

# Smart cities and attracting knowledge workers: Which cities attract highly-educated workers in the 21st century?<sup>\*</sup>

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**Abstract.** Regional policy-makers have long sought to attract highly-educated workers with a view to stimulating economic growth and vibrancy. Previous studies over the decades leading up to the new millennium show human capital divergence across cities, where the share of college graduates grew faster in cities that had larger initial shares of college-educated workers. However, labour markets have changed significantly post-2000, likely affecting migration decisions of highly-skilled workers. Additionally, past studies have not controlled for important changes in industry education levels and overall industry composition that may influence city-level college graduate growth. We use detailed 4-digit NAICS industry employment data combined with public micro-data to construct measures of industry skill upgrading and changes in industry composition to control for their effects on human capital growth. We find agglomeration forces, rather than initial graduate share, explains college-graduate share growth post-2000. We also decompose graduates into bachelors and postgraduate degree holders to determine whether different forces are at play on growth of graduates at different education levels.

# **JEL classification:** J1, J4, J6, O1, O2, O4, R1

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## 1 Introduction

City and regional officials are concerned with attracting highly-educated workers to their jurisdictions for several reasons. First, a large literature supports the positive association between college graduates and economic growth in cities and regions (Glaeser et al. 1995; Glaeser and Shapiro 2003; Simon 1998; Simon and Nardinelli 2002; Whisler et al. 2008). This is in addition to the longer line of literature that links human capital and economic development at the national level (Barro 1991; Becker et al. 1994). Further, the intuitive nature of the relationship between a well-educated workforce and economic prosperity appeals to the broader public, possibly making policy interventions aimed at high-skill workers more politically feasible. Lastly, since education levels are a strong predictor of the propensity to migrate (Faggian and McCann 2009; Corcoran et al. 2010; Venhorst et al. 2010), policy-makers may view programmes aimed at attracting well-educated workers as likely to succeed.

Policy-makers, however, may have little influence over attracting well-educated migrants to their cities. Previous research has shown college graduate shares to be diverging across metropolitan areas over the past several decades (Berry and Glaeser 2005; Winters 2011). If initial levels of college graduates are the strongest predictor of future college graduate growth, policy efforts to attract highly-educated workers may be a misuse of valuable resources. Highly-educated cities will continue to attract well-educated workers, while lagging cities will lag further. Given the policy importance of understanding migration patterns of highly-educated workers and the knowledge gaps about where they move, we appraise net migration patterns of bachelor degree and post-graduate degree holders across US metropolitan areas.<sup>1</sup>

We contribute to the existing literature by testing several alternative hypotheses. First, we investigate whether metro area industry structure plays a significant role in attracting high-skill workers. Specifically, we determine whether places that had (*i*) fast growing 'smart' industries or (*ii*) industries that had significant skill upgrading experience higher levels of college graduate growth. We then assess whether places with fast employment growth, regardless of the education composition of their industries, attract college graduates. These industry composition and overall growth effects have been mostly unexplored in the previous literature. Second, previous studies focus predominantly on the migration of all college graduate degree holders. We examine whether different factors affect the growth of graduate or professional degree holders than those associated with growth of bachelor's degree holders. Lastly, we add to the literature by determining whether the across-the-board reduction in US migration rates post-2000 has been associated with differential patterns in recent metropolitan area college graduate growth.

Evaluating data from 1990–2000 and 2000–2010 on US metropolitan areas, we find agglomeration appears to be the predominant driver of human capital migration after 2000. We find little evidence of spatial divergence in human capital across cities both pre and post-2000, contrary to the studies by Berry and Glaeser (2005) and Winters (2011), which only considered pre-2000 data. Once we control for industry composition and state fixed effects, the initial share of college graduates has no statistically significant effect on future growth of college graduates. We find places with fast-growing smart industries attracted well-educated workers in the 1990s, though were not associated with human capital growth post-2000.

<sup>&</sup>lt;sup>1</sup> We assess the effects of city characteristics on college-educated worker net migration patterns, which is in contrast to an emerging literature primarily mostly from Europe and Australia that uses micro-data to assess how individual characteristics of well-educated migrants affect their migration decisions (Venhorst et al. 2010, 2011; Faggian et al. 2007; Arntz 2010; Corcoran et al. 2010; Faggian and McCann 2009; Gottlieb and Joseph 2006) also provide some micro evidence for the United States. Thus, while we will be concerned about the share of highly educated workers in a given metropolitan area, these studies focus on the individual migration decisions of recent university graduates.

The following section reviews the existing literature, followed Section 3 describing our theoretical model. Section 4 contains the details of our empirical model and data. Section 5 reviews our results and Section 6 concludes.

### 2 What attracts university graduates?

The question of what city characteristics are associated with human capital growth is couched in a larger debate about migration patterns of highly-educated workers. The past literature has raised several factors thought to be associated with greater shares of college-educated workers. In this discussion, the roles of urban-driven agglomeration effects are one key factor that could affect the shares of educated workers, whereas an alternative hypothesis is that industry composition drives the demand for these workers, and in turn their relative migration. We take an inductive approach in our discussion and empirical specification, in which we discuss these two factors and other potential explanations in the literature.

Because greater proportions of highly-educated workers are correlated with employment growth in cities (Simon and Nardonelli 2002; Glaeser and Shapiro 2003), researchers in both Europe and the United States have taken a keen interest in the migration decisions of university graduates (Faggian and McCann 2009; Venhorst et al. 2010, 2011; Gottlieb and Joseph 2006). While these studies can tell us much about the individuals that are migrating, they cannot speak about the places to which they migrate. Our study focuses on the aggregate characteristics of cities that attract well-educated workers rather than the migrant's personal attributes and our focus is on human capital rather than creative occupations.<sup>2</sup> That is, we are interested in what attracts 'smart' people – presumably positively correlated to educational attainment – to particular cities, that in turns helps create smart cities with the highest concentrations of university educated. Of course, having educated people does not ensure a smart city, but it likely at least represents a necessary first step.

Another line in the human capital literature seeks to explain the spatial allocation of human capital across regions. In the United States, Borjas et al. (1992) found that regions which offer higher wages for skilled labour attract more skilled internal migrants than regions with lower wages for skilled workers. However, in Europe there is weaker support for this relationship, where regional wage differentials are smaller. Recent work done by Arntz et al. (2014) finds that high-skill workers in Germany are attracted to regions with higher wages and employment probabilities, but also to places with greater wage and employment inequalities. The result is a self-reinforcing process that leads to greater regional employment and skill disparities.

Whether initial city-level college graduate shares influence future growth in educated workers is important because such a process would also suggest places with more college graduates would experience a virtuous cycle, but laggards would be at a competitive disadvantage. Berry and Glaeser (2005) find that cities with higher initial shares of college-educated workers saw greater increases in the proportion of college-educated workers living there during the 1970s, 1980s, and 1990s, suggesting divergence of human capital across cities. They attribute the persistence in human capital to skilled, but immobile, entrepreneurs increasingly hiring well-educated workers. Winters (2011) also finds skilled cities are becoming more educated over time in his investigation of migration into and out of so-called 'smart cities'.<sup>3</sup> He finds smart cities are growing in part because they are able to retain recent graduates from local universities, who had originally moved there to pursue higher education.

<sup>&</sup>lt;sup>2</sup> For a discussion of the distinction, see Comunian et al. 2010.

<sup>&</sup>lt;sup>3</sup> Winters defines smart cities as those that have a high percentage of college graduates.

Previous work in this area offers several explanations for why higher skilled workers might be attracted to places with more high-skilled workers. Moretti (2004) finds educated workers generate productivity spillovers in industries outside those in which they work, suggesting workers would be more productive, earn a higher wage, and thus have an incentive to move to cities with more highly-educated workers. Spillovers aside, if amenities such as retail shopping, restaurants, entertainment venues, and cultural offerings are normal goods and college graduates are associated with amenities, we would see a disproportionate levels of high skill workers migrating to places with more college-graduates. Indeed, Adamson et al. (2004) find urban amenities dominate productivity effects and urban disamenities. Though in a European context, Niedomsyl and Hansen (2010) find that jobs are more important than amenities to high-skilled workers. Amenities and jobs are associated with higher levels of college graduates and thus develop potential channels through which highly-educated cities might attract highly-educated workers and help to explain the findings identified by Berry and Glaeser (2005) and Winters (2011).

However, the productivity spillovers in Moretti's (2004) work were much smaller for highly-educated workers, raising doubts about whether spillovers are a main factor in college graduate attraction. Other forces may actually repel educated workers from areas with high concentrations of college graduates. Competition for good jobs may be fierce in cities where there is already an abundance of college-educated workers, driving skilled workers to places with lower initial levels of human capital. For instance, new graduates looking to work in the financial sector may find it difficult to distinguish oneself amongst the vast number of welleducated job candidates in (say) London. That same graduate might find an easier time finding a job in a city where fewer people have college degrees and the same specialized human capital as they do. If graduates are moving to places with fewer college-educated workers, we would expect to see a convergence of human capital across cities.

While past studies account for city demographic characteristics on human capital growth, they do not fully account for changes in city industry composition. If a particular city has a concentration of industries that are experiencing large increases in college-educated workers through industry up-skilling, it seems possible that the city will attract college graduates. Such attraction of college graduates would be due to a within industry demand effect. Alternatively, industry structure may be changing such that skill-intensive industries are growing more rapidly (or less rapidly) than less-skilled industries. Here, cities with concentrations of fast-growing high human capital sectors would also potentially be attractive for college graduates in their migration decisions. This between industry effect would also serve as a push or pull factor for educated workers.

