Human Capital Externalities and the Geographic Variation in Returns to Experience*

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Abstract

This paper provides evidence that the average human capital of a labor market has a positive effect on individual human capital accumulation and wage growth over the life cycle. The return to experience in a labor market is found to be increasing in the share of workers with a bachelor's degree or more (college share) in the market. An instrumental variable and panel data with individual fixed effects are used to address the potential endogeneity of college share and the sorting of workers across labor markets respectively. The effect of the college share of a labor market is shown to persist after workers leave the market, suggesting that a larger college share raises the return to experience through the accumulation of human capital valuable in all markets. The findings provide an explanation for the higher returns to experience in large cities and rich countries documented recently in the literature.

Keywords: Human Capital; Knowledge spillovers; Local Labor Markets; Return to Experience

JEL: J31, O15, R11

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1 Introduction

Human capital externalities have long been thought to be an important factor for optimal education policy and cross-country income differences. Two types of human capital externalities have been proposed in the literature[1]. The first one, referred to as the level effect of average human capital hereafter, hypothesizes that the average human capital of an economy has a direct effect on the productivity and, in turn, the *price* of individual human capital (Lucas (1988)), while the second one conjectures an effect of average human capital on the production, and consequently, the *stock* of individual human capital (Tamura (1991), Glaeser (1999) and Lucas (2004)), and I will refer to this as the growth effect of average human capital. Both the level and the growth effect predict a positive effect of average human capital on individual wages. Motivated by this, a growing literature quantifies the magnitude of human capital externalities by relating individual wages to measures of average human capital[2,3].

This paper provides evidence for the growth effect of average human capital. Distinguishing the growth effect from the level effect is important because the two effects have different implications for the causes and patterns of income differences across economies. For example, the level effect predicts that the wage premium from living in a high average human capital market is constant across workers of different levels of experience, while the growth effect predicts a wage premium that is increasing in experience. More importantly, while the productivity gain and the wage premium from the level effect is attached to the market and will be lost as a worker moves away from a market, the growth effect, because it raises the worker's level of human capital valuable in all markets, is embodied in the worker and can be taken to other markets as the worker moves.

To obtain evidence for the growth effect, this paper shifts the focus from wage level to wage growth with experience. If the same worker can accumulate more human capital in markets with a higher level of average human capital, we would expect that (1) returns to experience are higher in markets with a higher level of average human capital, and (2) for workers who have moved across markets, wages in one market should be positively related to the average human capital of the previous markets.

I start by documenting a positive correlation between average human capital, measured by the share of workers with a bachelor's degree or more (college share), and the return to experience across

[1] This article focuses on the externalities related to wages. However, it should be noted that human capital externalities may also appear as nonproduction externalities, for example, by reducing crime rates, by increasing civic participation, and by enhancing political stability. Davies (2003) provides a survey on nonproduction externalities.

[2] See, for example, Rauch (1993), Acemoglu and Angrist (2001), Moretti (2004a,c) and Ciccone and Peri (2006). Moretti (2004b) and Lange and Topel (2006) provide reviews of the literature. In a work in progress (Guo et al. (2015)), my coauthors and I revisit the effect of state average schooling on individual wages addressed in Acemoglu and Angrist (2001), and we find significant external effects of average schooling.

[3] A positive effect of average human capital on individual wages, however, may not be conclusive evidence of human capital externalities. For example, Acemoglu (1996) demonstrates that the social increasing return in human capital may arise as pecuniary externalities in a frictional environment featuring complementarity between human and physical capital. Additionally, as shown in studies like Mas and Moretti (2009) and Cornelissen et al. (2013), the wage of an individual worker may increase in the average productivity of coworkers due to the extra effort from social pressure.

local labor markets in the US. I then take three steps to show that this correlation reflects a causal effect of college share on individual human capital accumulation.

The first step rules out the possibility that the correlation between college share and the return to experience is due to the selection of workers with higher learning abilities into markets with larger college shares. In particular, I estimate a wage model with individual fixed effects using panel data from the National Longitudinal Survey of Youths 1979 (NLSY79). For workers who have moved across markets, I show that wage grows faster when the worker is in a market with a larger college share. In case that migration is not random, I also show that, for the same worker in the same market, wage grows faster when the college share of the market is higher. Assuming worker's learning ability is fixed over time, the faster wage growth in markets with larger college shares reflects a causal effect of the markets instead of sorting of workers across markets.

The second step provides evidence that the faster wage growth in markets with larger college shares is due to the accumulation of human capital valuable in all markets. Specifically, I use the sample of movers in the NLSY79 to show that, among workers currently in the same market, wages are positively related to the college share of the previous market. To address the potential concern of selective migration, I use workers who have moved at least twice and have been to at least three markets. For these workers, I can control for their wages as well as other labor market information in the first market to make sure that the workers currently in the same third market were comparable before moving into different second markets. The assumption is that, conditional on the wage and other labor market information at the end of the first market, workers currently in the same third market were not systematically different from each other when they moved into different second markets. Consistent with this assumption, I find that worker ability as measured by Armed Forces Qualification Test (AFQT) score is not significantly related to the college share of the second market. Using this strategy, I find a positive effect of the college share of the second market on wages in the third market, suggesting that markets with larger college shares raise wage growth through the accumulation of human capital valuable in all markets.

Finally, by exploiting the exogenous variation in college share driven by an instrumental variable, I show that the effect of markets with larger college shares on wage growth and human capital accumulation is due to college share itself as opposed to other characteristics of the markets. Following Moretti (2004a) and Shapiro (2006), the instrument used in this paper is the presence of land-grant colleges in a labor market. The validity of this instrument is supported by the facts that (1) land-grant colleges are evenly distributed geographically, and markets with and without land-grant colleges are not significantly different from each other in terms of human capital until recently when the land-grant colleges are of significant size, and (2) markets with land-grant colleges have a larger fraction of college graduates and a smaller fraction of high school graduates but are otherwise similar to markets without land-grant colleges in the fraction of workers with other levels of schooling, suggesting that the main effect of a land-grant college is to attract local students to attend and finish college. Using this instrument, I find a significantly positive effect of college share on returns to experience.

Overall, the evidence presented in this paper is consistent with the existence of human capital externalities where, through knowledge spillovers, the same worker can learn more in a market with a larger fraction of skilled workers (Tamura (1991), Glaeser (1999), Lucas (2004)). The estimates suggest that a one percentage point increase in the college share of a labor market raises the return to the first ten years of experience by about 0.5 percentage point. As the range of college shares across labor markets in 2000 is about 30 percentage points, the growth effect of average human capital implies that such a difference in college share will lead to a 15 percentage points difference in the return to the first ten years of experience.

