)	(0.037)	(0.034)	(0.053)	(0.048)
Metro > 400 per square mile	***0.078***	0.031	*0.001*	*0.016*	-0.094*	-0.155**
(SD)	(0.061)	(0.063)	(0.011)	(0.011)	(0.040)	(0.037)
Metro 200-400 per square mile	**0.024**	-0.006	-0.002	0.012♦	-0.015	-0.065*
(SD)	(0.037)	(0.037)	(0.007)	(0.007)	(0.031)	(0.030)
Non-Metro	-0.092**	-0.067*	-0.013♦	-0.005	-0.070**	-0.011
(SD)	(0.032)	(0.032)	(0.008)	(0.007)	(0.026)	(0.026)
Ln (dist. to four-year state coll.)	*-0.016*	-0.010	-0.004♦	-0.002	0.006	0.014
(SD)	(0.011)	(0.011)	(0.002)	(0.002)	(0.009)	(0.008)
July average high temperature (F)	*-0.006*	-0.004	-0.0025**	-0.0019*	-0.004	-0.002
(SD)	(0.004)	(0.004)	(0.0008)	(0.0008)	(0.003)	(0.003)
January avg. low temperature (F)	0.008**	0.007*	*0.0002*	-0.0003	0.002	-0.001
(SD)	(0.003)	(0.003)	(0.0005)	(0.0005)	(0.002)	(0.002)
Coast dummy	-0.065*	-0.069*	0.006	0.005	0.049♦	0.037
(SD)	(0.031)	(0.031)	(0.005)	(0.005)	(0.025)	(0.024)
Poverty rate (1990) %	**-0.005♦**	0.000	*-0.0011*	0.0004	-0.006♦	0.001
(SD)	(0.003)	(0.004)	(0.0008)	(0.0009)	(0.003)	(0.004)
Unemployment rate (1991-93) %	-0.028**	-0.035**	*-0.0029*	-0.0052**	-0.020*	-0.033**
(SD)	(0.007)	(0.008)	(0.0018)	(0.0017)	(0.010)	(0.010)
Ln average college wage (1990)		-0.105		-0.059		0.508**
(SD)		(0.219)		(0.041)		(0.160)
Ln avg. non-college wage (1990)		0.502*		0.182**		0.287
(SD)		0.243		(0.043)		(0.184)
Mining %	-0.012*	-0.018**	-0.0002	-0.0021♦	-0.002	-0.008
(SD)	(0.005)	(0.006)	(0.0011)	(0.0012)	(0.005)	(0.005)
Manufacturing %	***0.000***	0.000	-0.0007♦	-0.0011**	*-0.002*	-0.004**
(SD)	(0.002)	(0.002)	(0.0004)	(0.0004)	(0.002)	(0.001)
Information services %	0.026	0.022	0.0060*	0.0046♦	0.005	0.001
(SD)	(0.018)	(0.018)	(0.0027)	(0.0025)	(0.009)	(0.008)
Professional %	0.008	0.004	0.0017♦	0.0009	0.011*	0.000
(SD)	(0.008)	(0.008)	(0.0009)	(0.0008)	(0.005)	(0.005)
Arts and entertainment %	*0.023*	0.022	0.0041	0.0043	0.018♦	0.012
(SD)	(0.018)	(0.018)	(0.0033)	(0.0031)	(0.010)	(0.010)
Federal government %	0.001	0.000	0.0006	0.0002	0.002	0.004
(SD)	(0.007)	(0.007)	(0.0010)	(0.0009)	(0.004)	(0.004)
Military %	***0.006*****	0.008**	*0.0008*	0.0013*	-0.003♦	-0.002
(SD)	(0.002)	(0.002)	(0.0006)	(0.0006)	(0.002)	(0.002)
State and local government %	0.002	0.001	0.0001	-0.0002	**0.003**	0.002
(SD)	(0.003)	(0.002)	(0.0005)	(0.0005)	(0.002)	(0.002)
Midwest	*0.063*	0.047	0.003	-0.003	*0.058*	0.047
(SD)	(0.047)	(0.048)	(0.008)	(0.008)	(0.037)	(0.036)
South	0.230**	0.240**	-0.002	0.001	*0.047*	0.044
(SD)	(0.060)	(0.061)	(0.010)	(0.009)	(0.043)	(0.040)
West	0.185**	0.177**	-0.002	-0.026*	*0.069*	0.088*
(SD)	(0.065)	(0.065)	(0.012)	(0.012)	(0.046)	(0.044)
Non-Native	0.014**	0.014**	-0.0040**	-0.0037**	***0.008*****	0.007**
(SD)	(0.003)	(0.003)	(0.0011)	(0.0012)	(0.003)	(0.003)
Constant	-0.180	-0.730	0.180	0.093	0.099	-2.308**
(SD)	(0.347)	(0.535)	(0.069)	(0.110)	(0.284)	(0.484)
Sample = Consistent PUMAs						
Observations	312	312	312	312	312	312
R-squared	0.603	0.614	0.869	0.879	0.444	0.524

Regressions use Hubert-White robust standard error corrections. Column 1, 3, and 5 are identical to column 2 of Table 3.14, 3.15, and 3.16, respectively, except the geographic unit is broadened to consolidate 1990 PUMAs with 2005-2010 PUMAs. Bold indicates > 1.5 SD difference from Table 3.14, 3.15, or 3.16. Italics indicate change in significance.

** Significant at the 1% level * Significant at the 5% level ♦ Significant at 10% level

Figures

Figure 3.1A: Absolute High School Gain in the United States (1992-2008)

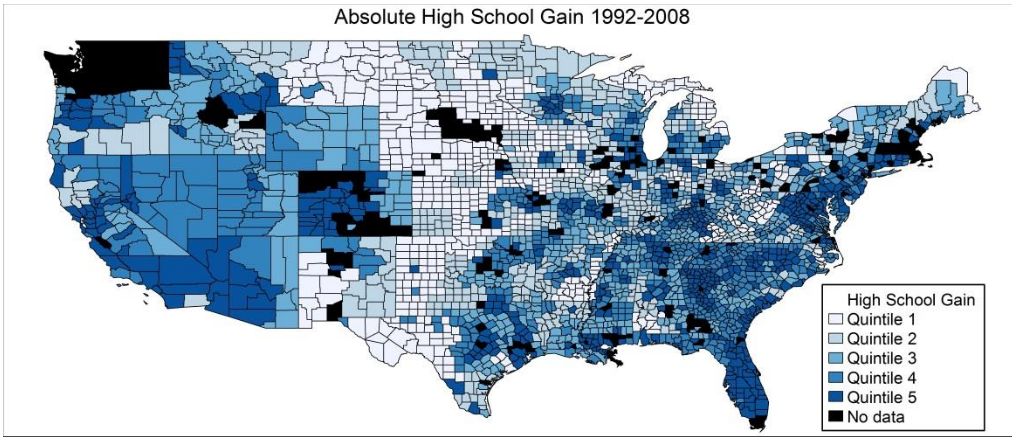


Figure 3.1B: Population Density in the United States (1990)

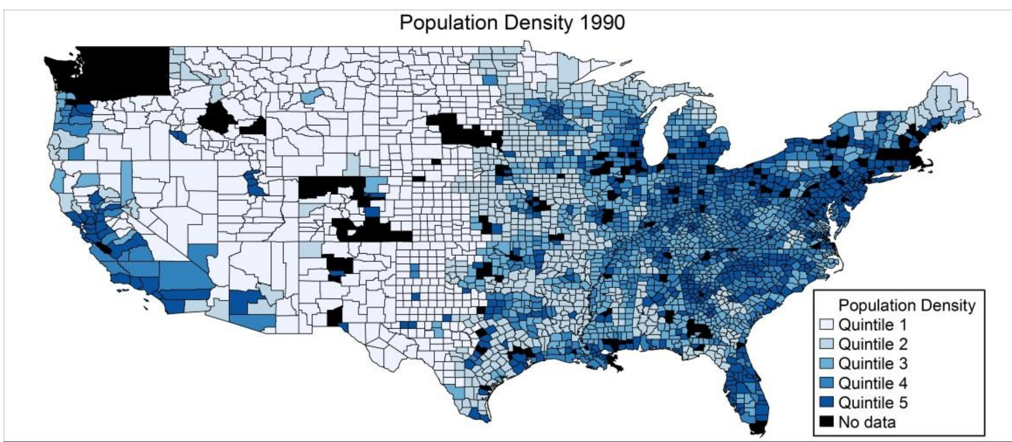


Figure 3.2A: Relative High School Gain in the United States (1992-2008)