Despite their potential importance, the industry composition effects on human capital growth has only seen limited investigation in the college graduate migration literature. Storper and Scott (2009) outline the dynamics of the manufacturing sectors of the US Rustbelt and electronics, aerospace, and software industries in the Sunbelt to show the importance of industry composition on city growth. Berry and Glaeser (2005) include the share of manufacturing workers in their regressions, but primarily as a control variable. They find manufacturing share has mixed effects on city college graduate growth, having a positive association in some cases, but a negative in others. We extend this literature by measuring the change in metropolitan statistical area (MSA) college graduate share due to relative changes in MSA industry employment shares (between industries) and changes in educated workers within industries. Indeed, finding that industry composition affects the attraction of college graduates would be evidence supporting local economic development initiatives that target specific industries.

Another key question in the literature has been whether agglomeration and city size has differential effects on workers across the skill distribution. Marshall (1890) believed benefits from agglomeration accrued primarily through input sharing, worker/employer matching, and

knowledge spillovers. If highly-educated workers are better suited to take advantage of these externalities, they will enjoy greater benefits from agglomeration and have more incentive to move to cities. For instance, college graduates may develop skills through formal education that allow them to more effectively engage with other people and better synthesize exchanged ideas, thereby increasing their ability to benefit from knowledge spillovers that predominate in dense settings. Highly-educated workers would then benefit more from migration to agglomerated areas. Indeed, Bacolod et al. (2009) find an urban wage premium for more skilled and more highly-educated workers. In a European context, Rodríguez-Pose and Tselios (2010) also find that returns to education are connected to regional and supra-regional education externalities. Better-educated workers are also more specialized and may benefit from agglomeration through thicker labour markets in larger cities (Arntz 2010; Puga 2010). Highly-specialized workers in small cities may only have one or two potential employers to choose from, but considerably more diverse employment options in larger cities. This is particularly true for so-called 'power couples', where both spouses are highly educated. These households seem to prefer heavily populated areas, presumably in order to find suitable jobs for both spouses (Costa and Kahn 2000).

Another reason agglomeration may attract highly-educated workers that the physical proximity afforded by urban agglomeration may foster innovation among individuals and firms. Several individual-level studies of entrepreneurs have linked innovation and educational attainment (Koellinger 2008; Ganotakis 2012). If better educated workers are more innovative and cities are important to innovation then better-educated workers would have incentive to move to more populous places to maximize their innovative potential. However, the literature is mixed about whether agglomeration is central to innovation. Agglomeration may provide value to innovators is by increasing the productive interactions between innovators. Crescenzi et al. (2014) find a relationship between physical proximity and collaborations between inventors. Additionally, increased contact with other economic agents in agglomerated areas tends to give rise to trust and openness, which favour innovation (Florida 2005; Rodríguez-Pose and Storper 2006). However, in their investigation of creative industries and occupations, Lee and Rodríguez-Pose (2014) find no evidence that urban firms in creative industries introduce any more product or process innovations than rural firms, supporting the findings of others that have questioned the link between urban settings and innovation (Turok 2003; Brewin et al. 2009; Fitjar and Rodríguez-Pose 2011).

Agglomeration may also affect educated-worker migration through consumption decisions. Dalmazzo and Blasio (2011) found an urban rent premium for educated workers in Italy, suggesting valuation of city amenities increases with education, consistent with Glaeser et al.'s (2001) conjectures for the United States. Adamson et al. (2004) find that amenity factors are a considerable attraction for higher-skilled workers to US metropolitan areas, though they also find skill-biased productivity factors are especially important for the very largest metropolitan areas in attracting a better-educated workforce. Florida (2002) and Florida et al. (2008) argue that diverse urban environments and concentrations of the creative class, which are closely associated with educational attainment, are attractive to both additional creative class workers and to firms that employ them.

Glaeser and Resseger (2010) investigate agglomeration's effect on migration decisions by studying the connection between city size and per-worker productivity. They find results consistent with Glaeser and Mare? (2001) where the agglomeration effect is higher for more skilled cities, suggesting skilled workers are more valuable in dense locations. Rational-acting college graduates would then move to cities to capitalize on wage differentials between high and low density areas. However, Winters (2011) finds an inverse migration association with initial population, running counter to typical agglomeration matching stories or Costa and Kahn's (2000) results for power couple matching.

Significant changes in migration patterns post-2000 may have altered the relevance of some of these previous results. Although Americans still have some of the highest internal migration rates in the world, between 1990 and 2010 the percentage of Americans who moved across state lines decreased by almost 50 per cent and migration rates are now similar to those in the 1940s. Kaplan and Schulhofer-Wohl (2012) attribute the decline in migration to two causes: first, the rise in non-tradable service sector jobs has led to a decline in geographic specificity of jobs. Second, they speculate that previously unavailable information about potential relocation destinations is now accessible on the internet and decreased travel costs allow potential movers to learn about important area characteristics before they move. Though, it is not clear why better information would not in fact encourage more movements, as distant jobseekers could identify more employment possibilities, reducing risk for risk-averse migrants. Using a different methodology, Partridge et al. (2012) find that migration responses to local economic shocks have greatly declined after 2000, which suggests college graduates may be less likely to migrate for economic reasons. Indeed, because college-educated workers are more likely to move than the general population, we would expect declining migration to affect trends in human capital growth across cities as well. Thus, basing current policy on pre-2000 results may be inappropriate.

The above discussion of the literature suggests many push and pull factors that lead well-educated workers to locations with more economic opportunities and more amenities. Previous evidence shows agglomeration forces and industry structure dynamics influence local economic vitality and thus likely influence the extent to which cities attract more educated workers. In particular, the literature points to the possibility of a virtuous cycle where high initial college graduate shares attract more well-educated workers. Moreover, city industry composition may affect the demand for college-educated workers though differential within or between-industry demand growth for high-skilled workers. The agglomeration literature suggests cities may have the best labour market matches and a greater variety of consumption opportunities. Highly-educated workers, and so they may be more responsive to changes in overall city-level economic conditions, such as employment growth, aside from any industry composition effects.

These main hypotheses are independent but they can become reinforcing in the long-run. For example, if agglomeration economies are linked to attracting a rising share of college graduates and a larger share of college graduates are associated with attracting more college graduates, the two effects would become mutually reinforcing in the long-run over the course of decades. Below we develop a conceptual framework to explain aggregate city-level growth in collegeeducated workers.

#### **3** Conceptual framework

We begin with a discussion of the city-specific factors that affect aggregate movements of well-educated workers. We are particularly interested in the migration decisions of workers with high levels of human capital, who may have different preferences than lower-skilled workers. We model the metropolitan area college graduate share in a spatial equilibrium framework. In equilibrium, differences in utility levels are equalized by factor prices, leaving households no incentive to move. Changes to factors in the household's utility calculation will lead to household migration. Many of these possible factors were discussed in the literature review.

One such factor that is continuously changing is the share of college graduates in each MSA. Such changes may alter the benefits/costs college-educated workers receive through increased/ decreased wages or more/less attractive man-made amenities. Places with greater shares of high-human capital workers may attract college-educated migrants if there is some positive externality that better-educated workers receive from being nearby other college-educated workers, including better labour market matching for them and their household. If college graduates are also more productive when they are near to other college graduates, their wages will increase, making migration more likely. This may lead to a virtuous cycle of increasing shares of college graduates for cities with high initial shares of graduates. However, college graduates may not benefit from being nearby other graduates if they see other college graduates as rivals. Such competition may lower their wages, leading to out migration of college graduates from places that have high shares of well-educated workers.

The above literature review suggests that relative metropolitan area economic conditions would also potentially affect aggregate migration patterns of college-educated workers if they affect the net benefits of migration. Likewise, the composition of industries can affect demand for college-educated workers due to between-industry differences in the use of highly-educated workers and due to differential within-industry growth rates of the shares of highly-educated workers. The literature also points to agglomeration and amenity effects that might directly affect highly-educated worker migration through their own wages and labour market match and indirectly through affecting quality of life (i.e., consumer city effects) and their spouse's economic opportunities. Finally, because of life cycle and other potential migration effects, metropolitan demographic characteristics could also affect aggregate migration behavior.

With these factors in mind in affecting individual and aggregate migration, the net migration of college-educated workers between periods 0 and *t* is then influenced by the initial MSA share of college-educated workers and other related factors, such that:

$$MigCOLLEGE_{0-t} = f(SHGRADS_0, ECON_{0-t}, AGGLOM_0, DEMOG_0, AMENITY_0),$$
 (1)

where *SHGRADS* is the initial period 0 MSA share of college-educated workers, *ECON* is economic structural effects of the MSA including industry composition measured in either the initial period or during the subsequent *t* years, *AGGLOM* is the agglomeration influences, measured in period 0, *DEMOG* is the MSA's demographic characteristics measured in period 0, such as MSA age structures, race makeup, and immigrant prevalence, and *AMENITY* reflects the natural attractiveness of the MSA, such as temperature, rainfall, proximity to water, and topography.

The variables are generally measured in period 0 to mitigate any endogeneity concerns. We describe further steps taken to address possible simultaneity bias below. In addition, the underlying factors affecting the migration decision may change over time due to different economic conditions or changes in preferences. One such change we discuss is how the sluggish labour markets post-2000 may have altered the relative preferences of college-educated workers for larger cities. Thus, comparing the 1990s, in which past research is centered, to the post 2000 period will allow us to assess whether relative preferences changed.

#### 4 Empirical model and data

We combine data from several publicly available datasets, along with four-digit NAICS industry-level proprietary employment data from Economic Modeling Specialists International (EMSI), for use in our empirical analysis. Our sample includes 358 Metropolitan Statistical Areas (MSAs) as defined by the US Census Bureau in 2003. Our base models consider the periods covering 1990–2000 and 2000–2010 separately. Sensitivity analysis will assess whether unmeasured fixed effects are influencing our main conclusions.