While there is strong evidence of knowledge spillovers in specific settings like elementary school teaching (Jackson and Bruegmann (2009)) and medical science research (Azoulay et al. (2010)), direct evidence of knowledge spillovers at the labor market level is scant. Choi (2011) makes inferences about learning externalities by calibrating a growth model to the macro data of US. In contrast, this paper provides evidence for knowledge spillovers in the context of local labor markets using micro data. The findings of this paper contribute to the literature on the causes and consequences of differences in labor market outcomes across local labor markets within a country (Moretti (2011)).

This paper also contributes to the recent literature on the geographic variation in returns to experience. For example, Glaeser and Mare (2001), Yankow (2006), Baum-Snow and Pavan (2012) and De la Roca and Puga (2015) find that wage grows faster with experience in large cities than smaller cities and rural areas, Lagakos et al. (2014, 2015) find that the experience-wage profiles are on average twice as steep in rich countries as in poor countries. Because large cities and rich countries tend to have larger fractions of college-educated workers[4], the growth effect of college share estimated in this paper provides an explanation for the higher returns to experience in large cities and rich countries.

It's important to note that the growth effect in this paper refers to the effect of average human capital on individual human capital accumulation and wage growth over the life cycle. It's not the effect of average human capital on the growth of an economy over time in terms of employment (population) or income (productivity)[5]. However, if workers can accumulate more human capital and experience faster wage growth in markets with higher levels of average human capital, they will have an incentive to move into those markets, leading to a positive correlation between average human capital and employment (population) growth across markets. Faster population growth, in turn, can lead to faster income growth in the existence of agglomeration economies. Consequently, the growth effect estimated in this paper is likely a contributor to the effect of average human capital on economic growth studied in the literature.

The results in this paper provide a justification for subsidizing higher education. In particular, as

[4]For example, the correlation between population of workers and college share across the labor markets used in this paper is 0.44. At the country level, using data from the World Development Indicators, one percentage point increase in the fraction of workers with tertiary education is associated with a $986 increase in GDP per capita in 2000.

[5]For works in this literature, see, for example, Glaeser et al. (1995), Simon (1998), Simon and Nardinelli (2002), Glaeser and Shapiro (2003), and Shapiro (2006).

a direction for future research, the effects of college share estimated in this paper can be incorporated into models of the effect of public subsidies to higher education on the college share of the labor force[6] to solve for the optimal level of subsidies.

Finally, the growth effect estimated in this paper also has implications for understanding individual migration decisions. While the migration literature typically focuses on the effect of the differences in income levels on individual locational choices (Kennan and Walker (2011)), the geographic variation in returns to experience and human capital accumulation provide another motivation for migration. Quantifying the magnitude of this motivation contributes to the understanding of the geographic mobility of workers and the rise and decline of cities. This is left for future research.

The rest of this paper proceeds as follows. Section 2 uses a simple model to outline the empirical strategies I use to estimate the growth effect of average human capital. Section 3 introduces the data and documents a positive correlation between college share and the return to experience across local labor markets in the US. Section 4 estimates the effect of markets with larger college shares on the return to experience with the panel data from NLSY79. Section 5 estimates the effect of markets with larger college shares on human capital accumulation using the sample of movers in NLSY79. Section 6 uses the presence of land-grant colleges as an instrument to estimate the causal effect of college share on the return to experience using the 2000 census. Section 7 concludes the paper.

2 Empirical Framework

This section presents a simple model of wage determination and human capital accumulation. The model allows me to discuss the issues in identifying the effect of average human capital on the return to experience and individual human capital accumulation, and to outline my solutions to these issues.

Let the wage $w_{i,t}$ and human capital $h_{i,t}$ of individual i at time t be determined by

$$w_{i,t} = p_{c_{i,t},t} h_{i,t} \tag{1}$$

$$\log h_{i,t} = \log h_{i,t_0} + B\left(e_{i,t}, \theta_i, C\left(i,t\right)\right) \tag{2}$$

where $c_{i,t}$ is the current labor market of residence, $p_{c,t}$ is the price (rental rate) of human capital in market c at time t, h_{i,t_0} is the stock of human capital for individual i at the time of labor market entry t_0[7], and $B\left(\bullet\right)$ is the amount of human capital accumulated since time t_0 that depends on work experience $e_{i,t}$, learning ability θ_i, and $C\left(i,t\right) = \left\{c_{i,\tau}\right\}_{\tau=t_0}^{t}$, the sequence of labor markets the individual has been to since time t_0.

Equation (1) says that individual wage is given by the product of human capital and its price. Human capital price is allowed to vary across markets as well as over time. It subsumes all de-

[6] See Kennan (2015) for an example of such models.

[7] Clearly, t_0 varies across individuals, and the individual i subscript is omitted for simplicity.

terminants of the productivity of individual human capital. One such factor is the average human capital of the market. In a seminal work, Lucas (1988) proposes an external effect of average human capital on the productivity of individual human capital. This effect will be reflected on the price of human capital[8]. Relatedly, Acemoglu (1996) shows that the effect of average human capital on worker productivity may be pecuniary in a frictional environment with complementary between human and physical capital. Distinguishing these alternative explanations is beyond the scope of this paper. Instead, I simply assume that the price of human capital could vary with the average human capital of a market, and refer to this as the level effect of average human capital.

Equation (2) breaks individual human capital at any time into two parts, one part accumulated before entering the labor market h_{i,t_0}, most likely through schooling, and another part accumulated from work experience $B(\bullet)$. We expect the amount of human capital accumulated on the job to increase with experience $\frac{\partial B(\bullet)}{\partial e} \geq 0$, and individuals with higher learning ability can accumulate more human capital with the same amount of experience $\frac{\partial B(\bullet)}{\partial \theta} \geq 0$. The human capital accumulation technology is also allowed to vary across labor markets. If there are knowledge spillovers, a worker will learn more and accumulate more human capital in markets with more skilled workers. This would be the case if, as assumed in Glaeser (1999), the probability of learning at any time depends positively on the fraction of skilled workers in a labor market. Tamura (1991) assumes that the average human capital of an economy has a direct effect on the productivity of individual human capital production[9], and explores theoretically its implications on income convergence. Using a similar human capital production technology, Lucas (2004) investigates the implications of knowledge spillovers on rural-to-urban migration. A direct implication of these models is a positive effect of average human capital on individual human capital accumulation. I will refer to this effect as the growth effect of average human capital. The goal of this paper is to estimate this growth effect empirically.