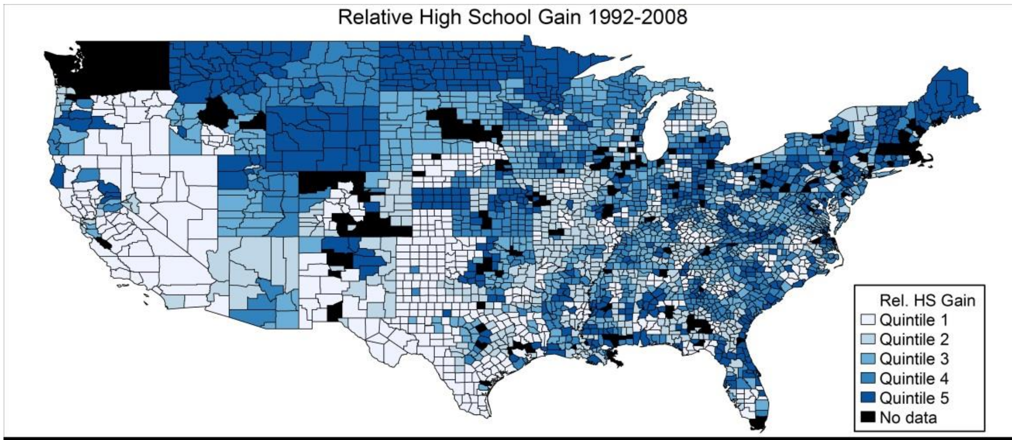


Figure 3.2B: Relative College Gain in the United States (1990-2008)

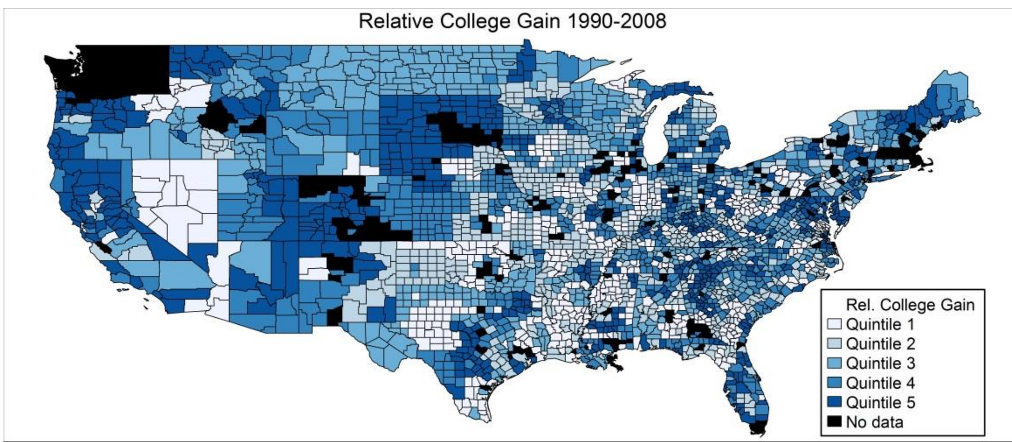
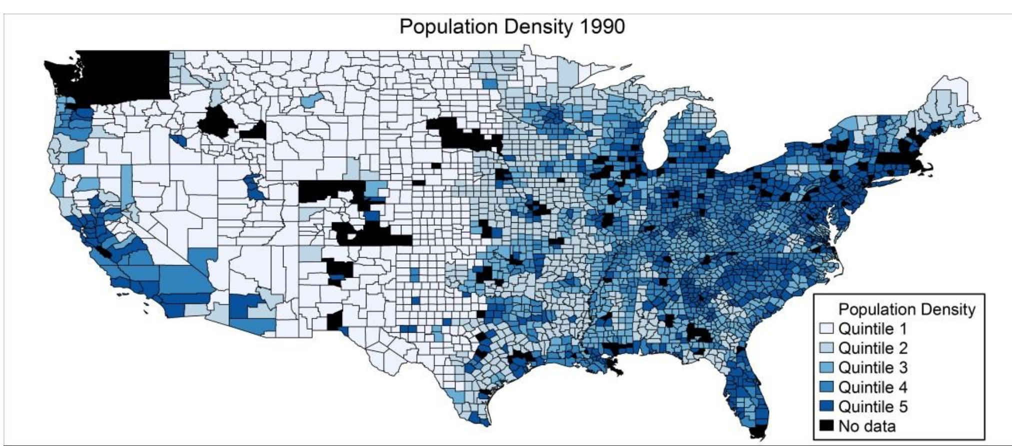


Figure 3.2C: Population Density in the United States (1990)



Appendix

Appendix Table A.1 Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Origin UI Claims %	0.035*	0.032*	0.035*						
(SE)	(0.009)	(0.009)	(0.009)						
UI Claims (1-1000 mi)	-0.059*	-0.052*	-0.016						
(SE)	(0.011)	(0.010)	(0.024)						
Origin Unem Rate %				0.016*	0.015*	0.019*			
(SE)				(0.007)	(0.007)	(0.007)			
Unem. Rate (1-1000 mi)				-0.018*	-0.033*	0.061*			
(SE)				(0.009)	(0.009)	(0.027)			
Origin Emp Growth %							-0.033*	-0.031*	-0.034*
(SE)							(0.011)	(0.011)	(0.010)
Emp Growth (1-1000 mi)							0.071*	0.057*	-0.007
(SE)							(0.014)	(0.013)	(0.047)
Origin Pop Growth %							0.007	0.008	0.009
(SE)							(0.013)	(0.012)	(0.012)
Pop Growth % (1-1000 mi)							-0.064	-0.030	0.011
(SE)							(0.043)	(0.035)	(0.049)
Employed	-0.480*	-0.481*	-0.478*	-0.478*	-0.480*	-0.479*	-0.479*	-0.481*	-0.481*
(SE)	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)	(0.029)	(0.029)	(0.030)	(0.03)
Unemployed	0.225*	0.223*	0.222*	0.223*	0.223*	0.223*	0.228*	0.226*	0.225*
(SE)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.033)	(0.033)
Less than HS	-0.097*	-0.096*	-0.096*	-0.096*	-0.095*	-0.096*	-0.096*	-0.096*	-0.096*
(SE)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)
Some College	0.209*	0.210*	0.210*	0.206*	0.210*	0.209*	0.208*	0.210*	0.210*
(SE)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
College Graduate	0.732*	0.735*	0.732*	0.730*	0.733*	0.732*	0.731*	0.735*	0.735*
(SE)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
Married	-0.111*	-0.108*	-0.107*	-0.110*	-0.107*	-0.107*	-0.110*	-0.108*	-0.107*
(SE)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Child Present	-0.319*	-0.318*	-0.317*	-0.318*	-0.317*	-0.317*	-0.318*	-0.318*	-0.318*
(SE)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)

(Table Continued Below)