The empirical specification follows from the review of the literature, in particular the Glaeser and Berry model, augmented by the alternative hypotheses described in the conceptual

discussion.<sup>4</sup> The dependent variables in our models are the difference in share of MSA population over the age of 25 who have graduated from college between time t and t-1. In our initial models, we consider MSA share of all college graduates. In later models, we disaggregate college graduate share into MSA share of bachelor's degree holders and MSA share of graduate or professional degree holders. Graduate share variables come from the 1990 and 2000 Decennial Census and the 2010 American Community Survey (ACS) 1-year estimates. Our empirical model takes the following form:

$$Grad_{t} - Grad_{t-1} = \alpha + \beta_1 Grad_{t-1} + \beta_2 Econ + \beta_3 Agglom + \beta_4 Demog + \beta_5 Amenity + \sigma_s + \varepsilon$$
, (2)

where *Grad* is the initial-period share of MSA population over 25 with a college degree, *Econ* is a vector of industry composition and growth variables, *Agglom* contains MSA population, *Demog* includes MSA demographics, and *Amenity* is a measure natural amenities within the MSA. The model includes the standard intercept term,  $\alpha$ , state fixed effects,  $\sigma_s$ , and an error term,  $\varepsilon$ . We describe the specific variables included in each vector below.

The  $Grad_{t-1}$  term will help us assess whether there is divergence in the college graduate share as suggested by research from the period of the 1990s, or whether college graduate shares are now converging post 2000. A key contribution of our model is in also assessing the role of MSA industry demand in attracting college graduates in the Econ term. These variables follow from shift-share framework. A key advantage of these demand-shift variables is that because the predicted growth rates are based on the corresponding national growth rate for the industry, even though they are measured during the same period as the dependent variable, the demand shifters are exogenous to the college graduate growth rate of a particular county. Indeed, shift share variables are routinely used as exogenous demand shifters or used as exogenous instruments in regional and urban economics dating back to Bartik (1991) (e.g., Bound and Holzer 2000; Partridge et al. 2012). This is particularly important in our case because the expected growth of college graduates could in turn affect contemporaneous job creation and industry composition effects (for example), meaning that the use of exogenous measures mitigates or eliminates any simultaneity bias. Likewise, using exogenous variables is important because the cross-sectional nature of our regressions could exclude omitted fixed effects that are correlated with the explanatory variables. By using exogenous demand shifters, this potential problem should be greatly mitigated or eliminated, though we will consider first difference approaches below to further address this concern.

The first two demand-shift variables relate to the industry composition of the MSA to test whether it is industry-specific factors that influence college graduate migration. We refer to the first industry composition demand variable as the *within*-industry education growth, for which we describe data sources below. It is defined by the following equation:

$$EduWINDGr = \sum_{i} employment_{ij}^{t-1} * edugr_{i,USA}^{t,t-1},$$
(3)

where *employment*<sup>t-1</sup><sub>ij</sub> is the *initial* employment share of industry *i* in MSA *j* in year t - 1 and  $edugr_{i,USA}^{t,t-1}$  is the *national* growth rate of the share of college graduates working in industry *i* between *t* and t - 1. This summation can be interpreted as the predicted increase in the college graduate share of workers in MSA *j* if skill upgrading in each industry *i* in MSA *j* occurred at the specific industry's national educational growth rate over the previous decade. MSAs with larger concentrations of industries that experienced significant skill upgrading over the previous

<sup>&</sup>lt;sup>4</sup> The empirical specification also follows quite closely the one used by Partridge et al. (2012) in using measures of exogenous shocks to identify the migration response.

decade may expect to see overall growth in the share of college-educated workers relative to non-college-educated workers within the MSA.

The second measure of industry education is the between industry educational growth variable. This measure accounts for the demand for MSA workers with a college degree attributable to highly-educated industries growing differently than less-skilled industries in the MSA. If MSA industries that initially employ a larger share of college-educated workers grew faster than those that employ fewer college graduates, the overall share of college workers within the MSA may also grow. This variable is defined:

$$EduBINDGr = \sum_{i} employment_{ij}^{t-1} * edu_{ij}^{t-1} * empgr_{i,USA}^{t,t-1},$$
(4)

where again  $employment_{ij}^{t-1}$  is the share of employment of industry *i* in MSA j in year t - 1 and  $edu_{ij}^{t-1}$  is the proportion of workers in industry *i* in MSA *j* with a college degree in time t - 1. The last term in the equation,  $empgr_{i,USA}^{t,t-1}$  is the national total employment growth rate in industry *i* over the previous decade. This summation can be interpreted as the predicted increase in the share of workers with a college degree in MSA *j* if employment in each of the MSA's *i* industries had the same employment growth rate as industry *i*'s national employment growth rate (holding the initial college graduate share fixed in industry *i*).

Also included in the *Econ* vector is the predicted overall or aggregate employment growth in the MSA given each of its industries grew at their respective national employment growth rate. We refer to this as the industry mix variable and it is defined as:

$$IndMix = \sum_{i} employment_{ij}^{t-1} * empgr_{i,USA}^{t,t-1},$$
(5)

where again  $employment_{ij}^{t-1}$  is the share of employment of industry *i* in MSA j in year t - 1 and  $empgr_{i,USA}^{t,t-1}$  is the national employment growth rate in industry *i* over the previous decade. As with the between and within-industry measures, *IndMix* is an exogenous measure of whether the MSA had a composition of industries that were fast growing in general and is a good predictor of how fast a given area grew over the period. Hence, we can assess whether it is faster growing places in general that are attracting college-educated workers, and not the skill-intensity or skill-upgrading of a location's industry composition.

The data sources for these three ECON demand shifters are as follows. The 4-digit NAICS employment data give us a more refined measure of employment than the publicly available 1 or 2-digit NAICS codes typically used in previous studies. Education shares are from the 2010 ACS and 1990 and 2000 Decennial Census micro-data made available through International Public Use Microdata (Ruggles et al. 2010). It is possible to calculate industry education shares for most industry-MSA pairs, however in some MSAs, certain industries are not large enough, so that sufficient workers are included in the census or ACS samples. In such cases, we use state or census division level industry education values to calculate industry growth rates.

The ECON vector also includes the MSA's manufacturing industry employment share in the empirical model using EMSI data in its construction. Including the manufacturing share follows Berry and Glaeser (2005) to account for any skill-upgrading that might be occurring in the sector due to fierce global competition, which may attract college graduates even as lower-skilled workers are let go on balance.

Lastly, the ECON vector includes the 10-year lagged log of *per capita* personal income. We would expect educated workers to be attracted to wealthier metropolitan areas, but as a populace becomes more educated, *per capita* income should rise as well. We include the log of initial *per capita* income from the Bureau of Economic Analysis so as not to confound the initial college graduate share effect with an income effect that would attract migrants.

The Agglom vector includes the log of 10-year lagged MSA population to account for agglomeration effects, such as matching or knowledge spillovers. The *Demog* vector includes demographic control variables to account for differential migration effects depending on composition by age and race. These include the percentage of the population that is white, and percentage of the population in age cohorts 18-24, 25-54, 55-64, 65-84, and over 84. In particular, including the 18-24 year old share should partially account for MSAs with larger college populations, that may be attractive to retaining new college graduates (Winters 2011). The percentage of the population that is foreign born is included in the model as well. It is not immediately clear whether larger shares of immigrants attract or repel better educated workers. In some instances, college graduates may see immigrants as complements that increase their own productivity and the additional diversity may also be a pull factor (Ottaviano and Peri 2006). Alternatively, if cultural avoidance affects where college graduates migrate, MSAs with higher concentrations of immigrants may see slower growth in highly-educated workers (Alesina and Ferrara 2000, 2005; Ali et al. 2012). To avoid endogeneity, we use 10 year lagged values for all demographic variables. We will use staged regressions to assess whether omitting these variables affect the results to assess the role of multicollinearity and possible endogeneity. All of these demographic variables are from the 1990 and 2000 censuses.

Amenity includes the US Department of Agriculture Economic Research Service's one to seven natural amenity scale. This index combines information on January and July temperatures, sunlight, and humidity, distance to water, and topography to create a measure of natural attractiveness. Workers from across all levels of education have been moving to warmer climates over the past half century. We include this variable to determine whether MSAs with more desirable natural attributes attract knowledge workers in higher proportions than less naturally attractive places, consistent with the notion that amenities are normal or superior goods. State fixed effects are included in all models to control for unobservable differences between states that affect the growth of highly-educated workers.

In the discussion of the empirical results, we conduct sensitivity analysis to assess the robustness of our results. Some examples include sensitivity to multicollinearity, omitted variables, and whether the Great Recession affects our key post-2000 results.

## **5** Results

Before we discuss the regression results, we first get a sense of which MSAs were at tails of the distribution according to college graduate share. Table 1 shows which MSAs had the highest and lowest initial shares of college graduates and also the most and least college graduate share growth from 1990–2000 and 2000–2010. There are two panels in Table 1. Panel A shows the top ten MSAs according to 1990 college graduate share, 2010 college graduate share, 2010 bachelor's degree share, 2010 graduate/professional degree share, and 1990–2000 and 2000–2010 college graduate share growth. Panel B shows the corresponding bottom ten MSAs according to the same measures as in panel A.

Column (1) of panel A shows in 1990 the ten MSAs that had the highest shares of their populations having graduated from college. The list is comprised mostly of MSAs that are home to a large university as observed by Winters (2011). Most of the same places are in the top ten in 2010 as seen in column (2), though their order is somewhat different. The corresponding columns in panel B show the MSAs with the smallest college graduate shares, most of which are smaller MSAs that have recently had slower than average population growth. There is considerable persistence in the bottom ten MSAs between 1990 and 2010 as shown in column (2) of panel B. Six of the bottom ten MSAs in 1990 are in the bottom ten MSAs again in 2010.