Assume both the level and the growth effect are positive, they both lead to a higher wage for workers in a market with a higher level of average human capital. The two effects, however, have different implications. Essentially, the level effect is attached to the market, and it induces a parallel shift of the experience-wage profile. The growth effect, on the other hand, is embodied in the worker, and it leads to a rotation of the experience-wage profile, resulting in a larger wage premium for more experienced workers. When a worker moves from a high average human capital market to a low average human capital market, her wage will drop due to the level effect. However, her wage will

[8]The technology of goods production with human capital externalize as given in equation (11) of Lucas (1988) is $AK^{\beta}(uhN)^{1-\beta}h_a^{\gamma}$, where A is TFP, K is physical capital, N is population, h is human capital, u is the fraction of human capital used in goods production (the rest is used in the production of human capital itself), and h_a is the average human capital of the economy. In this formulation, γ is a measure of the external effect of human capital. Ignoring u and N, profit maximization by a typical firm with such a production function implies that the price of human capital is given by $p = (1-\beta)AK^{\beta}h^{-\beta}h_a^{\gamma}$ and the price of physical capital is given by $r = \beta AK^{\beta-1}h^{1-\beta}h_a^{\gamma}$. If the interest rate r is fixed at the world level, we have $p = (1-\beta)\left(\frac{\beta}{r}\right)^{\frac{\beta}{1-\beta}} A^{\frac{1}{1-\beta}} h_a^{\frac{\gamma}{1-\beta}}$, with $\frac{\gamma}{1-\beta}$ being the elasticity of human capital price with respect to average human capital.

[9]The human capital production function as given in equation (2) of Tamura (1991) is $H_{i,t+1} = A\overline{H}_t^{\delta}(\tau_{i,t}H_{i,t})^{1-\delta}$, where $H_{i,t}$ is the stock of human capital of individual i at time t, A is FTP, $\overline{H}$ is the average human capital of the society, and τ is the fraction of time spent on human capital production (the rest is used in goods production).

still be higher than what she could have earned had she never been to the high average human capital market, and this wage premium is due to the extra amount of human capital accumulated in the high average human capital market (the growth effect).

For simplicity, the model ignores other determinants of individual wages like search friction and learning about own ability[10]. The assumption is that these factors are not important for understanding the geographic variation of wages in general and the growth effect of average human capital in particular. Consistent with this assumption, Baum-Snow and Pavan (2012) find that differences in labor market search frictions and distributions of firm-worker match quality contribute little to observed city size wage premium. The impact of search friction and other factors on the estimation of the growth effect of average human capital is left for future research.

2.1 Identification of the Growth Effect

Combining equations (1) and (2), we have

$$\log w_{i,t} = \log p_{c_{i,t},t} + \log h_{i,t_0} + B\left(e_{i,t}, \theta_i, C\left(i,t\right)\right) \tag{3}$$

Equation (3) is the basis for the empirical specifications of this paper. As implied by this equation, the growth effect of average human capital can be estimated by relating measures of the return to experience to measures of average human capital across markets. Practically, however, there are at least three complications.

First, workers across markets may have different learning abilities θ_i. It's possible that workers with high levels of (unobserved) learning ability θ_i will sort into labor markets with high levels of average human capital. In this case, the positive correlation between average human capital and the return to experience across markets may be attributed to the higher learning ability of workers in markets with higher average human capital as opposed to the causal effect of average human capital.

Secondly, the return to experience may be different from the accumulation of human capital transferable across markets (general human capital). For example, individual wage may grow with experience in the absence of human capital accumulation if human capital price is increasing in experience. This would be the case if human capital of young and old workers are not perfect substitutes and the demand for old workers is higher than that of young workers. Besides, not all human capital is general and transferable across markets, and some human capital may be specific to a particular market. For example, the knowledge that a lawyer has accumulated about her customers in one market may not be as useful when she moves to another. For these reasons, the effect of average human capital on the return to experience may not be equal to its effect on the accumulation of human capital valuable in all markets[11].

[10] See Rubinstein and Weiss (2006) for a review of the literature on post schooling wage growth.

[11] Although the effect on the return to experience is important itself, as discussed earlier, the effect on the accumulation of general human capital is more important because it's embodied in workers and can be taken to other markets as the workers move across markets, and it's more closely related to the idea of knowledge spillovers. For

Lastly, average human capital is not the only difference across labor markets. Labor markets differ widely from each other in geographical location, natural resources, industry structure, population as well as economic and other policies, all of which could be correlated with average human capital while at the same time affecting individual human capital accumulation and wage growth. In this case, the positive correlation between average human capital and the return to experience across labor markets may be the result of some omitted labor market characteristics.

I take three steps to address these concerns. First, to control for the potential bias due to the sorting of workers across labor markets, I use panel data from the National Longitudinal Survey of Youths 1979 (NLSY79) to estimate the effect of average human capital on the return to experience with individual fixed effects. Because the effect of average human capital on the return to experience is estimated from the same individual over time, while individual learning ability is assumed to be fixed, estimates with individual fixed effects are free from the potential bias due to the correlation between average human capital and individual learning ability.

Secondly, to show that the effect of average human capital on the return to experience works through the accumulation of general human capital, I use the sample of workers in the NLSY79 who have moved across markets to estimate the effect of average human capital of the previous market on wages in the current market. In particular, to confirm that the effect of average human capital of the previous market on wages in the current market is due to general human capital accumulation as opposed to the sorting of workers with higher stocks of human capital into markets with higher levels of average human capital, I use the sample of workers who have moved at least twice and have been to at least three markets. For these workers, I can control for their wages as well as other information while they were in the first market to make sure that they were comparable before moving into different second markets, and then regress their wages in the third market against the average human capital of the second market to estimate the effect of average human capital on general human capital accumulation.

Lastly, I use an instrumental variable (IV) for average human capital to address the potential bias due to omitted variables. Following Moretti (2004a) and Shapiro (2006), the instrument I use is the presence of land-grant colleges in a labor market. The validity of this instrument and the relevant results are discussed later in section 6. The IV estimates also address the potential concern of reverse causality that workers with more human capital move into markets with higher levels of average human capital in anticipation of the faster wage growth there.