Appendix Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age	-0.118*	-0.123*	-0.122*	-0.118*	-0.123*	-0.122*	-0.119*	-0.123*	-0.123*
(SE)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Age Squared (× 100)	0.079†	0.093*	0.092*	0.080†	0.091*	0.090*	0.082†	0.092*	0.091*
(SE)	(0.045)	(0.045)	(0.046)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Age Cubed (× 100,000)	-0.085	-0.096	-0.088	0.063	0.100	-0.090	-0.015	-0.101	-0.093
(SE)	(0.343)	(0.343)	(0.343)	(0.344)	(0.344)	(0.344)	(0.343)	(0.344)	(0.344)
Female	-0.096*	-0.092*	-0.091*	-0.096*	-0.092*	-0.091*	-0.096*	-0.092*	-0.091*
(SE)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Hispanic	-0.534*	-0.533*	-0.530*	-0.531*	-0.530*	-0.529*	-0.530*	-0.531*	-0.530*
(SE)	(0.114)	(0.114)	(0.113)	(0.114)	(0.114)	(0.113)	(0.114)	(0.114)	(0.114)
Black	-0.397*	-0.396*	-0.394*	-0.397*	-0.396*	-0.395*	-0.396*	-0.397*	-0.396*
(SE)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)	(0.076)
Nonmetropolitan	0.281†	0.283†	0.280†	0.278†	0.281†	0.278†	0.279†	0.282†	0.281†
(SE)	(0.162)	(0.162)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)	(0.161)
Time	-0.003	0.049*		0.011	0.062*		0.007	0.057*	
(SE)	(0.008)	(0.020)		(0.010)	(0.021)		(0.009)	(0.020)	
Time Squared (× 100)	-0.098*	-0.498*		-0.137*	-0.580*		-0.118*	-0.510*	
(SE)	(0.025)	(0.146)		(0.031)	(0.157)		(0.027)	(0.143)	
Time Cubed (× 1,000)		0.083*			0.101*			0.082*	
(SE)		(0.028)			(0.032)			(0.027)	
1983			-0.169*			-0.303*			-0.196*
(SE)			(0.045)			(0.070)			(0.062)
1984			-0.113*			-0.348*			-0.116*
(SE)			(0.054)			(0.104)			(0.050)
1986			0.026			-0.014			0.039
(SE)			(0.101)			(0.078)			(0.107)
1987			-0.033			-0.068			-0.054
(SE)			(0.096)			(0.076)			(0.084)
1988			-0.006			-0.008			-0.019
(SE)			(0.118)			(0.097)			(0.108)
1989			0.188			0.242*			0.160
(SE)			(0.133)			(0.108)			(0.111)

(Table Continued Below)

Appendix Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1990			0.221†			0.329*			0.200†
(SE)			(0.137)			(0.117)			(0.116)
1991			0.106			0.216*			0.072
(SE)			(0.119)			(0.105)			(0.094)
1992			0.011			0.021			-0.066
(SE)			(0.094)			(0.083)			(0.087)
1993			0.041			0.004			0.008
(SE)			(0.102)			(0.089)			(0.089)
1996			-0.172			-0.077			-0.187
(SE)			(0.133)			(0.108)			(0.114)
1997			-0.189†			-0.102			-0.248*
(SE)			(0.117)			(0.093)			(0.078)
1998			-0.135			-0.032			-0.173†
(SE)			(0.134)			(0.104)			(0.099)
1999			-0.224			-0.093			-0.283*
(SE)			(0.142)			(0.114)			(0.088)
2000			-0.240†			-0.073			-0.307*
(SE)			(0.149)			(0.131)			(0.099)
2001			-0.323*			-0.150			-0.396*
(SE)			(0.158)			(0.135)			(0.105)
2002			-0.357*			-0.199			-0.444*
(SE)			(0.146)			(0.137)			(0.107)
2003			-0.426*			-0.362*			-0.530*
(SE)			(0.125)			(0.108)			(0.106)
2004			-0.498*			-0.446*			-0.567*
(SE)			(0.125)			(0.110)			(0.106)
2005			-0.480*			-0.423*			-0.552*
(SE)			(0.138)			(0.111)			(0.101)
2006			-0.442*			-0.361*			-0.518*
(SE)			(0.157)			(0.115)			(0.099)
2007			-0.567*			-0.445*			-0.631*
(SE)			(0.160)			(0.120)			(0.104)

(Table Continued Below)

Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
2008			-0.591*			-0.447*			-0.670*
(SE)			(0.149)			(0.117)			(0.101)
2009			-0.719*			-0.609*			-0.815*
(SE)			(0.145)			(0.121)			(0.104)
2010			-0.873*			-1.019*			-1.012*
(SE)			(0.096)			(0.084)			(0.130)
2011			-0.798*			-1.026*			-0.872*
(SE)			(0.103)			(0.109)			(0.099)
2012			-0.714*			-0.890*			-0.763*
(SE)			(0.127)			(0.104)			(0.099)
NH	0.658	0.656	0.658	0.606	0.606	0.613	0.587	0.586	0.584
(SE)	(1.688)	(1.689)	(1.681)	(1.68)	(1.681)	(1.678)	(1.682)	(1.687)	(1.685)
VT	-0.445	-0.442	-0.437	-0.371	-0.373	-0.360	-0.393	-0.397	-0.395
(SE)	(1.55)	(1.551)	(1.543)	(1.548)	(1.549)	(1.546)	(1.548)	(1.552)	(1.551)
MA	1.164	1.156	1.152	1.169	1.156	1.160	1.145	1.137	1.132
(SE)	(1.569)	(1.572)	(1.564)	(1.565)	(1.568)	(1.565)	(1.566)	(1.572)	(1.571)
RI	0.056	0.064	0.061	0.157	0.161	0.161	0.157	0.158	0.156
(SE)	(1.511)	(1.513)	(1.505)	(1.507)	(1.508)	(1.505)	(1.508)	(1.512)	(1.510)
CT	1.11	1.112	1.107	1.148	1.148	1.148	1.128	1.130	1.127
(SE)	(1.504)	(1.505)	(1.497)	(1.499)	(1.500)	(1.497)	(1.500)	(1.505)	(1.503)
NY	1.078	1.074	1.073	1.036	1.032	1.041	1.035	1.033	1.033
(SE)	(1.473)	(1.475)	(1.468)	(1.466)	(1.468)	(1.465)	(1.467)	(1.472)	(1.471)
NJ	0.975	0.974	0.985	1.030	1.022	1.029	1.022	1.013	1.009
(SE)	(1.47)	(1.472)	(1.464)	(1.466)	(1.468)	(1.465)	(1.466)	(1.471)	(1.469)
PA	0.88	0.886	0.901	0.976	0.973	0.983	0.984	0.980	0.978
(SE)	(1.453)	(1.455)	(1.447)	(1.447)	(1.449)	(1.446)	(1.448)	(1.453)	(1.451)
OH	0.811	0.812	0.831	0.795	0.790	0.806	0.811	0.806	0.804
(SE)	(1.462)	(1.463)	(1.454)	(1.458)	(1.46)	(1.456)	(1.458)	(1.463)	(1.462)
IN	1.159	1.170	1.200	1.167	1.171	1.186	1.172	1.173	1.172
(SE)	(1.455)	(1.456)	(1.444)	(1.449)	(1.45)	(1.447)	(1.449)	(1.454)	(1.452)
IL	0.99	0.993	1.016	0.984	0.981	0.993	0.998	0.994	0.993
(SE)	(1.458)	(1.459)	(1.451)	(1.450)	(1.452)	(1.449)	(1.451)	(1.456)	(1.454)

(Table Continued Below)

Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
MI	0.549	0.554	0.563	0.651	0.646	0.657	0.683	0.682	0.680
(SE)	(1.443)	(1.444)	(1.436)	(1.443)	(1.445)	(1.441)	(1.448)	(1.453)	(1.452)
WI	0.651	0.663	0.684	0.796	0.797	0.809	0.788	0.786	0.785
(SE)	(1.459)	(1.460)	(1.452)	(1.453)	(1.454)	(1.451)	(1.454)	(1.458)	(1.457)
MN	1.197	1.203	1.219	1.176	1.180	1.183	1.171	1.174	1.174
(SE)	(1.477)	(1.478)	(1.468)	(1.472)	(1.473)	(1.470)	(1.473)	(1.477)	(1.476)
IA	0.854	0.862	0.889	0.902	0.902	0.911	0.888	0.887	0.885
(SE)	(1.463)	(1.465)	(1.454)	(1.460)	(1.462)	(1.459)	(1.459)	(1.463)	(1.462)
MO	1.38	1.390	1.422	1.405	1.407	1.417	1.410	1.408	1.406
(SE)	(1.464)	(1.466)	(1.454)	(1.459)	(1.46)	(1.457)	(1.459)	(1.464)	(1.462)
ND	0.354	0.353	0.378	0.348	0.347	0.334	0.318	0.318	0.318
(SE)	(1.484)	(1.486)	(1.477)	(1.479)	(1.481)	(1.478)	(1.479)	(1.484)	(1.482)
SD	0.135	0.133	0.181	0.059	0.057	0.049	0.031	0.022	0.022
(SE)	(1.479)	(1.480)	(1.473)	(1.472)	(1.474)	(1.470)	(1.470)	(1.475)	(1.473)
NE	0.857	0.856	0.898	0.750	0.749	0.745	0.715	0.707	0.704
(SE)	(1.471)	(1.473)	(1.466)	(1.465)	(1.466)	(1.463)	(1.468)	(1.473)	(1.471)
KS	0.852	0.857	0.892	0.851	0.852	0.851	0.835	0.828	0.825
(SE)	(1.475)	(1.476)	(1.465)	(1.469)	(1.47)	(1.468)	(1.467)	(1.472)	(1.471)
DE	-0.238	-0.237	-0.220	-0.223	-0.229	-0.214	-0.236	-0.245	-0.246
(SE)	(1.48)	(1.481)	(1.473)	(1.475)	(1.476)	(1.473)	(1.476)	(1.480)	(1.479)
MD	1.411	1.411	1.423	1.357	1.357	1.365	1.346	1.344	1.344
(SE)	(1.482)	(1.484)	(1.474)	(1.475)	(1.477)	(1.473)	(1.476)	(1.481)	(1.479)
VA	1.553	1.553	1.563	1.467	1.467	1.473	1.453	1.451	1.450
(SE)	(1.455)	(1.456)	(1.446)	(1.451)	(1.452)	(1.449)	(1.452)	(1.456)	(1.455)
WV	0.307	0.316	0.334	0.366	0.367	0.373	0.398	0.397	0.396
(SE)	(1.461)	(1.463)	(1.455)	(1.458)	(1.459)	(1.456)	(1.458)	(1.462)	(1.460)
NC	0.75	0.745	0.762	0.803	0.787	0.799	0.796	0.782	0.780
(SE)	(1.467)	(1.470)	(1.462)	(1.461)	(1.465)	(1.462)	(1.464)	(1.471)	(1.469)
SC	0.981	0.987	1.011	1.023	1.020	1.029	1.031	1.023	1.020
(SE)	(1.473)	(1.475)	(1.465)	(1.469)	(1.470)	(1.467)	(1.470)	(1.474)	(1.472)
GA	1.386	1.394	1.422	1.411	1.411	1.426	1.418	1.414	1.415
(SE)	(1.461)	(1.462)	(1.452)	(1.456)	(1.457)	(1.454)	(1.458)	(1.463)	(1.461)

(Table Continued Below)

Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FL	1.321	1.320	1.351	1.248	1.242	1.254	1.264	1.250	1.250
(SE)	(1.543)	(1.545)	(1.534)	(1.533)	(1.535)	(1.532)	(1.531)	(1.538)	(1.538)
KY	0.772	0.781	0.809	0.817	0.817	0.829	0.840	0.835	0.834
(SE)	(1.464)	(1.466)	(1.457)	(1.460)	(1.461)	(1.458)	(1.461)	(1.466)	(1.464)
TN	1.254	1.263	1.290	1.298	1.299	1.311	1.316	1.313	1.311
(SE)	(1.454)	(1.455)	(1.446)	(1.449)	(1.45)	(1.447)	(1.450)	(1.454)	(1.452)
AL	0.879	0.890	0.919	0.968	0.971	0.980	0.976	0.974	0.972
(SE)	(1.45)	(1.451)	(1.443)	(1.448)	(1.449)	(1.446)	(1.449)	(1.453)	(1.451)
MS	0.650	0.654	0.689	0.672	0.667	0.671	0.703	0.692	0.690
(SE)	(1.462)	(1.463)	(1.455)	(1.457)	(1.459)	(1.456)	(1.457)	(1.462)	(1.461)
AR	0.690	0.699	0.733	0.801	0.798	0.804	0.818	0.808	0.806
(SE)	(1.466)	(1.467)	(1.454)	(1.460)	(1.462)	(1.458)	(1.460)	(1.465)	(1.463)
LA	1.404	1.414	1.457	1.412	1.417	1.419	1.434	1.429	1.427
(SE)	(1.47)	(1.471)	(1.461)	(1.465)	(1.466)	(1.463)	(1.466)	(1.470)	(1.468)
OK	1.084	1.086	1.125	1.028	1.029	1.028	1.021	1.013	1.012
(SE)	(1.479)	(1.481)	(1.470)	(1.472)	(1.473)	(1.47)	(1.472)	(1.476)	(1.473)
TX	1.207	1.210	1.262	1.164	1.158	1.177	1.189	1.173	1.173
(SE)	(1.483)	(1.484)	(1.473)	(1.484)	(1.486)	(1.482)	(1.485)	(1.490)	(1.486)
MT	0.425	0.426	0.447	0.427	0.426	0.421	0.451	0.425	0.425
(SE)	(1.494)	(1.496)	(1.488)	(1.489)	(1.491)	(1.488)	(1.492)	(1.497)	(1.494)
ID	0.553	0.558	0.566	0.658	0.661	0.634	0.697	0.666	0.665
(SE)	(1.475)	(1.476)	(1.469)	(1.472)	(1.474)	(1.471)	(1.469)	(1.475)	(1.473)
WY	0.497	0.506	0.546	0.512	0.516	0.522	0.506	0.491	0.493
(SE)	(1.465)	(1.466)	(1.460)	(1.459)	(1.460)	(1.457)	(1.457)	(1.461)	(1.457)
CO	1.512	1.519	1.550	1.450	1.458	1.450	1.470	1.457	1.455
(SE)	(1.477)	(1.479)	(1.468)	(1.471)	(1.472)	(1.469)	(1.474)	(1.478)	(1.475)
NM	0.671	0.677	0.731	0.634	0.634	0.633	0.666	0.644	0.643
(SE)	(1.477)	(1.478)	(1.471)	(1.468)	(1.47)	(1.467)	(1.470)	(1.475)	(1.473)
AZ	1.708	1.717	1.760	1.676	1.681	1.669	1.710	1.686	1.683
(SE)	(1.469)	(1.470)	(1.467)	(1.464)	(1.466)	(1.462)	(1.471)	(1.474)	(1.470)
UT	1.072	1.078	1.100	1.032	1.037	1.034	1.054	1.032	1.032
(SE)	(1.485)	(1.487)	(1.48)	(1.479)	(1.481)	(1.477)	(1.488)	(1.493)	(1.490)

(Table Continued Below)

Table A.1 (Continued) Complete Results of Logistic Regressions in Table 2.3

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
NV	0.856	0.861	0.859	0.866	0.877	0.832	0.923	0.891	0.887
(SE)	(1.478)	(1.480)	(1.471)	(1.473)	(1.475)	(1.476)	(1.474)	(1.477)	(1.479)
WA	1.421	1.427	1.411	1.444	1.459	1.405	1.483	1.461	1.456
(SE)	(1.482)	(1.484)	(1.478)	(1.479)	(1.480)	(1.481)	(1.472)	(1.476)	(1.471)
OR	0.963	0.975	0.974	1.062	1.076	1.035	1.116	1.091	1.086
(SE)	(1.475)	(1.476)	(1.469)	(1.467)	(1.468)	(1.466)	(1.464)	(1.469)	(1.465)
CA	1.087	1.095	1.121	1.143	1.144	1.141	1.192	1.157	1.154
(SE)	(1.503)	(1.504)	(1.492)	(1.501)	(1.503)	(1.500)	(1.506)	(1.512)	(1.507)
Constant	-0.553	-0.700	-0.997	-0.849	-0.791	-1.386	-0.807	-0.922	-0.783
(SE)	(1.14)	(1.132)	(1.136)	(1.124)	(1.127)	(1.128)	(1.126)	(1.125)	(1.133)
Observations = 1,365,067									
Pseudo R-Squared	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082	0.082