The large increases in the overall share of the US population with at least a college degree are evident throughout Table 1. Both the ten highest shares and ten lowest shares increased in

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Table

							Pane	l A. Top	ten M	ISAs							
(1)				(2)			(3)			(4)			(5)			(9)	
Collé	ge share 1990			College share 201	0		Bachelors share 2010		Ū	rad/Prof. share 2010		Δ in e	ollege share 1990–20	000	$\Delta$ in	college share 2000–2	2010
Rk	MSA Name	Share	Rk	MSA Name	Share	Rk	MSA Name	share 1	šk	MSA Name	Share I	ĸ	MSA Name	Share	Rk	MSA Name	Share
	Boulder, CO	42.1		Boulder, CO	57.5		Boulder, CO	33	1.	thaca, NY	31.2	1. B	oulder, CO	10.2		Columbia, MO	9.1
6	Ann Arbor, MI	41.9	5.	Ithaca, NY	53.4	6	Columbia, MO	28.4	2.	Ann Arbor, MI	25	2. R	aleigh-Cary, NC	7.8	5	Wilmington, NC	8.1
Э.	Ithaca, NY	41.7	3.	Ann Arbor, MI	50.4	З.	Lawrence, KS	28.2	З. Е	3 oulder, CO	24.5	3. S	an Jose, CA	7.7	3.	Missoula, MT	7.9
4	Corvallis, OR	41.3	4.	Lawrence, KS	49.9	4	Fort Collins, CO	28.1	4. V	Vashington, DC	22.3	4.	harlotte, NC-SC	7.4	4.	Lawrence, KS	7.2
5.	Lawrence, KS	38.4	5.	Columbia, MO	49	5.	Raleigh-Cary, NC	27.8	5.	Corvallis, OR	22	5. F	ort Collins, CO	7.2	5.	Charleston, SC	6.9
6.	Ames, IA	38.4	9.	Ames, IA	48.4	9.	Ames, IA	27.6	6. L	awrence, KS	21.7	6. H	olland, MI	7.2	9.	Johnson City, TN	6.8
7.	Iowa City, IA	37.6	7.	Corvallis, OR	48	7.	Bloomington, IL	27.4	7. A	Ames, IA	20.8	7. B	loomington, IL	7.2	7.	Dubuque, IA	6.8
×.	Washington, DC	37.5	°.	Washington, DC	46.8	×.	San Francisco, CA	26.5	.8 0	Columbia, MO	20.6	8. V	/ilmington, NC	7.1	×.	Sioux Falls, SD	6.7
9.	Columbia, MO	34.7	9.	Fort Collins, CO	45.8	9.	Corvallis, OR	26	9. S	tate College, PA	20.2	9. C	harlottesville, VA	6.9	9.	Bismarck, ND	6.7
10.	Bridgeport, CT	34.2	10.	Iowa City, IA	45.6	10.	Madison, WI	26 ]	0. S	an Jose, CA	19.8 1	0. B	oston, MA-NH	6.6	10.	Roanoke, VA	6.5
							Panel	B. Botto	m ten	MSAs							
E				(2)			(3)			(4)			(5)			(9)	
Collé	ge share 1990			College share 201	0		Bachelors share 2010			Grad/Prof. share 20	10	∆ in	college share 1990–2	000	ΔC	ollege share 2000–20	010
Rk	MSA Name	Share	Rk	MSA Name	Share	Rk	MSA Name	Share	Rk	MSA Name	Share	Rk	MSA Name	Share	ĸ	MSA Name	Share
349.	Monroe, MI	10.5	349.	. Danville, IL	13.5	349.	Visalia, CA	8.9	349.	Houma, LA	4	349.	El Centro, CA	0.6 3	49.	Oshkosh, WI	-0.6
350.	Altoona, PA	10.5	350.	. Visalia, CA	13.4	350.	Albany, GA	8.8	350.	Brownsville, TX	4	350.	Yuba City, CA	0.5 3	50.	Idaho Falls, ID	-0.7
351.	Dalton, GA	10.3	351.	Vineland, NJ	13.2	351.	Morristown, TN	8.7	351.	Madera, CA	3.9	351.	Las Cruces, NM	0.4 3	51.	Cheyenne, WY	-0.7
352.	Morristown, TN	10.3	352.	. El Centro, CA	13.2	352.	El Centro, CA	8.7	352.	Vineland, NJ	3.9	352.	Madera, CA	0.3 3	52.	Wenatchee, WA	-0.8
353.	Gadsden, AL	10.2	353.	. Dalton, GA	13.2	353.	Merced, CA	8.5	353.	Merced, CA	3.8	353.	Bakersfield, CA	0.2 3	53.	Wichita Falls, TX	-0.8
354.	Danville, VA	9.9	354.	. Odessa, TX	13.1	354.	Dalton, GA	8.5	354.	Odessa, TX	3.7	354.	Visalia, CA	-0.3 3	54.	Decatur, AL	-0.9
355.	El Centro, CA	9.7	355.	. Houma, LA	13	355.	Danville, IL	8.2	355.	Laredo, TX	3.3	355.	Casper, WY	-0.3 3	55.	Lawton, OK	-1.3
356.	Houma, LA	9.7	356.	. Gadsden, AL	12.9	356.	Gadsden, AL	8.2	356.	Pine Bluff, AR	3.3	356.	Yuma, AZ	-0.9 3	56.	Monroe, LA	-1.6
357.	Steubenville, OH	1 9.5	357.	. Merced, CA	12.3	357.	Cumberland, MD-WV	8	357.	Hanford, CA	3.1	357.	Merced, CA	-1-	57.	Casper, WY	-2
358.	Hanford, CA	6	358.	. Hanford, CA	10.9	358.	Hanford, CA	7.8	358.	Rocky Mount, NC	2.8	358.	Midland, TX	-1.5 3	58.	Midland, TX	-4.5

absolute terms between 1990 (column (1)) 2010 (column (2)). Comprehensive growth in human capital was most evident in the 1990s, when all but five MSAs had positive growth in their college graduate share. It is noteworthy that nine of the ten MSAs in column (5) of panel B are in border states, where large shares of lower-skill immigrants may be influencing the college-educated shares. Human capital growth was not as inclusive post-2000, where 18 MSAs had a smaller share of their population holding college degrees in 2010 than in 2000. This may suggest human capital divergence post-2000, but this requires further investigation to control for other possibly confounding factors.

#### 5.1 Growth in college graduates – regression results

Table 2 contains the results for our initial models that investigate the determinants of growth in MSA college graduate share for the decades of 1990–2000 and 2000–2010. We present three

		1990–2000			2000-2010	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial share of college grads	0.093***	0.03	0.034	0.04**	0.05*	0.034
	(6.71)	(1.34)	(1.02)	(2.06)	(1.74)	(0.97)
Log of population	0.149	0.08	0.088	0.53***	0.49***	0.58***
	(1.63)	(1.11)	(1.07)	(5.27)	(5.90)	(5.23)
Share of manufacturing	-0.014	-0.013	-0.015	$-0.05^{**}$	-0.053	-0.073**
	(-1.02)	(-0.98)	(-1.11)	(-2.55)	(-1.4)	(-1.98)
Log of per capita income	3.240***	2.123**	0.782	-0.905	-0.742	-0.724
	(3.45)	(2.38)	(0.7)	(-0.96)	(-0.90)	(-0.61)
Within industry education growth		0.297	0.278		0.267	0.353
		(0.99)	(1.01)		(0.5)	(0.68)
Between industry education growth		0.325***	0.26**		-0.192	-0.209
		(2.87)	(2.27)		(-0.93)	(-0.99)
Overall industry mix job growth		0.049	0.057		0.025	-0.001
		(1.33)	(1.46)		(0.31)	(-0.02)
Percentage white			0.016			0.036***
-			(1.45)			(2.93)
Percentage 18-24			0.01			0.045
-			(0.18)			(0.69)
Percentage 25–54			0.139*			0.018
e			(1.7)			(0.22)
Percentage 55–64			-0.35**			-0.025
e			(-2.27)			(-0.11)
Percentage 65–84			0.222**			0.154
C			(2.35)			(1.38)
Percentage over 84			-0.346			-0.793*
-			(-1.04)			(-1.72)
Percentage foreign born			-0.012			0.014
			(-0.50)			(0.69)
Amenity scale			0.084			0.198**
			(1.5)			(2.32)
Constant	-31.36***	-21.13***	-14.274	4.421	2.632	-2.669
	(-3.87)	(-2.75)	(-1.61)	(0.52)	(0.36)	(-0.23)
Ν	358	358	358	358	358	358
R-sq	0.62	0.663	0.688	0.455	0.459	0.509

Table 2. Determinants of the difference in MSA share of college graduates (1990–2000 and 2000–2010)

*Notes*: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

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models for each decade to test the sensitivity of our results. We start with a parsimonious model similar to that used in Berry and Glaeser (2005) which controls for initial share of college graduates, population, share of total employment from manufacturing, and *per capita* income. To this model we add our within and between-industry education growth variables, along with our industry mix variable to control for overall metro area demand shifts. We then include all of our demographic variables and other controls. All of the models control for state fixed effects.

We are able to replicate Berry and Glaeser's (2005) results to a very close approximation, though not perfectly because we have a slightly larger sample of MSAs. To compare, Berry and Glaeser find a coefficient of 0.117 on the initial share of college graduates for the 1990–2000 model, where we report a coefficient of 0.093 in Table 2. An additional difference is that we use state fixed effects, whereas they use Census regional fixed effects, accounting for some of the difference. Indeed when we use regional fixed effects, we get a coefficient of 0.121 (not shown). This suggests we can be fairly confident that our later results are not attributable to the differences in which MSAs are included in the sample. We also find a positive and significant coefficient on log of per capita income, consistent with Berry and Glaeser's results. For the 1990s model, when we include our within and between-industry education growth variables, the coefficient on initial share of college graduates is reduced by about 65 per cent and is no longer statistically significant. In this specification, the between-industry education growth variable is positive and strongly significant. The within-industry education growth variable is positive, though not statistically significant. The reduction in statistical significance and magnitude of the initial college graduate share coefficient in our models provides some evidence against divergence of human capital among cities once industry composition effects are accounted for. It is possible that during the 1990s, graduates were moving in response to differences in MSA industry structure skill composition and less so to be near other college-educated workers.