3 Data

This paper uses data from two sources. The first is the 5% state file of the 2000 census from the Integrated Public Use Microdata Series (IPUMS) (Ruggles et al. (2015)). This data provides individual level observations on a range of economic and demographic information, including labor income, labor supply and the geographic location of residence. Only individuals between 16 and 65

this reason, it's useful to estimate not only the effect on the return to experience but also the effect on general human capital accumulation.

years old who were not enrolled in school are included for analysis. Individual wages are calculated by dividing the wage and salary income in the previous year by the product of usual hours worked per week and weeks worked in the previous year. Experience is calculated as age minus years of schooling minus 6 if years of schooling is larger than 10. Otherwise, experience is equal to age minus 16. In addition to the 2000 census, I also use the 1980 and 1990 censuses to calculate labor market characteristics in those two years. Variables in the 1980 and 1990 censuses are defined in the same way as the 2000 census.

Following Autor and Dorn (2013), labor markets in this paper are defined as Commuting Zones (CZs) which are clusters of counties characterized by strong commuting ties within CZs and weak commuting ties across CZs. The concept of CZs were initially developed by Tolbert and Sizer (1996), where 741 CZs were delineated from all US counties and county equivalents using a special version of 1990 census that identifies labor market areas in which individuals live and work. This definition has at least three advantages over the more commonly used definition based on Metropolitan Statistical Areas (MSAs). First, CZs cover the whole country while the definition based on MSAs typically ignores rural areas. Second, CZs are consistently defined over time while the definitions of MSAs change over time. Lastly, and most importantly, because the classification uses actual commuting data, CZs are based on economic geography rather than incidental factors such as minimum population.

Similar to Moretti (2004a,c) and Shapiro (2006), average human capital of a labor market is measured by the share of workers with a bachelor's degree or more (college share)[12]. This measure is calculated for each CZ using workers between 26 and 65 years old.

The first column of table 1 reports the summary statistics from the 2000 census sample. The average worker is living in a CZ with a college share of 0.28. This is larger than the average college share across the 741 CZs, which is about 0.22, because CZs with a larger college share also have a larger population[13]. The number of individuals reported in table 1 is larger than the relevant number of respondents in the original IPUMS data. This arises from the imperfect assignment of workers into CZs[14], in which case a worker may appear multiple times in the sample, one for each CZ he/she could potentially belong to. The weight for each observation is adjusted accordingly, and all statistics are calculated with the resulting weight.

[12]Because information on degrees is not available in 1980, college graduates there are defined as workers with 16 years of schooling or more.

[13]The correlation between college share and population of workers across CZs is 0.44

[14]To match CZs with the geographic information available in the IPUMS, I follow the algorithm in Autor and Dorn (2013). The match is imperfect because the smallest geographic units available in the IPUMS (County groups in 1980, and PUMAs in 1990 and 2000) may straddle the boundary of one or more CZs, in which case all workers in that geographic unit (County group or PUMA) are assigned to each of the relevant CZs with a positive probability given by the fraction of the population in that geographic unit that belongs to each of the CZs. For example, if county group A is consisted of two counties (1 and 2) that belong to CZ 1 and CZ 2 respectively, and the fraction of county group A's population that belongs to county $i \in \{1, 2\}$ is given by p_i. All respondents in county group A will be assigned to both CZ 1 and CZ 2, and their weights in CZ i will be adjusted by p_i.

Table 1: Summary Statistics

	2000 Census	NLSY79
Log hourly wage	2.63	1.80
	(0.73)	(0.62)
Years of schooling	13.27	13.43
	(2.25)	(2.20)
Years of experience	20.95	7.43
	(11.57)	(3.68)
College share	0.28	0.24
	(0.07)	(0.06)
Average college share		0.22
		(0.05)
Number of CZs	741	490
Number of Individuals (N)	7,637,502	5752
$N \times T$		46272

Standard deviations of continuous variables are in parentheses.

3.1 College Shares and Returns to Experience in 2000 Census

Before introducing the second data source, I document in this subsection a positive correlation between college shares and returns to experience across labor markets. To get a measure of the return to experience for each labor market, I run the following regression using the 2000 census

$$\log w_i = \alpha_c + X_i\gamma + \beta_{1,c}Exp_i + \beta_{2,c}Exp_i^2 + \beta_3 Exp_i^3 + \beta_4 Exp_i^4 + \epsilon_i$$

where w_i is the hourly wage of worker i, α_c is a fixed effect for CZ c, X_i is a vector of individual characteristics including education, gender and race, and Exp_i is years of work experience. Note that β_1 and β_2 are allowed to vary by CZs, which allows me to calculate for each CZ the return to the first ten years of experience given by

$$RE_c = 10\beta_{1,c} + 10^2\beta_{2,c} + 10^3\beta_3 + 10^4\beta_4 \tag{4}$$

Figure 1 presents the estimated college shares and returns to experience across the 741 CZs covering the US. Clearly, there is a positive correlation between the two variables. A one percentage point increase in college share is associated with a 0.38 percentage point increase in the return to the first ten years of experience[15].

[15]Results are similar when β_3 and β_4 are also allowed to vary across CZs. However, for many smaller CZs, β_3 and β_4 are not precisely estimated, resulting in noisy measures of returns to experience. Results are also similar when the return to the first ten years of experience is calculated as the difference between the average wage of workers with exactly ten years of experience and the average wage of workers with exactly zero year of experience in each labor market. Finally, to get rid of the cohort effect, I also calculate a measure of the return to experience for each labor market as the difference between the average wage of workers with exactly ten years of experience in 2000 and the average wage of workers with exactly zero year of experience in 1990, and this measure of the return to experience,

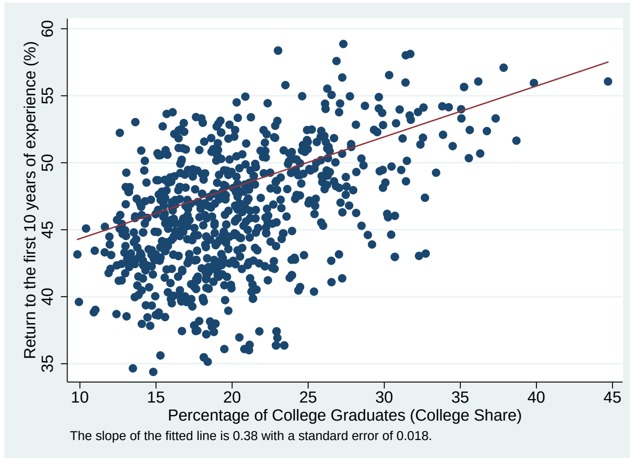

Figure 1: College Shares and Returns to Experience across CZs in 2000 Census

To check the robustness of the correlation in figure 1 to the definition of labor markets, figure 2 plots the same correlation treating each state as a labor market. College shares and returns to experience are significantly positively correlated with each other across states, suggesting that the correlation is not specific to the definition of labor markets used in this paper.