See Table 2.3

* Significant at 5% level

⧫ Significant at 10% level

Appendix Table A.2 Complete Results of Logistic Regressions in Table 2.4

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves	Interstate Moves
Origin UI Claims %	0.032*	0.031*	0.032*	0.036*
(SE)	(0.008)	(0.009)	(0.009)	(0.009)
UI Claims (Border) %	-0.037*			
(SE)	(0.007)			
UI Claims (1-500 mi) %		-0.039*		
(SE)		(0.009)		
UI Claims (1-1000 mi) %			-0.052*	
(SE)			(0.010)	
U.S. UI Claims %				-0.058*
(SE)				(0.011)
Employed	-0.481*	-0.481*	-0.481*	-0.482*
(SE)	(0.030)	(0.030)	(0.030)	(0.030)
Unemployed	0.224*	0.224*	0.223*	0.223*
(SE)	(0.033)	(0.033)	(0.032)	(0.032)
Less than HS	-0.096*	-0.096*	-0.096*	-0.101*
(SE)	(0.032)	(0.032)	(0.032)	(0.033)
Some College	0.209*	0.210*	0.210*	0.213*
(SE)	(0.019)	(0.019)	(0.019)	(0.019)
College Graduate	0.734*	0.735*	0.735*	0.733*
(SE)	(0.059)	(0.059)	(0.059)	(0.059)
Married	-0.108*	-0.108*	-0.108*	-0.107*
(SE)	(0.022)	(0.022)	(0.022)	(0.023)
Child Present	-0.318*	-0.318*	-0.318*	-0.316*
(SE)	(0.024)	(0.024)	(0.024)	(0.025)
Age	-0.123*	-0.124*	-0.123*	-0.127*
(SE)	(0.019)	(0.019)	(0.019)	(0.019)
Age Squared (× 100)	0.091*	0.092*	0.093*	0.100*
(SE)	(0.045)	(0.045)	(0.045)	(0.044)
Age Cubed (× 100,000)	-0.094	-0.098	-0.096	-0.167
(SE)	(0.345)	(0.345)	(0.343)	(0.338)
Female	-0.092*	-0.092*	-0.092*	-0.093*
(SE)	(0.016)	(0.016)	(0.016)	(0.016)
Hispanic	-0.533*	-0.533*	-0.533*	-0.530*
(SE)	(0.114)	(0.114)	(0.114)	(0.114)
Black	-0.397*	-0.397*	-0.396*	-0.395*
(SE)	(0.076)	(0.077)	(0.076)	(0.077)
Nonmetropolitan	0.280	0.282†	0.283†	0.275†
(SE)	(0.162)	(0.162)	(0.162)	(0.161)
Time	0.060*	0.056*	0.049*	0.047*
(SE)	(0.020)	(0.020)	(0.020)	(0.021)
Time Squared (× 100)	-0.536*	-0.518*	-0.498*	-0.491*
(SE)	(0.144)	(0.144)	(0.146)	(0.149)
Time Cubed (× 1000)	0.087	0.085*	0.083*	0.081*
(SE)	(0.279)	(0.028)	(0.028)	(0.028)
NH	0.734	0.644	0.656	0.657
(SE)	(1.690)	(1.691)	(1.689)	(1.694)
VT	-0.392	-0.451	-0.442	-0.451
(SE)	(1.552)	(1.553)	(1.551)	(1.555)
MA	1.217	1.131	1.156	1.150
(SE)	(1.571)	(1.575)	(1.572)	(1.574)

(Table Continued Below)

Table A.2 (Continued) Complete Results of Logistic Regressions in Table 2.4

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves	Interstate Moves
RI	0.152	0.044	0.064	0.054
(SE)	(1.513)	(1.514)	(1.513)	(1.516)
CT	1.171	1.089	1.112	1.097
(SE)	(1.504)	(1.508)	(1.505)	(1.508)
NY	1.191	1.071	1.074	1.070
(SE)	(1.483)	(1.476)	(1.475)	(1.476)
NJ	1.087	0.971	0.974	0.990
(SE)	(1.469)	(1.474)	(1.472)	(1.473)
PA	0.973	0.899	0.886	0.908
(SE)	(1.456)	(1.457)	(1.455)	(1.457)
OH	0.985	0.830	0.812	0.832
(SE)	(1.464)	(1.465)	(1.463)	(1.465)
IN	1.316	1.218	1.170	1.197
(SE)	(1.457)	(1.457)	(1.456)	(1.457)
IL	1.112	1.024	0.993	1.021
(SE)	(1.459)	(1.461)	(1.459)	(1.46)
MI	0.659	0.555	0.554	0.559
(SE)	(1.449)	(1.446)	(1.444)	(1.448)
WI	0.810	0.690	0.663	0.680
(SE)	(1.459)	(1.46)	(1.460)	(1.462)
MN	1.340	1.229	1.203	1.219
(SE)	(1.477)	(1.478)	(1.478)	(1.479)
IA	0.961	0.889	0.862	0.894
(SE)	(1.468)	(1.467)	(1.465)	(1.467)
MO	1.491	1.414	1.390	1.440
(SE)	(1.466)	(1.467)	(1.466)	(1.467)
ND	0.387	0.283	0.353	0.388
(SE)	(1.485)	(1.486)	(1.486)	(1.488)
SD	0.193	0.118	0.133	0.199
(SE)	(1.479)	(1.481)	(1.480)	(1.482)
NE	0.915	0.848	0.856	0.883
(SE)	(1.474)	(1.476)	(1.473)	(1.473)
KS	0.885	0.833	0.857	0.888
(SE)	(1.476)	(1.478)	(1.476)	(1.474)
DE	-0.111	-0.245	-0.237	-0.232
(SE)	(1.48)	(1.483)	(1.481)	(1.478)
MD	1.503	1.418	1.411	1.395
(SE)	(1.485)	(1.486)	(1.484)	(1.486)
VA	1.633	1.556	1.553	1.570
(SE)	(1.457)	(1.458)	(1.456)	(1.455)
WV	0.411	0.333	0.316	0.347
(SE)	(1.464)	(1.464)	(1.463)	(1.465)
NC	0.809	0.748	0.745	0.752
(SE)	(1.468)	(1.471)	(1.470)	(1.471)
SC	1.101	0.981	0.987	1.026
(SE)	(1.475)	(1.476)	(1.475)	(1.476)
GA	1.471	1.378	1.394	1.428
(SE)	(1.464)	(1.463)	(1.462)	(1.464)
FL	1.433	1.337	1.320	1.362
(SE)	(1.536)	(1.545)	(1.545)	(1.544)
KY	0.872	0.822	0.781	0.822
(SE)	(1.466)	(1.468)	(1.466)	(1.468)

(Table Continued Below)