In column 3, several demographic variables are associated with the decadal change in MSA college graduate share from 1990–2000. MSA growth of college graduate share was positively associated with the share of prime age workers, people age 25–54. The coefficient on the MSA share of population age 25–54 is 0.139, suggesting that each additional percentage point of MSA population in this age cohort is associated with a 0.14 per cent increase in the share of college-educated workers. It is likely that college graduates are locating in the most productive places, where larger shares of the population are in their prime working years. Conversely, college graduate share growth was inversely associated with the share of MSA population in the 55–64 range in the 1990s, but positively linked to the population share in the 65–84 range. It is possible places with larger shares of seniors have greater healthcare needs, attracting well educated workers in healthcare and healthcare-related fields, beyond what would be expected given the industry composition effects.

The story changes post-2000, as there is a clear shift in growth patterns towards places with larger populations. The positive initial MSA share of college graduates coefficient is (weakly) robust to the inclusion of our industry structure variables post-2000 in column 5, but significance disappears once we add demographic variables in column 6. Even without industry or demographic control variables in the model in column 4, the coefficient on initial share is less than half its value in the previous decade. The most conservative interpretation of our results suggest that initial share of college graduates has a dramatically reduced role in its association with highly-educated workers post-2000. If we consider the full model that includes both industry structure and demographic variables, we find little evidence of ongoing human capital divergence across MSAs. Rather, the models suggest population/agglomeration becomes the key driver of changes in MSA college graduate share. Each log point increase in the MSA population is associated with a 0.6 per cent increase in the share of the population with college degrees.

There are several reasons why college-educated workers may prefer places with larger populations outlined in the agglomeration literature. College workers may be attracted to thicker labour markets, where there are more abundant and diverse employment opportunities that allow highly-educated workers to reap the benefits of their specialized skills more completely. The greater importance placed on population may be a result of risk adverse workers moving to places with more opportunity post-2000 when there was increased labour market uncertainty, especially in the later years of the decade during the Great Recession. In the years after 2000, demographic factors influencing college graduate share growth have changed somewhat. College graduates are now associated with places that are more white and with more natural amenities, while negatively associated with higher shares of the elderly.<sup>5</sup> Finally, the pull of natural amenities appears to be greater post-2000 (compare columns 3 and 6).

### 5.2 Growth by education level

Next we disaggregate our dependent variables into those whose highest level of education is a bachelor's degree and those who have earned a graduate or professional degree to determine whether differences exist across higher levels of education. Table 3 displays the results for these models. We omit the most parsimonious models for each decade for the sake of brevity. It is important to note that in this case, we also disaggregate the initial share of college graduates variable into the initial share of the population whose highest level of education is a bachelor's degree and the initial share of the population whose highest level of education is a graduate or professional degree. In both decades, neither the initial share of MSA population with a bachelor's degree are associated with growth in the share of MSA population with a bachelor's degree. Conversely, places with higher initial shares of bachelor's degree holders. This trend holds across both decades and the estimated effect is larger post-2000.

Winters (2011) finds that smart cities are growing in part because students who come for their higher education tend to stay after graduation, increasing the share of MSA population with college degrees. It seems our result is not likely due to postgraduates staying in the city in which they graduated, as we find a negative relationship between initial MSA share of population with graduate or professional degrees and growth in graduate or professional share in the full 2000–2010 model. Workers with graduate or professional degrees may see bachelor's degree educated workers as complements, but see other workers with graduate or professional degrees as substitutes.

The effect of initial population on growth in MSA share of bachelor's degree holders is positive and significant in both decades. Post-2000 it is almost four times as large as in the 1990s, again suggesting the increasing importance of agglomeration for bachelor degree holders in the latter decade. However, the effect does not hold for growth in share of population with graduate or professional degrees. This suggests agglomeration externalities may be different for workers with higher levels of education. Workers with only a bachelor's degree may benefit more from thicker labour markets and may be seeking out places with larger populations to buffer against labour market sluggishness post-2000, which is further explored below. Conversely, those with post-secondary degrees may be so highly specialized that they migrate to places for specific jobs or to work in a specific industry hub located in certain cities.

<sup>&</sup>lt;sup>5</sup> At the suggestion of a referee, we examined whether there were other racial/ethnic features related to the growth of college graduates. For example, we examined whether there were differing racial/ethnic/age characteristics for MSAs depending on how fast the MSA gained college graduates. Specifically we divided the MSAs into the top 25 per cent of MSAs in terms of college graduate share growth, the middle 50 per cent in terms of college graduate share growth, and the bottom 25 per cent in terms of growth of the share of college graduates. However, we found no clear demographic pattern except the top 25% had more whites. We leave it to further research to assess if there are other demographic differences in the MSAs that had the fastest growth of the share of college graduates.

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		Bac	chelor's			Graduate/pi	rofessional	
	1990	-2000	2000	-2010	1990–	2000	2000-	2010
Initial share of bachelor's	0.041	0.013	-0.031	-0.041	0.076***	0.074***	0.118***	0.127***
Initial share of graduate/professionals	-0.014	-0.025	0.031	0.042	-0.048	-0.011	-0.044	-0.093**
to the second	(-0.38)	(-0.50)	(0.83)	(0.88) 0.400***	(-1.82)	(-0.34)	(-1.06)	(-2.04)
Log or population	(1.05)	(1.75)	(5.88)	(5.06)	-0.008 (-0.21)	-0.03)	0.004 (1.14)	0.108
Share of manufacturing	-0.005	-0.007	-0.053**	-0.069***	-0.005	-0.006	-0.004	-0.007
	(-0.56)	(-0.68)	(-2.20)	(-2.72)	(-0.80)	(-1.01)	(-0.17)	(-0.34)
Log of per capita income	0.844 (1.59)	0.882 (1.16)	-1.392** (-2.36)	1021- 	0.008 (1.41)	-0.312	0.279	0.244
Within industry education growth	0.284	0.219	0.937	0.919	0.473	0.457	-0.147	-0.046
	(0.78)	(0.66)	(1.49)	(1.43)	(1.57)	(1.58)	(-0.29)	(-0.08)
Between industry education growth	0.238*	0.210	-0.144	-0.116	0.499***	0.385***	0.112	0.113
Overall industry mix iob growth	(1.00)	(0.049*)	(60.0-) -0.006	-0.027	0.010	0.012	0.006	0.009
	(1.66)	(1.68)	(-0.11)	(-0.46)	(0.60)	(0.71)	(0.12)	(-0.20)
Per cent white		0.011		$0.034^{***}$		0.004		-0.003
		(1.28)		(3.16)		(0.85)		(-0.36)
Percentage 18–24		0.033		-0.033		-0.007		0.093**
		(0.90)		(-0.62)		(-0.22)		(2.32)
Percentage 23-34		100.0		-0.040		0.08/**		0.061
Percentage 55–64		-0.232*		-0.150		-0.093		0.110
)		(-1.91)		(-0.82)		(-1.34)		(0.83)
Percentage 65-84		0.104		0.050		$0.123^{***}$		0.135*
, ,		(1.56)		(0.52)		(2.89)		(1.79)
Percentage 84		0.042		(-0.94)		-0.400***		(-1.97)
Percentage foreign born		-0.024		0.022		0.017		-0.002
)		(-1.60)		(1.32)		(1.31)		(-0.15)
Amenity scale		0.043		0.062		0.036		$0.133^{***}$
		(1.03)		(0.94)		(1.54)		(3.08)
Constant	$-8.961^{*}$	$-11.926^{**}$	11.173*	9.588	-6.574	-0.762	-3.797	-8.847
	(-1.94)	(-2.01)	(1.76)	(1.15)	(-1.55)	(-0.18)	(-0.63)	(-1.22)
N	358	358	358	358	358	358	358	358
R-sq	0.591	0.617	0.338	0.378	0.668	0.703	0.478	0.517
Notes: $* p < 0.1, ** p < 0.05, *** p < 0.0$	1.							

Industry structure also played an important role for both bachelor's and postgraduate degree holders in the 1990s. Specifically for the 1990–2000 results, between-industry education growth has a positive and significant relationship to growth in the share of MSA population with a graduate or professional degree, but no statistically significant relationship with the growth in the share of bachelor degree holders (at least in the base models). Conversely, growth in the share of MSA population with only a bachelor's degree has a positive association with the industry mix employment growth variable, but this was statistically insignificant for the graduate/professional degree share. In the 1990s, more specialized graduate and professional workers may have targeted places whose highly-educated industries were growing fast, regardless of the strength of the entire local economy. This is consistent with the previous evidence that graduate and professional workers are moving to places with higher initial shares of bachelor degree holders.

Some other trends to note are that in both decades, larger shares of retirees (age 65–84) are positively linked to shares of graduate and professional degree holders, but this association changes for the share of elderly (over age 85). The relationship between initial shares of retirees and elderly with MSA postgraduate share growth are the only relationships that hold across both decades, other than postgraduate growth's relationship with initial share of MSA population with only a bachelor's degree. Also, post-2000, places with higher natural amenity levels are positively associated with the graduate and professional degree holder share of MSA population.

# 5.3 Robustness checks and sensitivity results

We estimated several additional models to assess the robustness of our results.<sup>6</sup> First we wanted to assess whether using MSA employment growth rather than the industry mix employment growth variable affects the results. Industry mix is considered an exogenous instrument for employment growth because it relies on national level employment growth for each industry within the MSA. We re-estimate our baseline models from Table 2, but use the industry mix growth variable as an instrument for MSA employment growth and report the results in columns (1)–(2) and columns (6)–(7) of Table 4. We find little difference between results of these models that include the instrumented employment growth and the original industry mix results in Table 2. The statistical insignificance of the initial share coefficients did not change in the 1990–2000 models and in the 2000–2010 models, the initial share coefficients became insignificant, further supporting our conclusion that cities are not on divergent human capital growth paths. The robustness checks also support the importance of agglomeration to college graduate growth post-2000 and provide some evidence that agglomeration may have also mattered in the 1990s (column 2).