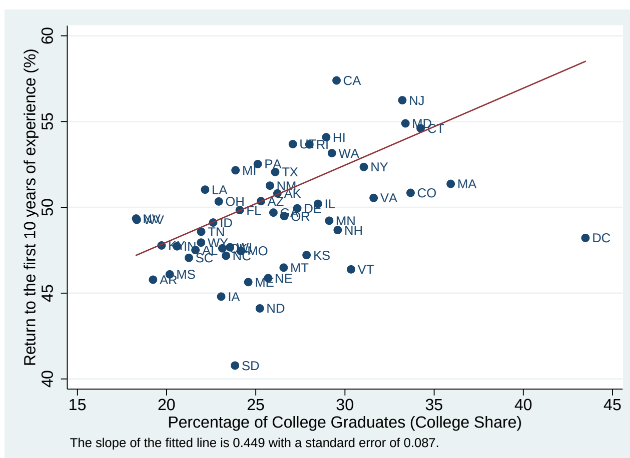

Figure 2: College Shares and Returns to Experience across States in 2000 Census

With the return to experience varying across markets, the wage level is still higher in markets with larger college shares. This can be seen in figure 3, which plots the regression-adjusted wage level α_c against the college share for each labor market. While the existing empirical literature on human capital externalities focuses on establishing a causal interpretation of the correlation shown in figure 3[16], the goal of this paper is to establish a causal interpretation of the correlation in figure 1.

although very noisy in many cases given the small samples, is positively correlated with the college share of the labor market.

[16] A typical practice of this literature is to restrict the return to experience to be constant across markets.

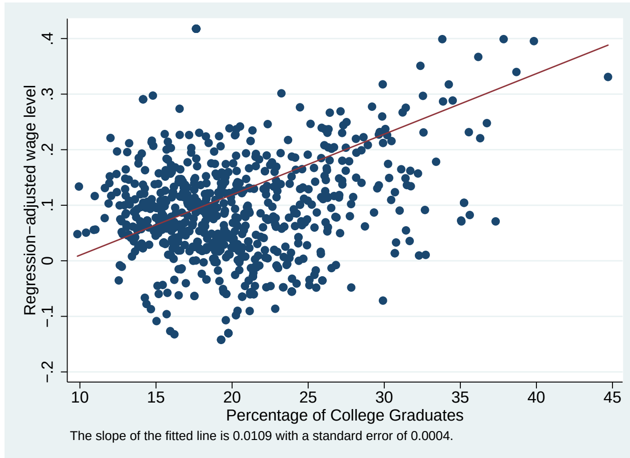

Figure 3: College Shares and Wage Levels across CZs in 2000 Census

3.2 NLSY79

The second data set used in this paper is the National Longitudinal Survey of Youths 1979 (NLSY79). The NLSY79 is a nationally representative sample of 12,686 young men and women who were 14-22 years old when they were first surveyed in 1979. These individuals were interviewed annually through 1994 and are currently interviewed on a biennial basis. I drop both the military sample and the sample of economically disadvantaged respondents, and use only the 9763 men and women in the cross-sectional sample and the supplemental samples of Hispanics and Blacks. I use only the panel covering the years 1979-1994. The wage information used is the "hourly rate of pay in the current and most recent job" deflated with CPI-U. In years when a respondent reported to have been enrolled in school since the last survey, the wage is set to be missing even if it's available. Experience is defined in the same way as in the IPUMS data. As a measure of ability, I use the percentile score of Armed Forces Qualification Test (AFQT).

I use the geocoded version of the NLSY79, where the state and county of residence for each respondent at the time of each survey is identified[17]. Given the state and county of residence, I can ascertain the CZ of residence for each respondent at the time of each survey. Following Moretti (2004a), I interpolate the college shares estimated from the 1980 and 1990 censuses for all years from 1979 to 1994 covered by our NLSY79 sample.

Given the college share for each labor market in each year, I can calculate the average college share of all labor markets an individual has been to since the year of labor market entry (when experience is zero). For example, suppose an individual entered the labor market in CZ_1, stayed in CZ_1 for two years when the college shares were 20% and 21% respectively, and then moved to CZ_2 with a college share of 25%. The average college share for this individual in the first three years will be 20%, 20.5% ($\frac{20\%+21\%}{2}$) and 22% ($\frac{20\%+21\%+25\%}{3}$). In order to calculate the average college share for a particular individual in a particular year, we need to know the individual's CZ of residence in

[17] I thank the Bureau of Labor Statistics for making the confidential locational information available.

each year since the year of labor market entry.

The second column of table 1 reports the summary statistics of the NLSY79 sample. The number of individuals is smaller than 9763, and this is because individuals with no valid information for one or more of the key variables like wage and average college share are not included. In particular, many respondents entered the labor market before the first wave of the NLSY79, and the CZs of residence for these individuals before the survey are not available. These respondents are excluded because none of the average college share can be calculated for them.

Relative to the census sample, the average wage in the NLSY79 is lower because (1) the NLSY79 covers an earlier period, and (2) workers in the NLSY79 are younger and have fewer years of experience (7.43 vs 20.95)[18]. Additionally, the NLSY79 only covers 490 of the 741 CZs. Due to these differences, the estimates from the NLSY79 may be different quantitatively from the estimates with the census.

The average college share is smaller than the college share, because the former places greater weight on the college share when the respondents were young. For example, the college share of the market where a respondent was working with zero year of experience will be reflected in the average college share of all subsequent years when the respondent was surveyed.

4 Evidence on Returns to Experience from the NLSY79

This section estimates the impact of college shares on returns to experience using the longitudinal data from NLSY79. The main goal is to show that the faster wage growth with experience in markets with larger college shares is a causal effect of the markets rather than being driven by the sorting of workers with higher learning abilities into those markets.