Table A.2 (Continued) Complete Results of Logistic Regressions in Table 2.4

VARIABLES	Interstate Moves	Interstate Moves	Interstate Moves	Interstate Moves
TN	1.371	1.277	1.263	1.297
(SE)	(1.455)	(1.457)	(1.455)	(1.457)
AL	0.946	0.889	0.890	0.928
(SE)	(1.453)	(1.453)	(1.451)	(1.454)
MS	0.803	0.640	0.654	0.686
(SE)	(1.465)	(1.464)	(1.463)	(1.464)
AR	0.760	0.691	0.699	0.755
(SE)	(1.465)	(1.465)	(1.467)	(1.469)
LA	1.458	1.399	1.414	1.473
(SE)	(1.472)	(1.473)	(1.471)	(1.473)
OK	1.114	1.029	1.086	1.148
(SE)	(1.481)	(1.481)	(1.481)	(1.483)
TX	1.305	1.225	1.210	1.270
(SE)	(1.481)	(1.484)	(1.484)	(1.483)
MT	0.508	0.456	0.426	0.436
(SE)	(1.497)	(1.498)	(1.496)	(1.498)
ID	0.687	0.600	0.558	0.559
(SE)	(1.478)	(1.478)	(1.476)	(1.478)
WY	0.531	0.454	0.506	0.567
(SE)	(1.466)	(1.468)	(1.466)	(1.469)
CO	1.521	1.416	1.519	1.569
(SE)	(1.478)	(1.481)	(1.479)	(1.475)
NM	0.702	0.604	0.677	0.739
(SE)	(1.478)	(1.481)	(1.478)	(1.48)
AZ	1.854	1.774	1.717	1.776
(SE)	(1.473)	(1.470)	(1.470)	(1.471)
UT	1.102	1.012	1.078	1.099
(SE)	(1.486)	(1.489)	(1.487)	(1.487)
NV	0.956	0.857	0.861	0.844
(SE)	(1.478)	(1.481)	(1.480)	(1.481)
WA	1.607	1.501	1.427	1.400
(SE)	(1.481)	(1.484)	(1.484)	(1.486)
OR	1.095	1.038	0.975	0.964
(SE)	(1.474)	(1.476)	(1.476)	(1.480)
CA	1.202	1.042	1.095	1.125
(SE)	(1.509)	(1.502)	(1.504)	(1.508)
Constant	-0.974	-0.831	-0.700	-0.638
(SE)	(1.134)	(1.136)	(1.132)	(1.142)
Observations		1,365,067	1,365,067	1,365,067
Pseudo R-Squared		0.082	0.082	0.082

See Table 2.4
* Significant at 5% level
♦ Significant at 10% level

Table A.3 Complete Results of Logistic Regressions in Table 2.5

VARIABLES	Interstate Moves (LMC = UI Claims)	Interstate Moves (LMC = Unemp. Rate)	Interstate Moves (LMC = Employ. Growth)
UI Claims Diff ($LMC_{o,t} - LMC_{o,t}$)	0.019*		
(SE)	(0.009)		
Unemp. Rate Diff ($LMC_{o,t} - LMC_{o,t}$)		0.236†	
(SE)		(0.140)	
Emp Growth Diff ($LMC_{o,t} - LMC_{o,t}$)			-0.658*
(SE)			(0.178)
Origin Population Growth			0.911
(SE)			(1.308)
Population Growth, 1-1000 mi			-1.126
(SE)			(3.441)
Employed	-0.475*	-0.477*	-0.480*
(SE)	(0.030)	(0.029)	(0.030)
Employed × ($LMC_{o,t} - LMC_{-o,t}$)	0.039*	0.060*	-0.071*
(SE)	(0.007)	(0.013)	(0.022)
Unemployed	0.230*	0.229*	0.229*
(SE)	(0.032)	(0.033)	(0.033)
Unemployed × ($LMC_{o,t} - LMC_{-o,t}$)	-0.040*	-0.045*	0.125*
(SE)	(0.010)	(0.017)	(0.027)
Less than HS	-0.096*	-0.091*	-0.096*
(SE)	(0.032)	(0.032)	(0.032)
Less than HS × ($LMC_{o,t} - LMC_{-o,t}$)	-0.008	0.026†	-0.006
(SE)	(0.009)	(0.014)	(0.028)
Some College	0.214*	0.213*	0.208*
(SE)	(0.019)	(0.019)	(0.019)
Some College × ($LMC_{o,t} - LMC_{-o,t}$)	0.026*	0.035*	-0.002
(SE)	(0.010)	(0.014)	(0.021)
4 Year Degree	0.738*	0.738	0.733*
(SE)	(0.060)	(0.060)	(0.059)
4 Year Degree × ($LMC_{o,t} - LMC_{-o,t}$)	0.032*	0.048*	-0.008
(SE)	(0.011)	(0.014)	(0.021)
Married	-0.108*	-0.107*	-0.108*
(SE)	(0.021)	(0.021)	(0.022)
Married × ($LMC_{o,t} - LMC_{-o,t}$)	0.000	-0.003	-0.010
(SE)	(0.007)	(0.010)	(0.015)
Child Present	-0.320*	-0.317*	-0.317*
(SE)	(0.024)	(0.024)	(0.025)
Child Present × ($LMC_{o,t} - LMC_{-o,t}$)	-0.021*	-0.005	0.030*
(SE)	(0.006)	(0.009)	(0.015)
Age	-0.122*	-0.125*	-0.123*
(SE)	(0.019)	(0.019)	(0.019)
Age × ($LMC_{o,t} - LMC_{-o,t}$)	0.005*	-0.019†	0.043*
(SE)	(0.001)	(0.011)	(0.015)
$Age^2 \times 100$	0.089*	0.095*	0.091*
(SE)	(0.045)	(0.044)	(0.045)
$Age^2 \times (LMC_{o,t} - LMC_{-o,t}) \times 100$	-0.020*	0.048†	-0.099*
(SE)	(0.005)	(0.027)	(0.037)
$Age^3 \times 10{,}000$	-0.006	-0.012	-0.009
(SE)	(0.030)	(0.034)	(0.034)
$Age^3 \times (LMC_{o,t} - LMC_{-o,t}) \times 10{,}000$	-0.020*	-0.037†	0.072*
(SE)	(0.005)	(0.021)	(0.030)

(Table Continued Below)

Table A.3 (Continued) Complete Results of Logistic Regressions in Table 2.5

VARIABLES	Interstate Moves (LMC = UI Claims)	Interstate Moves (LMC = Unemp. Rate)	Interstate Moves (LMC = Employ. Growth)
Female	-0.094*	-0.092*	-0.093*
(SE)	(0.016)	(0.016)	(0.016)
Female × $(LMC_{o,t} - LMC_{-o,t})$	-0.006	-0.004	0.0410*
(SE)	(0.006)	(0.011)	(0.018)
Hispanic	-0.529*	-0.528*	-0.530*
(SE)	(0.117)	(0.113)	(0.114)
Hispanic × $(LMC_{o,t} - LMC_{-o,t})$	0.044*	-0.020	-0.039
(SE)	(0.019)	(0.020)	(0.034)
Black	-0.400*	-0.395*	-0.397*
(SE)	(0.078)	(0.076)	(0.077)
Black × $(LMC_{o,t} - LMC_{-o,t})$	0.045*	0.015	-0.092*
(SE)	(0.016)	(0.025)	(0.026)
Non-Metro	0.268	0.277†	0.278†
(SE)	(0.163)	(0.162)	(0.161)
Non-Metro × $(LMC_{o,t} - LMC_{-o,t})$	-0.069*	-0.023	0.129*
(SE)	(0.017)	(0.027)	(0.032)
Time	0.048*	0.065*	0.064*
(SE)	(0.020)	(0.023)	(0.021)
Time × $(LMC_{o,t} - LMC_{-o,t})$	-0.005	-0.011†	0.008
(SE)	(0.004)	(0.006)	(0.008)
$Time^2 \times 100$	-0.502	-0.555*	-0.548
(SE)	(0.444)	(0.154)	(0.145)
$Time^2 \times (LMC_{o,t} - LMC_{-o,t}) \times 100$	0.027	0.034	0.009
(SE)	(0.036)	(0.049)	(0.006)
$Time^3 \times 10{,}000$	0.830	0.894*	0.874*
(SE)	(0.281)	(0.287)	(0.271)
$Time^3 \times (LMC_{o,t} - LMC_{-o,t}) \times 10{,}000$	-0.030	0.002	-0.135
(SE)	(0.078)	(0.109)	(0.133)
NH	0.614	0.605	0.592
(SE)	(1.688)	(1.687)	(1.685)
VT	-0.399	-0.409	-0.413
(SE)	(1.545)	(1.558)	(1.551)
MA	1.142	1.165	1.153
(SE)	(1.568)	(1.572)	(1.57)
RI	0.01	0.150	0.156
(SE)	(1.509)	(1.51)	(1.511)
CT	1.076	1.145	1.147
(SE)	(1.501)	(1.503)	(1.503)
NY	1.067	1.046	1.044
(SE)	(1.471)	(1.471)	(1.47)
NJ	0.936	1.021	1.018
(SE)	(1.467)	(1.471)	(1.47)
PA	0.867	0.975	0.99
(SE)	(1.45)	(1.452)	(1.451)
OH	0.799	0.787	0.813
(SE)	(1.458)	(1.462)	(1.461)
IN	1.146	1.152	1.186
(SE)	(1.452)	(1.453)	(1.453)
IL	0.973	0.980	0.998
(SE)	(1.455)	(1.455)	(1.454)
MI	0.536	0.652	0.685
(SE)	(1.439)	(1.447)	(1.451)
WI	0.656	0.772	0.788
(SE)	(1.453)	(1.458)	(1.457)