Columns (3) and (8) in Table 4 show the results when using the overall college graduate share as the dependent variable but accounting for the potential endogeneity of the initial graduate share and initial population. Specifically, we use two-stage least squares regressions to estimate the same model as in Table 2 (columns (3) and (6)), but using 1970 MSA college graduate share and 1950 log of population as deep-lagged instruments for 1990 (and 2000) college graduate share and 1990 (and 2000) log of population. The availability of college graduate shares limits our analysis to the available 267 MSAs for which the data was available. Instrumenting for initial college shares and population did not affect the initial college graduate

 $<sup>^{6}</sup>$  In addition to the models described below, we also separately estimated models that respectively (*i*) replaced demographic variables with deeper time lags from 10 years before the start of the period; (*ii*) controlled for those living in group quarters; and (*iii*) models that spanned the entire 1990–2010 period. All of these additional robustness checks yielded results similar to our results in Table 2 for initial graduate shares and population and we do not discuss them further.

$ \begin{array}{c c c c c c c c c c c c c c c c c c c $			lable 4. D(				graduates 1000		2000-2010		
$ \begin{array}{c ccccc} (1) & (2) & (3)' & (4)' & (5)' & (6) & (7) & (8)' & (9)' & (0)' \\ \mbox{Initial probation} & (-13) & (-13)' & (-13)$			All graduates		Bachelor's	Grad/Prof		All graduates		Bachelor's	Grad/Prof
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(1)	(2)	(3) <sup>a</sup>	(4) <sup>a</sup>	(5) <sup>a</sup>	(9)	(1)	(8) <sup>a</sup>	(9) <sup>a</sup>	(10) <sup>a</sup>
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Initial share college grads	-0.009	0.031	-0.097	-0.232*	0.033	0.038	0.034	-0.109	-0.131	-0.062
$ \begin{array}{{ccccccccccccccccccccccccccccccccccc$	)	(-0.25)	(0.85)	(-1.40)	(-1.93)	(0.63)	(1.20)	(0.89)	(-1.60)	(-1.24)	(-1.06)
$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	Log of initial population	0.176	0.200*	0.102	0.150*	-0.067	$0.49^{***}$	$0.58^{***}$	$0.62^{***}$	$0.38^{***}$	$0.22^{***}$
$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$		(1.60)	(1.65)	(1.00)	(1.94)	(-1.28)	(6.35)	(5.36)	(5.13)	(4.18)	(2.65)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Initial share of manufacturing	-0.001	0.001	-0.016	-0.014	-0.003	-0.051	-0.074*	-0.077*	-0.070**	0.014
Log per apria income $-103$ $-203$ $-231$ $-049$ $-0324$ $-1110$ $230$ Within eduction growth $1075$ $1025$ $033$ $(139)$ $(139)$ $(130)$ $(120)$ $(027)$ <td></td> <td>(-0.04)</td> <td>(0.03)</td> <td>(-0.93)</td> <td>(-1.10)</td> <td>(-0.36)</td> <td>(-1.31)</td> <td>(-1.73)</td> <td>(-1.72)</td> <td>(-2.44)</td> <td>(0.76) 0.765***</td>		(-0.04)	(0.03)	(-0.93)	(-1.10)	(-0.36)	(-1.31)	(-1.73)	(-1.72)	(-2.44)	(0.76) 0.765***
Within education growth $(222)$ $(132)$ $(133)$	Log per capita income	4.138**	2.602	2.493*	2.813*	0.469	-0.542	-0.724	3.540**	0/11/0	2.60***
Writing current of grown         10.0		(777)	(1.33)	(1.81)	(6/.1)	(1.01)	(10.0-)	(-0.6/) 0.245	(2.14)	(0./1) 1 776**	(3.41)
$ \begin{array}{cccccc} \mbox{Berveau duction growth} & (1,3) & (1,0) & ($	Within education growth	C/0.1	700.1	0.543	170.0	*904.0	0.575	0.540	C/1.1	1./20**	0.288
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	D	(66.1)	(1.39) 0.006	(CU.I)	(/0.0)	(1.88) 0.162**	(0/.0)	(c/ .0) 000 0	(1.49)	(70.7)	(0.04) 0.41***
Employment growth         0.01         0.020         0.010         0.000         0.010	Detween education growin	051.0	-0.00	0.494	170.0	(3 <i>C C)</i>	(00.0-)	-0.200	-1100	(12.0-)	
Industry mix growth         (11)<	Employment growth	0 121	0 148	(10.0)	(70.7)	((77.7)	0.019	-0.004	(01.17)	(11.0)	(00.7)
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(111)	(1.13)				(0.33)	(-0.06)			
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Industry mix growth	~	~	0.068	0.025	0.042**	~	~	0.049	0.035	$0.100^{**}$
$ \begin{array}{ccccc} \mbox{Percentage while} & -0.037 & 0.023^{***} & 0.021^{***} & 0.037 & 0.06^{****} & 0.05^{*****} & 0.05^{*****} & 0.05^{******} & 0.05^{************************************$	•			(1.55)	(0.74)	(2.24)			(0.57)	(0.57)	(2.28)
Percentage 18-24 $(-0.76)$ $(2.00)$ $(2.10)$ $(0.83)$ $(1.55)$ $(4.72)$ $(4.40)$ $(0.06)$ Percentage 18-24 $(0.06)$ $(0.116)$ $(0.119)$ $(0.119)$ $(0.13)$ $(0.13)$ $(0.13)$ $(0.13)$ $(0.24)$ $(0.01)$	Percentage white		-0.037	$0.023^{**}$	$0.021^{**}$	0.004		0.037	$0.06^{***}$	$0.05^{***}$	0.007
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(-0.76)	(2.00)	(2.10)	(0.83)		(1.55)	(4.72)	(4.40)	(0.96)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Percentage 18-24		0.063	$0.134^{*}$	$0.119^{**}$	0.006		0.040	0.130	-0.015	$0.135^{**}$
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(0.66)	(1.67)	(2.42)	(0.14)		(0.39)	(1.35)	(-0.24)	(2.46)
Percentage 55-64 $(0.33)$ $(1.99)$ $(1.72)$ $(1.90)$ $(0.11)$ $(-0.40)$ $(-100)$ $(0.70)$ Percentage 55-64 $0.643$ $-0.387^{***}$ $-0.126^{**}$ $(0.13)$ $(-0.40)$ $(-100)$ $(0.70)$ Percentage 55-64 $0.643$ $-0.387^{***}$ $-0.126^{**}$ $(0.13)$ $(-0.61)$ $(0.73)$ Percentage 65-84 $(-0.51)$ $(-2.56)^{***}$ $(-1.73)^{***}$ $(-0.12)$ $(0.13)$ $(-0.61)$ $(0.73)$ Percentage 65-84 $-0.192$ $(-2.26)^{***}$ $(-1.73)^{***}$ $0.122^{****}$ $0.137$ $-0.033$ $-0.041$ $0.02$ Percentage foreign born $-0.199$ $0.009$ $-0.232$ $(-2.18)^{****}$ $0.013^{****}$ $0.013^{*****}$ $0.013^{*****}$ $0.013^{******}$ $0.013^{********}$ $0.013^{************************************$	Percentage 25-54		0.087	$0.184^{**}$	$0.116^{*}$	0.081*		0.014	-0.036	-0.075	0.039
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(0.93)	(1.99)	(1.72)	(1.90)		(0.11)	(-0.40)	(-1.00)	(0.71)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Percentage 55-64		0.643	-0.489**	-0.387**	-0.126*		-0.044	0.049	-0.116	0.103
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$			(0.70)	(-2.43)	(-2.26)	(-1.73)		(-0.12)	(0.18)	(-0.65)	(0.70)
Percentage over 84 $(-0.51)$ $(2.56)$ $(1.98)$ $(2.47)$ $(-0.32)$ $(-0.42)$ $(0.6)$ Percentage over 84 $1.266$ $-0.584$ $-0.109$ $-0.491$ $(-0.42)$ $(0.63)$ $(-0.42)$ $(0.63)$ $(-0.42)$ $(0.6)$ Percentage foreign born $-0.109$ $-0.022$ $(-0.31)$ $(-1.34)$ $(-0.32)$ $(-1.33)$ $(-0.42)$ $(-0.63)$ $(-0.13)$ $(-0.99)$ $(-0.13)$ $(-0.42)$ $(-0.63)$ Percentage foreign born $-0.116$ $(0.09)$ $(-0.32)$ $(-1.34)$ $(-1.34)$ $(-1.34)$ $(-1.34)$ $(-1.33)$ $(-0.24)$ <	Percentage 65–84		-0.192	0.280 **	$0.147^{**}$	$0.122^{**}$		0.158	-0.003	-0.041	0.055
Percentage over 84 $1.266$ $-0.534$ $-0.109$ $-0.491^{***}$ $-0.834$ $-0.537$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.637$ $-0.137$ $-0.630$ $(-1.41)$ $(-2.279)$ $(-0.89)$ $(-0.89)$ $(-0.31)$ $(-1.57)$ Percentage foreign born $-0.019$ $0.009$ $-0.022$ $0.031^{**}$ $0.015$ $(0.019)$ $(0.02)$ $-0.01$ Amenity scale $(-1.70)$ $(-1.34)$ $(2.18)$ $(0.72)$ $(1.10)$ $(0.72)$ $(-0.018)$ $(0.018)$ $(0.012)$ $(-0.018)$ Amenity scale $(1.62)$ $(1.10)$ $(0.72)$ $(1.57)$ $(2.64)$ $(1.131)$ $(1.27)$ $(-0.24)$ $(-0.24)$ $(-0.24)$ $(-2.24)$ $(-0.28)$ $(-2.24)$ $(-0.88)$ $(-2.39)$ $(-2.34)$ $(-0.28)$ $(-2.3)$ $(-2.34)$ $(-2.24)$ $(-0.28)$ $(-2.34)$ $(-2.49)$			(-0.51)	(2.56)	(1.98)	(2.47)		(1.36)	(-0.03)	(-0.42)	(0.69)
Percentage foreign born $(0.33)$ $(-1.41)$ $(-0.32)$ $(-2.79)$ $(-1.03)$ $(-0.89)$ $(-0.31)$ $(-1.32)$ $(-1.33)$ $(-2.9)$ $(-2.9)$ $(-2.9)$ $(-2.9)$ $(-2.9)$ $(-2.9)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3)$ $(-2.3$	Percentage over 84		1.266	-0.584	-0.109	-0.491***		-0.834	-0.537	-0.137	-0.604
Percentage foreign born $-0.019$ $0.009$ $-0.022$ $0.013$ $0.019$ $0.022$ $-0.01$ Amenity scale $(-1.38)$ $(0.36)$ $(-1.34)$ $(2.18)$ $(0.79)$ $(0.81)$ $(1.27)$ $(-0.98)$ Amenity scale $(-1.71)$ $(-2.18)$ $(0.79)$ $(0.81)$ $(1.27)$ $(-0.98)$ Amenity scale $(1.62)$ $(1.10)$ $(0.72)$ $(0.79)$ $(0.11)$ $(0.29)$ $(2.06)$ Constant $-47.1^{+*}$ $-39.1^{*}$ $-32.105$ $-31.11$ $-7.92^{*}$ $-2.758$ $-6.249$ $-44.6^{**}$ $15.059$ $-32.0$ Constant $(-2.21)$ $(-1.71)$ $(-2.64)$ $(-1.83)$ $(-0.24)$ $(-2.9)$ $(-2.8)$ $(-2.8)$ $(-2.8)$ $(-2.8)$ $(-2.8)$ $(-3.9)$ $(-2.8)$ $(-0.88)$ $(-3.9)$ N $35.8$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$ $267$			(0.83)	(-1.41)	(-0.32)	(-2.79)		(-1.03)	(-0.89)	(-0.31)	(-1.55)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Percentage foreign born		-0.019	0.009	-0.022	$0.031^{**}$		0.015	0.019	0.022	-0.016
Amenity scale $0.176$ $0.072$ $0.037$ $0.045$ $0.20^{***}$ $0.114$ $0.018$ $0.06$ $(1.62)$ $(1.10)$ $(0.72)$ $(1.57)$ $0.20^{***}$ $0.114$ $0.018$ $0.05$ $(1.62)$ $(1.10)$ $(0.72)$ $(1.57)$ $(2.64)$ $(1.31)$ $(0.29)$ $(2.06)$ Constant $-47.1^{**}$ $-39.1^{*}$ $-32.105$ $-31.11$ $-7.92^{*}$ $-6.249$ $-44.6^{**}$ $15.059$ $-32.0^{*}$ Constant $(-2.21)$ $(-1.71)$ $(-2.69)$ $(-2.34)$ $(-1.85)$ $(-0.24)$ $(-0.43)$ $(-0.88)$ $(-3.9)$ N $358$ $267$ $267$ $267$ $358$ $267$ <t< td=""><td></td><td></td><td>(-0.89)</td><td>(0.36)</td><td>(-1.34)</td><td>(2.18)</td><td></td><td>(0.79)</td><td>(0.81)</td><td>(1.27)</td><td>(-0.98)</td></t<>			(-0.89)	(0.36)	(-1.34)	(2.18)		(0.79)	(0.81)	(1.27)	(-0.98)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Amenity scale		0.176	0.072	0.037	0.045		$0.20^{***}$	0.114	0.018	$0.091^{**}$
Constant $-47,1^{**}$ $-39,1^{*}$ $-32,105$ $-31,11$ $-7,92^{*}$ $-2.758$ $-6.249$ $-44,6^{**}$ $15,059$ $-32,0^{*}$ $-32,0^{*}$ $(-2.21)$ $(-1,71)$ $(-2.69)$ $(-2.34)$ $(-1,85)$ $(-0.24)$ $(-0.43)$ $(-2.49)$ $(-0.88)$ $(-3.92)$ $(-3.9$			(1.62)	(1.10)	(0.72)	(1.57)		(2.64)	(1.31)	(0.29)	(2.08)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Constant	$-47.1^{**}$	-39.1*	-32.105	-31.11	-7.92*	-2.758	-6.249	-44.6**	15.059	$-32.0^{***}$
N 358 358 267 267 267 358 358 267 267 267 267 267 267 267 267 267 267		(-2.21)	(-1.71)	(-2.69)	(-2.34)	(-1.85)	(-0.24)	(-0.43)	(-2.49)	(-0.88)	(-3.95)
	Z	358	358	267	267	267	358	358	267	267	267
R-sq 0.540 0.424 0.501 0.585 0.576 0.471 0.502 0.540 0.573 0.502 0.57	R-sq	0.540	0.454	0.561	0.385	0.573	0.471	0.505	0.277	0.233	0.324
	<sup>a</sup> In the IV models in columns (:	3), (4), (5) and (8), (	9), (10) the endoger	nous variables are in	itial share of college	graduates and log of	f population. The e	cogenous instrument	ts are 1970 share of	college graduates a	nd log of 1950