I use the following empirical specification to approximate the model in equation (3)

$$\begin{aligned}\log w_{i,t} \quad = \quad & \alpha_c + \pi CS_{c,t} + Z_{c,t}\lambda + X_{i,t}\gamma + \beta_{1,i}Exp_{i,t} + \beta_{2,i}Exp_{i,t}^2 \\ & + \beta_{3,i}Exp_{i,t} \times ACS_{i,t} + \beta_{4,i}Exp_{i,t}^2 \times ACS_{i,t} + Exp_{i,t} \times AZ_{i,t}\mu + \alpha_t + \epsilon_{i,t} \end{aligned} \tag{5}$$

where α_c is the fixed effect of the worker's market of residence at time t, $CS_{c,t}$ is the college share of the current labor market c for worker i at time t, and $Z_{c,t}$ is a vector of other characteristics of the market discussed later. Together, the first three terms are used to control for the price of human capital $p_{c,t}$. $X_{i,t}$ is a vector of individual characteristics including education, gender and race, and it's used to model the initial human capital h_{i,t_0}. The function of human capital accumulation $B(\bullet)$ in equation (3) is approximated with a polynomial of experience $Exp_{i,t}$ and its interactions with the average college share $ACS_{i,t}$ and other characteristics of the labor markets $AZ_{i,t}$, where $ACS_{i,t}$ is the average college share of all markets worker i has been to from the time of labor market entry t_0 to the present time t, and variables in the vector $AZ_{i,t}$ are defined similarly for all variables included

[18]The age of the oldest worker in the NLSY79 sample is 37, while it is 65 in the Census.

in the vector Z. α_t is a year fixed effect used to control for changes in the macro economy that affect all workers in all markets in the same way. All approximation errors, as well as measurement errors in the data, are subsumed in $\epsilon_{i,t}$.

In equation (5), the price of human capital is allowed to vary across markets and over time through the variation in college share $CS_{c,t}$, and π is a measure of the level effect of average human capital. Note that the coefficients βs are allowed to vary across individuals, which is used to model the dependence of $B(\bullet)$ on learning ability θ_i. The impact of the average college share on the return to experience is modeled through the interaction terms $Exp_{i,t} \times ACS_{i,t}$ and $Exp_{i,t}^2 \times ACS_{i,t}$, in this way the impact is allowed to vary with the level of experience. $\beta_3 \equiv \overline{\beta_{3,i}}$ and $\beta_4 \equiv \overline{\beta_{4,i}}$ are the key parameters of interest.

Although the primary goal of this section is to address the potential bias due to the selection of workers across markets, I also control for some labor market characteristics to deal with the potential bias from omitted variables. In particular, two sets of labor market characteristics are included in the vectors Z and AZ. The first is the (log) population of workers in the market. As assumed in Glaeser (1999), the agglomeration of workers in large markets, by increasing the probability of bilateral meetings across workers, is likely to raise the speed of learning and the return to experience. If population growth and the variation in the college share of a labor market over time are correlated, the estimated effect of average college shares on returns to experience may be biased if the variation in population is not accounted for. Secondly, to address the potential concern of reverse causality that college graduates move into certain markets in anticipation of the faster wage growth there, I follow Moretti (2004a) by controlling for some measures of market-specific labor demand shocks. In particular, I adapt a measure of labor demand shifts proposed by Katz and Murphy (1992). The index captures exogenous shifts in the relative demand for different education groups that are predicted by the industry mix of the labor market. As noted by Bound and Holzer (2000), industry-specific demand shocks at the national level have a differential impact on local labor markets because different labor markets specialize in the production of different goods. A shock to a given industry at the national level is likely to have a larger impact on labor markets where that industry employs a larger share of the local labor force.

Specifically, the shock index is defined as

$$shock_c^j = \sum_d \left(\eta_{d,c} \triangle E_d^j \right)$$

where d is an index for two-digit industries, $\eta_{d,c}$ is the share of hours worked in industry d in labor market c in 1980 (with $\sum_d \eta_{d,c} = 1$ for all c), and $\triangle E_d^j$ is the change in the log of total hours worked in industry d by workers in education group j between 1980 and 1990 at the national level. Both $\eta_{d,c}$ and $\triangle E_d^j$ are calculated using the census data. $shock_c^j$ represents the labor demand shock to workers in education group j in labor market c between 1980 and 1990. In estimation, I include this index for two education groups: college or more and less than college. As with college shares, I interpolate this index for all years covered by our sample of NLSY79. Given the interpolated index for each labor market in each year, I can calculate the average shock index since the year of labor market entry for each respondent of NLSY79 in each year. In estimation, four variables summarizing labor demand shocks are included, the shock index for college or more, the shock index for less than college, the interaction between the average shock index for college or more and experience, and the interaction between the average shock index for less than college and experience.

4.1 OLS Estimates

Ignoring the variation of βs across individuals, the first column in the upper panel of table 2 reports the OLS estimates of equation (5). Consistent with Moretti (2004a), the college share of the current labor market has a positive impact on wage level, a 1 percentage point increase in the college share of a labor market is associated with a 1.4% increase in individual wages. Different from Moretti (2004a) which assumes that the return to experience is constant across workers in all markets, I find the return to experience is increasing in the average college share of the labor markets an individual has been to since labor market entry. The marginal effect of the average college share is decreasing with experience, and the total effect reaches its maximum at about $\frac{\hat{\beta}_3}{-2\hat{\beta}_4} \approx 8.4$ years of experience.

To evaluate the magnitude of the estimates, panel B calculates the growth effect of a 1 percentage point increase in the average college share in the first 10 years, defined as $GE_{10} = 10\beta_3 + 10^2\beta_4$, the total effect $TE_{10} = \pi + GE_{10}$, and the contribution of the growth effect $\frac{GE_{10}}{TE_{10}}$. Suppose there are two identical workers entering the labor market at the same time, one in a market with a college share that is always 1 percentage point larger than the other. According to the estimates in panel A, in the first year, the worker in the market with a large college share will earn $\hat{\pi} = 1.4\%$ more than the other worker. This difference will rise over time to $\hat{TE}_{10} = 2.3\%$ after 10 years, with the growth effect being $\hat{GE}_{10} = 0.89\%$ and contributing to 38% of the total effect.

Another way to evaluate the growth effect is to compare it with the average return to experience. Assume $\beta_{3,i} = \beta_{4,i} = \mu = 0$ and re-estimate equation (5), we have $\hat{\beta}_1 = 0.0685$ and $\hat{\beta}_2 = -0.0025$. The estimated return to the first 10 years of experience is thus $10\hat{\beta}_1 + 10^2\hat{\beta}_2 = 0.435$. If the college share in one market is 10 percentage points higher than another, the return to 10 years of experience is predicted to be $10\hat{GE}_{10} = 0.089$ larger, which is about 20% $\left(\frac{0.089}{0.435}\right)$ of the average return to the first 10 years of experience.

Although not reported here, I find the population of workers is positively associated with the return to experience, while the measures of labor demand shocks are not significantly related to the return to experience.