(Table Continued Below)

Table A.3 (Continued) Complete Results of Logistic Regressions in Table 2.5

VARIABLES	Interstate Moves (LMC = UI Claims)	Interstate Moves (LMC = Unemp. Rate)	Interstate Moves (LMC = Employ. Growth)
MN	1.181	1.173	1.179
(SE)	(1.476)	(1.476)	(1.476)
IA	0.86	0.889	0.907
(SE)	(1.458)	(1.466)	(1.462)
ND	1.383	1.401	1.413
(SE)	(1.463)	(1.463)	(1.462)
SD	0.331	0.335	0.361
(SE)	(1.483)	(1.485)	(1.482)
MO	0.007	0.020	0.028
(SE)	(1.484)	(1.477)	(1.474)
NE	0.782	0.718	0.721
(SE)	(1.471)	(1.469)	(1.472)
KS	0.828	0.838	0.841
(SE)	(1.475)	(1.476)	(1.47)
DE	-0.248	-0.246	-0.237
(SE)	(1.478)	(1.478)	(1.479)
MD	1.444	1.372	1.367
(SE)	(1.481)	(1.481)	(1.48)
VA	1.549	1.467	1.465
(SE)	(1.455)	(1.457)	(1.455)
WV	0.415	0.439	0.44
(SE)	(1.455)	(1.459)	(1.46)
NC	0.741	0.766	0.778
(SE)	(1.466)	(1.468)	(1.47)
SC	0.980	1.001	1.027
(SE)	(1.471)	(1.472)	(1.473)
GA	1.387	1.403	1.405
(SE)	(1.458)	(1.461)	(1.463)
FL	1.325	1.237	1.261
(SE)	(1.539)	(1.539)	(1.536)
KY	0.817	0.836	0.858
(SE)	(1.462)	(1.465)	(1.464)
TN	1.270	1.292	1.318
(SE)	(1.451)	(1.453)	(1.453)
AL	0.910	0.961	0.982
(SE)	(1.446)	(1.451)	(1.452)
MS	0.681	0.704	0.718
(SE)	(1.460)	(1.465)	(1.462)
AR	0.768	0.813	0.825
(SE)	(1.463)	(1.466)	(1.465)
LA	1.398	1.431	1.432
(SE)	(1.468)	(1.469)	(1.469)
OK	1.030	1.029	1.035
(SE)	(1.481)	(1.476)	(1.474)
TX	1.216	1.180	1.195
(SE)	(1.48)	(1.488)	(1.489)
MT	0.415	0.445	0.481
(SE)	(1.493)	(1.493)	(1.495)
ID	0.620	0.668	0.671
(SE)	(1.473)	(1.477)	(1.475)
WY	0.474	0.498	0.491
(SE)	(1.464)	(1.471)	(1.462)
CO	1.521	1.447	1.452
(SE)	(1.475)	(1.474)	(1.476)
NM	0.639	0.650	0.647
(SE)	(1.480)	(1.473)	(1.474)
AZ	1.710	1.658	1.678
(SE)	(1.467)	(1.468)	(1.472)
UT	1.078	1.019	1.037
(SE)	(1.481)	(1.484)	(1.491)

(Table Continued Below)

Table A.3 (Continued) Complete Results of Logistic Regressions in Table 2.5

VARIABLES	Interstate Moves (LMC = UI Claims)	Interstate Moves (LMC = Unemp. Rate)	Interstate Moves (LMC = Employ. Growth)
NV	0.831	0.844	0.888
(SE)	(1.476)	(1.478)	(1.475)
WA	1.409	1.439	1.458
(SE)	(1.481)	(1.485)	(1.474)
OR	0.952	1.064	1.101
(SE)	(1.474)	(1.472)	(1.468)
CA	1.046	1.146	1.156
(SE)	(1.500)	(1.505)	(1.512)
Constant	-0.687	-0.932	-0.955
(SE)	(1.129)	(1.119)	(1.122)
Observations	1,365,067	1,365,067	1,365,067
Pseudo R-Squared	0.083	0.082	0.083

See Table 1.5

* Significant at 5% level

♦ Significant at 10% level

Table A.4: Absolute High School Gain (OLS, Compare to Table 2.14)

VARIABLES	(1)	(2)	(3)	(4)
Metro > 400 per square mile	-0.054	-0.037	-0.091*	--
(SD)	(0.033)	(0.056)	(0.043)	--
Metro 200-400 per square mile	0.000	0.017	-0.010	--
(SD)	(0.026)	(0.044)	(0.035)	--
Non-Metro	-0.124**	--	--	--
(SD)	(0.022)	--	--	--
Ln (dist. to four-year state coll.)	-0.026*	-0.014	-0.018	-0.066**
(SD)	(0.007)	(0.012)	(0.009)	(0.013)
July average temperature (F)	-0.003	-0.002	0.010*	-0.012**
(SD)	(0.002)	(0.004)	(0.004)	(0.004)
January avg. temperature (F)	0.005**	0.004	0.005	0.012**
(SD)	(0.002)	(0.003)	(0.002)	(0.003)
Coast dummy	-0.080**	-0.033	-0.059	-0.111**
(SD)	(0.021)	(0.053)	(0.031)	(0.040)
Poverty rate (1990) %	-0.011**	-0.006	-0.016**	-0.008**
(SD)	(0.002)	(0.007)	(0.004)	(0.003)
Unemployment rate (1991-93) %	-0.021**	-0.034	-0.030**	-0.009
(SD)	(0.004)	(0.019)	(0.007)	(0.006)
Neighbors' unemployment %		-0.013	-0.014	-0.001
(SD)		(0.015)	(0.009)	(0.010)
Mining %	-0.015**	-0.020*	-0.018**	-0.008*
(SD)	(0.003)	(0.009)	(0.004)	(0.004)
Manufacturing %	-0.004**	-0.006*	-0.006**	0.000
(SD)	(0.001)	(0.003)	(0.002)	(0.002)
Information services %	0.013*	-0.006	0.013*	0.033*
(SD)	(0.005)	(0.012)	(0.004)	(0.017)
Professional %	0.010*	0.030**	-0.004	0.010
(SD)	(0.005)	(0.009)	(0.005)	(0.009)
Arts and entertainment %	0.040**	0.011	0.016	0.096**
(SD)	(0.012)	(0.025)	(0.014)	(0.017)
Federal government %	-0.005	-0.002	-0.009*	-0.005
(SD)	(0.003)	(0.006)	(0.004)	(0.004)
Military %	0.000	-0.002	-0.002	0.010**
(SD)	(0.002)	(0.005)	(0.003)	(0.003)
State and local government %	-0.001	-0.002	-0.001	0.000
(SD)	(0.002)	(0.003)	(0.002)	(0.002)
Midwest	0.116**	0.172**	0.104	0.124*
(SD)	(0.027)	(0.065)	(0.039)	(0.052)
South	0.313**	0.289**	0.237**	0.241**
(SD)	(0.037)	(0.087)	(0.059)	(0.054)
West	0.202**	0.221*	0.142**	0.195**
(SD)	(0.037)	(0.088)	(0.053)	(0.055)
Non-Native %	0.012**	0.015**	0.014*	0.006
(SD)	(0.002)	(0.004)	(0.003)	(0.004)
Constant	0.622**	0.564	-0.129	-0.994**
(SD)	(0.192)	(0.300)	(0.341)	(0.325)
Sample	All CGAs	Metro Center	Suburb	Non-Metro
Observations	915	203	380	332
R-squared	0.584	0.583	0.543	0.540

Regressions employ Hubert-White robust standard error corrections. Initial stock of high school graduates is based on the National Center for Education Statistics' Common Core of Data, 1991-1993. Growth of high school graduates is then based on the 2006-2010 5% Public Use Microdata Sample of the ACS. See Table 3.2 for details.