share results, producing negative and insignificant results in the both cases. The population results were unchanged – being statistically insignificant in the 1990s (column 3) and positive and significant in the 2000–2010 model (column 8), further strengthening our original findings about larger population attracting college graduates after 2000.

We next repeat the instrumental variable analysis treating population and the initial college graduate share as endogenous using the same instruments as before, but where we split the dependent variable into those with bachelor's degrees and those with graduate/professional degrees (columns 4–5 and 9–10). In this case, given data availability for the lagged instrument, we can only use the lagged total college graduate share. The initial college graduate share in this model remains insignificant except in the 1990–2000 bachelor's degree model, in which the coefficient is negative and significant, in total further supporting the notion that graduate shares are not diverging. For the population results, we continue to see that growth in bachelor's degrees is linked to larger cities in both decades, with the graduate/professional degree share being positively linked to population in the 2000–2010 decade. In this case, there is also some evidence that the graduate/professional degree share is positively associated with stronger overall job growth (industry mix growth) regardless of the industry composition in both decades.

Another concern is that cross sectional models can be affected by unobservable factors that influence the effects of key covariates on the dependent variable. This concern would be problematic if the omitted MSA fixed effect is correlated with the explanatory variables such as the demographic variables. First-difference models control for omitted unobservable time-invariant factors that may bias cross-sectional models by 'differencing out' their effects. Thus, we first-difference the data across decades and re-estimate the models. Note that first-difference models have a key advantage over fixed effects models in that they do not rely on the assumption of strict exogeneity of the residuals and are thus a more robust estimator than fixed effects models (Wooldridge 2010).

The results in Table 5 are the first-difference analogue of those in Table 2, where the independent and dependent variables are the difference between the 1990 variables and the 2000 variables. For instance, if the initial share of college graduates in MSA *i* was 20 per cent in 1990 and 25 per cent in 2000, the initial share value for MSA *i* in the first-difference model is 5 per cent (25 - 20 = 5). This allows us to assess how the change in initial share of college graduates affects the change in college graduate share growth between the two decades. Columns 1-3report the results for all college graduates, with the results for bachelor's degree only and graduate/professional degrees being respectively reported in columns 4-6 and 7-9. In all of these specifications, we find that initial MSA college graduate share has a negative relationship with the change in MSA college graduate share, even after differencing out any time invariant unobservable factors. This result is statistically significant at the 1 per cent level in all nine specifications. Likewise the coefficient on the log of initial population is positive and statistically significant at the 1 per cent level for all nine specifications, supporting our results in the cross-sectional models. Hence the first difference models give us greater confidence in our previous results that the growth of college graduates is not diverging and may be conditionally converging, whereas population is positively linked to the growth of college graduate shares in all cases. Finally, there is some evidence that having a concentration of industries that were upskilling (within industry education growth) was also positively associated with the growth in college graduate shares in these models. Yet, we cannot separate whether these results are mostly due to changes in the 1990s or after 2000 due to the first differencing.

Finally, we check to see how our post-2000 results are influenced by the Great Recession. We split 2000–2010 sample into 2000–2007 and 2007–2010 time periods. The results for all college graduates are reported in Table 6. It appears the Great Recession influenced how different factors affected MSA growth of college graduates. The coefficient on the initial MSA college graduate share is positive and significant in the pre-recession period, but turns negative