4.2 Estimates with Individual Fixed Effects

The estimates in column 1 may be biased estimates of the effect of average college share on the return to experience if the return to experience is allowed to vary across individuals. For example, assume $\beta_{2,i} = 0$ and $\beta_{4,i} = 0$ for all individuals but $\beta_{1,i}$ varies across individuals due to the variation in learning ability. Let $E\left(\beta_{1,i}|ACS\right)$ be the average return to experience among workers with an average college share given by ACS. As long as $\frac{\partial E(\beta_{1,i}|ACS)}{\partial ACS} \neq 0$, which would happen if workers

Table 2: Effects of College Shares on Wages: Baseline Estimates with the NLSY79

	(1)	(2)	(3)
Panel A: Level and growth effects			
College share	1.429***	1.037**	1.172**
	(0.389)	(0.432)	(0.476)
Average college share×Experience	0.219***	0.262***	0.238***
	(0.037)	(0.053)	(0.058)
Average college share×Experience^2	-0.013***	-0.016***	-0.015***
	(0.003)	(0.003)	(0.003)
Panel B: Contribution of the growth effect when experience is 10			
Growth effect when experience is 10	0.89	1.02	0.88
Total effect (Level+ Growth)	2.319	2.057	2.052
Growth effect/Total effect	0.38	0.50	0.43
Individual fixed effects		Yes	Yes
Individual×CZ fixed effects			Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Robust standard errors are in the parentheses.

with different ACS also have different learning ability[19], the OLS estimate of β_3 will be a biased estimate of the effect of average college share on the return to experience.

To control for this potential bias, I add an individual fixed effect into equation (5). With individual fixed effects, identification of βs, as well as other parameters of the model, comes from the comparison of relevant information for the same individual over time. For example, assume a worker experiences a wage growth of 5% in one year in a labor market with a college share of 20%, and in the next year he works in a labor market with a college share of 22% and experiences a wage growth of 5.2%. Assume $\beta_{2,i} = \beta_{4,i} = 0$, we have $\widehat{\beta_{1,i}} + 0.2\widehat{\beta_{3,i}} = 0.05$ and $\widehat{\beta_{1,i}} + 0.22\widehat{\beta_{3,i}} = 0.052$, which gives us $\widehat{\beta_{1,i}} = 0.03$ and $\widehat{\beta_{3,i}} = 0.1$. That is, the baseline return to one year's experience is 3% in all labor markets, and one percentage point increase in the college share of a labor market raises this return by 0.1%. If this is the only information we have, $\widehat{\beta_3} = \widehat{\beta_{3,i}} = 0.1$. Because β_3 is estimated from the same individual for whom the learning ability is assumed to be fixed over time, no ability bias is involved. If, on the other hand, we have information for other individuals, we can estimate $\beta_{3,i}$ in the same way for all individuals and weight these individual estimates of $\beta_{3,i}$ properly to get the estimate of β_3. Because ability bias is purged from the estimate of each $\beta_{3,i}$, the estimate of β_3 is also free from ability bias.

The second column of table 2 reports the estimates of equation (5) with individual fixed effects. Although the estimated level effect π decreases a little bit, the estimated growth effect is statistically significant and slightly larger than the OLS estimates in the first column, suggesting that the higher returns to experience in markets with larger college shares is not due to the selection of workers

[19]In our sample, AFQT is significantly positively related to both the college share of the current market and the average college share since labor market entry even after controlling for gender, race, education and experience.

with higher learning ability into those markets.

4.3 Estimates with Individual-By-Market Fixed Effects

With the inclusion of individual fixed effects, the variation in average college shares comes from two sources: the change in the college share of a labor market over time as the individual stays in that labor market, and the change in college shares associated with the change in labor markets as the individual moves. One concern is that the sample of movers is not random, and the wages around the time of a move may not be well described by the model in equation (1). For example, Kennan and Walker (2011) find that workers are more likely to move after receiving a bad wage draw from the current location, suggesting that wages around the time of a move may not be strongly related to human capital.

To address these concerns, in column 5 of table 2, I report the results of a specification of equation (5) with CZ-by-individual fixed effects. Under this specification, only the change in the college share of a labor market over time as the individual stays in that market is used for identification. Because none of the change in college shares involving moves across labor markets is used, there is no need to worry about the potential bias due to migration. The estimated growth effect declines a little bit, but is still statistically significant and contributes to about 43% of the total effect.

4.4 Robustness

In approximating equation (3) with the empirical specification of equation (5), I assume that human capital price $p_{c,t}$ varies across labor markets and over time only through the variation of college share CS and other labor market characteristics included in the vector Z. While this allows us to estimate the level effect of college share as in Moretti (2004a), it's not necessary for estimating the growth effect. Moreover, if the estimated level effect from equation (5) is somehow biased, it may also bias the estimated growth effect.

To investigate the robustness of the results, I estimate a version of equation (5) with CZ-by-year fixed effects given by

$$\begin{aligned} \log w_{i,t} &= \alpha_{c,t} + X_{i,t}\gamma + \beta_{1,i} Exp_{i,t} + \beta_{2,i} Exp_{i,t}^2 \\ &\quad + \beta_{3,i} Exp_{i,t} \times ACS_{i,t} + \beta_{4,i} Exp_{i,t}^2 \times ACS_{i,t} + AZ_{i,t}\mu + \epsilon_{i,t} \end{aligned} \tag{6}$$

Under this specification, human capital price is no longer restricted to be a function of college share and other labor market characteristics. Instead, it is allowed to vary freely both across labor markets and over time. The impact of college share on wage level can no longer be identified, but I can still identify the impact of average college share on the return to experience, which is the focus of this paper.

Table 3 reports the relevant results. Column 1 reports the OLS estimates, column 2 reports the estimates with individual fixed effects, and column 3 reports the estimates with individual-

Table 3: Effects of College Shares on Returns to Experience: Alternative Estimates with NLSY79

	(1)	(2)	(3)
Average college share×Experience	0.171***	0.209***	0.418***
	(0.042)	(0.075)	(0.121)
Average college share×Experience^2	-0.006*	-0.010***	-0.010**
	(0.003)	(0.004)	(0.004)
Individual fixed effects		Yes	
CZ×Individual fixed effects			Yes

*** $p < 0.01$, ** $p < 0.05$, $p < 0.1$
Robust standard errors are in the parentheses.

by-market fixed effects. The results in table 3 are generally similar to the estimates in table 2, suggesting that the estimated growth effect is not significantly affected by the potential bias in the estimated level effect[20].

I also estimate a version of equation (5) with a full set of experience dummies instead of a quadratic in experience. As pointed out in Murphy and Welch (1990), the age-earnings profile may not be well approximated by a quadratic function. By including a full set of experience dummies, I address the concern that the impact of average college share on the return to experience is driven by the misspecification of the experience-wage profile. The results from these specifications, reported in panel A of table 4, are very similar to those reported in table 2, suggesting that our results are robust to the specification of the baseline experience-wage profile.