** Significant at the 1% level

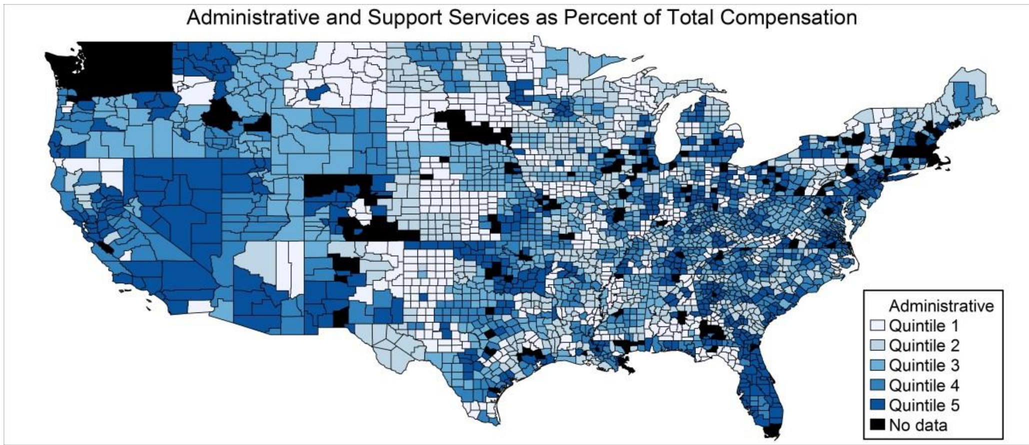
* Significant at the 5% level

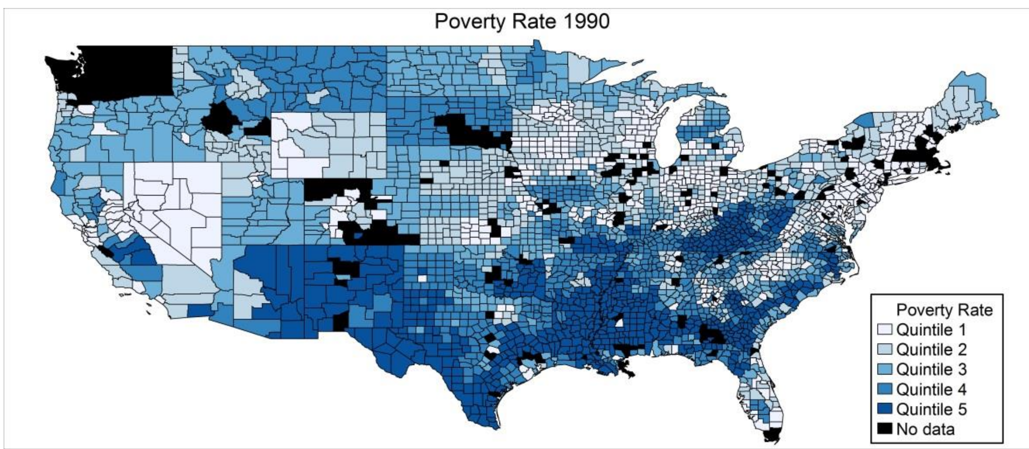
Appendix Table A.5: Absolute High School Gain, "Consistent PUMAs" (OLS)

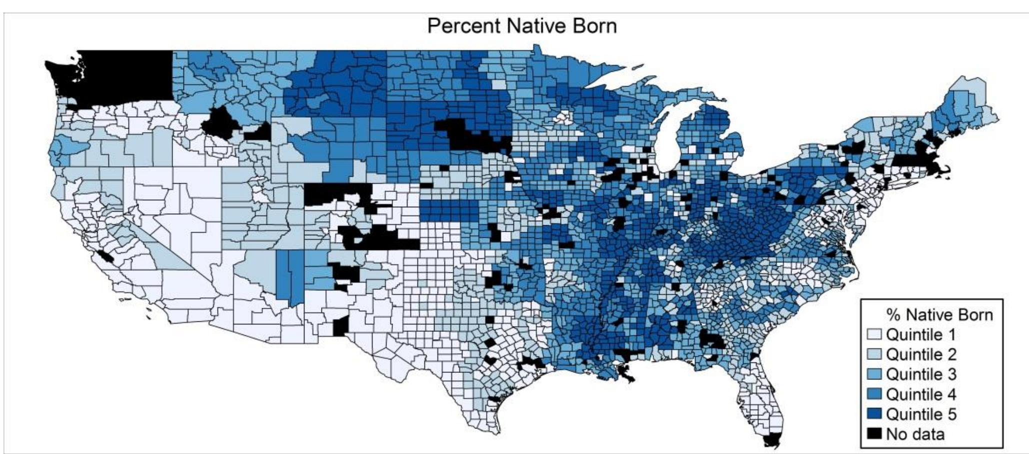
VARIABLES	(1)	(2)
Metro > 400 per square mile	**0.079**	0.033
(SD)	(0.062)	(0.063)
Metro 200-400 per square mile	0.006	-0.026
(SD)	(0.035)	(0.036)
Non-Metro	-0.120**	-0.092**
(SD)	(0.032)	(0.031)
Ln (dist. to four-year state coll.)	*-0.013*	-0.007
(SD)	(0.011)	(0.011)
July average temperature (F)	-0.006	-0.004
(SD)	(0.004)	(0.004)
January avg. temperature (F)	0.007**	0.005
(SD)	(0.003)	(0.003)
Coast dummy	*-0.042*	-0.048†
(SD)	(0.028)	(0.028)
Poverty rate (1990) %	***-0.004***	0.001
(SD)	(0.003)	(0.004)
Unemployment rate (1991-93) %	-0.029**	-0.037**
(SD)	(0.007)	(0.008)
Average college wage (1990)		-0.025
(SD)		(0.226)
Average non-college wage (1990)		0.451†
(SD)		(0.248)
Mining %	-0.013*	-0.018**
(SD)	(0.005)	(0.005)
Manufacturing %	**0.001**	0.000
(SD)	(0.002)	(0.002)
Information services %	0.029†	0.026
(SD)	(0.017)	(0.017)
Professional %	*0.009*	0.005
(SD)	(0.008)	(0.008)
Arts and entertainment %	*0.026*	0.025
(SD)	(0.018)	(0.018)
Federal government %	0.001	0.000
(SD)	(0.007)	(0.007)
Military %	***0.006*****	0.008**
(SD)	(0.002)	(0.002)
State and local government %	0.001	0.001
(SD)	(0.002)	(0.002)
Midwest	*0.065*	0.050
(SD)	(0.047)	(0.048)
South	0.245**	0.252**
(SD)	(0.059)	(0.060)
West	0.200**	0.195*
(SD)	(0.066)	(0.065)
Non-Native %	0.015**	0.016**
(SD)	(0.003)	(0.003)
Constant	*0.491*	-0.513
(SD)	(0.319)	(0.516)
Sample = Consistent PUMAs		
Observations	312	312
R-squared	0.594	0.606

Regressions use Hubert-White robust standard error corrections. Column 1 is identical to column 1 of Appendix Table A.4 except the geographic unit is broadened to consolidate 1990 PUMAs with 2005-2010 PUMAs. Bold indicates > 1.5 SD difference from Appendix Table A.4. Italics indicate change in significance.

** Significant at the 1% level * Significant at the 5% level † Significant at 10% level


Administrative and Support Services as Percent of Total Compensation
Administrative
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5
No data


Poverty Rate 1990
Poverty Rate
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5
No data


Percent Native Born
% Native Born
Quintile 1
Quintile 2
Quintile 3
Quintile 4
Quintile 5
No data

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