		Table 5. First Di	fference Models	of the Difference	e in MSA share o	f graduates			
		All graduates			Bachelor's		Gr	aduate/professio	nal
	(1)	(2)	(3)	(4)	(5)	(9)	(1)	(8)	(6)
Initial share college grads	-0.65***	-0.62***	-0.62***	-0.87***	$-0.84^{***}$	-0.8***	-0.66***	-0.68***	-0.71***
)	(-7.44)	(-7.71)	(-7.33)	(-7.55)	(-7.94)	(-7.36)	(-6.66)	(-6.61)	(-6.55)
Log of initial population	4.648***	4.518***	4.761***	$3.314^{***}$	3.144 * * *	2.893**	2.112***	1.982**	2.755***
•	(4.12)	(3.86)	(3.44)	(3.12)	(2.95)	(2.48)	(2.67)	(2.48)	(3.36)
Initial share of manufacturing	-0.026	-0.026	-0.025	-0.035	-0.033	-0.024	0.008	0.012	0.002
	(-0.65)	(-0.69)	(-0.65)	(-1.02)	(-1.00)	(-0.70)	(0.31)	(0.49)	(0.08)
Log per capita income	1.244	0.790	0.269	0.429	0.180	-0.217	2.547**	2.247*	2.320*
	(0.59)	(0.36)	(0.11)	(0.27)	(0.11)	(-0.12)	(2.16)	(1.86)	(1.80)
Within education growth		$0.904^{***}$	$1.078^{***}$		$0.969^{**}$	$0.906^{**}$		$1.219^{**}$	$1.618^{***}$
		(2.79)	(3.11)		(2.37)	(2.18)		(2.36)	(3.01)
Between education growth		0.010	-0.012		-0.069	-0.063		-0.047	-0.084
		(0.07)	(-0.08)		(-0.37)	(-0.34)		(-0.26)	(-0.43)
Overall industry mix job growth		0.047	0.037		0.048	0.037		0.005	-0.001
		(1.33)	(0.94)		(1.53)	(1.18)		(0.29)	(-0.07)
Percentage white			-0.054			0.004			-0.058
			(-1.44)			(0.00)			(-1.41)
Percentage 18–24			-0.209			-0.165			-0.056
			(-1.56)			(-1.53)			(-0.71)
Percentage 25–54			0.060			0.110			-0.059
			(0.38)			(0.91)			(-0.62)
Percentage 55-64			-0.020			-0.154			0.158
			(-0.08)			(-0.75)			(0.99)
Percentage 65–84			0.067			0.020			0.001
			(0.41)			(0.15)			(0.01)
Percentage over 84			-0.135			-0.056			-0.057
			(-0.25)			(-0.12) 0.008			(-0.17)
			-0.000			-0.100			-0.104
Constant	_0 133	0.100	(61.1–) 	076.0	0 368	0.14)	0 707	-0530	( <i>CE</i> .1–) 718 O
COIDStailt	1210	(11.0)	(300)	617.0	00.5.0	0.270	761.0-	(30 0 )	/ 10.0-
	(ст.п–)	(11.0)	(07.0-)	(0.44)	(70.0)	(10.0)	(/C.1-)	(co.n-)	(11.1–)
N	358	358	358	358	358	358	358	358	358
R-sq	0.422	0.440	0.455	0.414	0.429	0.442	0.371	0.385	0.412
<i>Notes</i> : $* p < 0.1$ , $** p < 0.05$ , $***$	p < 0.01.								

		2000–2007			2007-2010	
Initial share of college grads	0.04**	0.046**	0.050*	-0.050**	-0.075***	-0.145***
	(2.06)	(2.28)	(1.71)	(-2.52)	(-2.85)	(-4.25)
Log of population	0.53***	0.163*	0.190	0.330***	0.324***	0.399***
	(5.27)	(1.79)	(1.62)	(2.84)	(3.03)	(2.71)
Share of manufacturing	$-0.05^{**}$	0.011	-0.005	-0.053**	-0.050	-0.064
	(-2.55)	(0.47)	(-0.19)	(-2.17)	(-1.16)	(-1.58)
Log of per capita income	-0.905	-0.108	-0.446	0.033	-0.088	1.684
	(-0.96)	(-0.14)	(-0.48)	(0.03)	(-0.09)	(1.22)
Within industry education growth		0.859*	0.883*		0.907	2.058
		(1.81)	(1.80)		(0.62)	(1.47)
Between industry education growth		-0.247*	-0.235*		-0.258	-0.075
		(-1.80)	(-1.78)		(-1.02)	(-0.28)
Overall industry mix job growth		0.19***	0.17**		0.023	-0.022
		(2.60)	(2.10)		(0.23)	(-0.22)
Percentage white			0.023*			0.014
			(1.79)			(0.90)
Percentage 18-24			-0.031			0.176***
-			(-0.46)			(2.75)
Percentage 25–54			-0.009			0.195*
-			(-0.10)			(1.96)
Percentage 55-64			-0.028			-0.187
-			(-0.15)			(-1.25)
Percentage 65-84			-0.112			-0.073
-			(-0.90)			(-0.66)
Percentage over 84			0.657			0.921**
-			(1.26)			(2.47)
Percentage foreign born			0.005			-0.000
			(0.26)			(-1.63)
Amenity scale			0.012			0.234***
-			(0.16)			(2.60)
Constant	4.421	-3.363	-0.444	-2.628	-1.607	-29.14**
	(0.52)	(-0.48)	(-0.05)	(-0.27)	(-0.17)	(-2.18)
Ν	358	356	356	356	356	354
R-sq	0.455	0.346	0.360	0.224	0.230	0.306

Table 6. Determinants of the difference in the MSA share of college graduates (2000–2007 and 2007–2010)

*Notes*: \* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01.

and significant during the recession (with a much larger magnitude). Also, the agglomeration effect is of greater magnitude once the industry education variables are included and more strongly significant in all models during the recession years. Recessionary forces may be linked to the relative strengthening of the agglomeration forces, consistent with our previous conjecture that agglomeration forces (including labour market matching) are a stronger pull factor in sluggish labour markets. Also, increases in within-industry demands for college graduates (skill upgrading) and an overall fast-growing industry composition were associated with greater increases in college graduates pre-recession, but not post-recession. These again support our notion that labour market matching concerns play a key role in weak labour markets, supporting the positive agglomeration results.

## 6 Conclusion

Highly-educated workers are a strongly sought after commodity and are often the focus of policy interventions to enhance local economic development. Yet, only a few studies have

considered which city-level characteristics influence college graduate share growth and those have only typically investigated the decades prior to 2000. We investigate the decades 1990–2000 and 2000–2010 and compare how the factors attracting highly-educated workers may have changed. We also control for previously unconsidered exogenous measures of industry composition dynamics and overall labour demand growth that may have confounded results from previous studies.

Unlike past research, we find little evidence for human capital divergence across cities in either the 1990s or post-2000. Rather we find agglomeration to be the key factor attracting college graduates in the first decade of the new millennium. This may suggest workers are seeking thicker labour markets in the face of increasing labour market uncertainty, a result further supported by our examination of the pre and post-Great Recession periods separately. We also find some evidence that the growth of smart industries had a significant impact on attracting highly-educated workers in the 1990s, but the effect almost disappeared post-2000. The use of first-difference estimators further confirmed these patterns, suggesting that omitted time-invariant factors are not the cause of our results. Additionally, we find the agglomeration effect holds for workers with only bachelor's degrees, but the result is more mixed for attracting graduate or professional degree holders, though the first difference results also supported this effect for graduates and professionals. There was also weak evidence that having a composition of industries that are upskilling attracted more graduates, but again the evidence was mixed.

Our work seems to suggest that larger places with thick labour markets will continue to see growth in the share of their population holding college degrees, rather than places with high initial shares of educated workers. Such a pattern suggests that long-term leaders in the share of 'smart' people may not necessarily have the inside track in attracting even more smart people in the future. Our mixed results also provide evidence that the strategy of trying to identify and attract fast growing industries (or fast growing smart industries) will not ensure an increase in the proportion of well educated workers in the area.

From a policy standpoint, what can be done to help smaller cities attract more knowledge workers? It seems the best policies will help establish stable labour markets and employment opportunities. Such strategies may not seem as exciting as trying to create vibrant cultural and art communities or transforming into the hub of the next fast growing industry. However, fast growing industries had little impact on growth of highly-educated workers post-2000 and we should not expect attraction of fast growing industries to bring highly-educated workers to the region. Instead, policy-makers should pursue policies that focus on long-term growth across the board that provide more diverse and stable labour markets. To the extent that larger cities have an advantage in attracting highly-educated workers, trends post-2000 may suggest a turn-around from the patterns of the latter half of the 20th century. In the late 20th century, the largest American cities lagged smaller and medium-sized metropolitan areas in terms of growth (Partridge 2010). Such patterns should be closely monitored for changes.

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**Resumen.** Los formuladores de políticas regionales han tratado por mucho tiempo de atraer a trabajadores altamente cualificados con el fin de estimular el crecimiento económico y la vitalidad. Los estudios previos en las décadas anteriores al nuevo milenio muestran una divergencia en el capital humano por ciudades, según la cual la proporción de graduados universitarios crece más rápido en las ciudades con tasas iniciales mayores de trabajadores con educación universitaria. Sin embargo, los mercados de trabajo han cambiado significativamente después del año 2000, lo que probablemente ha afectado a las decisiones de migración de trabajadores altamente cualificados. Además, los estudios anteriores no han controlado los cambios importantes en los niveles de educación de la industria y la composición general de la industria que podrían influir en el crecimiento de graduados universitarios en cada ciudad. Se utilizan datos detallados NAICS de 4 dígitos del empleo en industrias combinados con microdatos públicos para el desarrollo de medidas de actualización de las cualificaciones en las industrias y de cambios en la composición de las industrias para el control de sus efectos sobre el crecimiento del capital humano. Se encontró que las fuerzas de aglomeración, en vez de las tasas iniciales de graduados, explicaron el crecimiento de la distribución de graduados universitarios posterior al año 2000. También se desagregaron los graduados de licenciatura y de posgrado para determinar si hay diferentes fuerzas en juego en el crecimiento de los graduados en función de los diferentes niveles de educación.

要約:地域政策当局は、経済成長の促進と活性化を狙って、長期にわたり高学歴労働者を引き付け る政策を模索してきた。西暦2000年までの数十年の間に行われた研究は、都市間の人的資本の多様 性を明らかにした。当初から大卒労働者の割合の高い都市では大卒生のシェアは早く増大する。し かし、2000年代に入り労働市場は大きく変貌し、その変化が高度技能労働者の移住意思決定に影響 を与える可能性が高い。さらに、従来の研究では、都市レベルでの大学卒業生の増加に影響を与え る可能性がある、産業の教育レベルならびに産業の全体的な構成における重要な変化がコントロー ルされていなかった。我々は、人的資本成長に対する効果をコントロールするため、公開されてい るミクロデータと組み合わせた詳細な、NAICSコード4桁の産業分類の雇用データを使って、産業の 技能向上と産業構成の変化に関する指標を構築した。当初の大学卒業生のシェアではなく集積力が 2000年代の大学卒業生のシェア増加を説明することが示された。さらに我々は、大学卒業生を学部 卒と大学院卒に分類して、学歴の異なる卒業生の増加には様々な要因の作用が存在するかどうかを 検討した。