In panel B of table 4, I repeat the estimations in table 2 without the supplemental sample of Hispanics and Blacks. Again, I find statistically significant estimates of the growth effect of average college share.

Recall that our measure of the college share of a labor market is allowed to vary over time, and this is done by interpolating the college shares calculated from the 1980 and 1990 censuses to all years covered by the NLSY79 sample. To check the sensitivity of the results with respect to this interpolation, I estimate a version of the model assuming that the college share of a labor market is fixed over time, and use the average of the college share in 1980 and the college share in 1990 as the measured college share for each labor market. Because the college share is now fixed over time, with the inclusion of labor market fixed effects, I can no longer estimate the level effect of college share, neither can I estimate the growth effect with individual-by-market fixed effects. However, I can still use workers who have moved across markets to estimate the growth effect of college share with and without individual fixed effects. Panel C of table 4 reports the estimates. College shares have a significant growth effect, suggesting that the previous estimates are robust to the interpolation of college shares.

In summary, empirical estimates in this section suggest that markets with larger college shares

[20] With 490 CZs and 15 years of data, the interaction between CZ and year gives 7350 dummies. With only 46272 observations, many of these dummies can't be precisely estimated. This likely has an effect on other estimates like the estimated β_3 in the third column of table 3, which is much larger than the relevant estimate in table 2.

Table 4: Effects of College Shares on Wages: Alternative Estimates with the NLSY79

	(1)	(2)	(3)
Panel A: Experience dummies			
College share	1.450***	1.029**	1.168**
	(0.390)	(0.431)	(0.476)
Average college share×Experience	0.219***	0.266***	0.241***
	(0.037)	(0.053)	(0.058)
Average college share×Experience^2	-0.013***	-0.017***	-0.015***
	(0.003)	(0.003)	(0.003)
Panel B: Without the supplemental sample of Hispanics and Blacks			
College share	1.907***	1.611***	1.799***
	(0.477)	(0.511)	(0.572)
Average college share×Experience	0.156***	0.194***	0.159**
	(0.048)	(0.067)	(0.072)
Average college share×Experience^2	-0.009***	-0.013***	-0.011**
	(0.003)	(0.004)	(0.004)
Sample size	30276	30276	30276
Panel C: College share is fixed over time			
Average college share×Experience	0.193***	0.291***	
	(0.036)	(0.054)	
Average college share×Experience^2	-0.010***	-0.017***	
	(0.003)	(0.003)	
Individual fixed effects		Yes	
Individual×CZ fixed effects			Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Robust standard errors are in the parentheses.

have a significantly positive effect on the return to experience: a one percentage point increase in the college share of a labor market increases the return to the first 10 years of labor market experience by about 0.9%, and this growth effect contributes to about 40% of the total effect of college share on the wage of workers with ten years of experience.

4.5 Level Effects with and without the Growth Effect

As the literature typically estimates the level effect of average human capital assuming there is no growth effect, it's useful to do so here and compare the resulting estimates with the ones in table 2 estimated jointly with the growth effect. If the growth effect is restricted to be zero in estimation, part of the true growth effect is likely to be reflected on the estimated level effect, resulting in larger estimates of the level effect than the ones where the growth effect is not restricted to be zero. By comparing the estimated level effects with and without growth effect, we can get some indirect evidence for the growth effect.

Table 5: Effects of College Shares on Wage Levels

	(3)	(4)	(5)
Panel A: No growth effect			
College share	1.675***	1.363***	1.454**
	(0.374)	(0.401)	(0.440)
Panel B: with growth effect			
College share	1.429***	1.037**	1.172**
	(0.389)	(0.432)	(0.476)
Panel C: Bias			
(A - B)/B	0.17	0.31	0.24
Individual fixed effects		Yes	
Individual×CZ fixed effects			Yes

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Robust standard errors are in the parentheses.

Table 5 reports the estimated level effect π by repeating the exercises in table 2 with the restriction that $\beta_{3,i} = \beta_{4,i} = 0$. Clearly, the estimated level effects in table 5 are larger than corresponding estimates in table 2. This can be viewed as indirect evidence for the growth effect, and suggests that the estimated effect of average human capital in the literature should be interpreted as a measure of the combined level and growth effects rather than level effect alone.

5 Evidence on Human Capital Accumulation from Movers

Theoretically, there are at least three potential sources of wage growth with experience: (1) the increase in the price of human capital, (2) the accumulation of market-specific human capital that has no value other than in the market where it's accumulated, and (3) the accumulation of general human capital that's valuable in all markets. In this section, I present some evidence that the faster wage growth in markets with larger college shares is due to the accumulation of general human capital.

5.1 Identification

One way to isolate the impact on general human capital is to use the information on movers across labor markets. As illustrated in figure 4, suppose we can observe two workers identical to each other at time 0. The two workers were then randomly assigned to two markets with different college shares and forced to stay there until time 1, after which they were both forced to another market and stayed there forever.

At any point after time 1, because both workers are in the same market 3 and faced with the

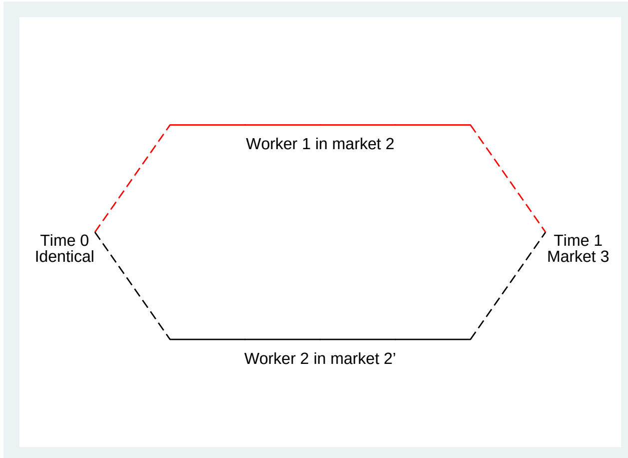

Figure 4: Illustration of Identification

same price of human capital[21], the difference in their wages is equal to the difference in their stocks of human capital[22]. However, because the two workers were identical at time 0, the difference in their human capital at any time in market 3 comes solely from the different amount of general human capital accumulated between time 0 and time 1.

Let $w_{i,t}$ be the wage of worker $i \in \{1, 2\}$ at time $t \geq 1$ in market 3, and let ACS_c be the average college share of market $c \in \{1, 2\}$ between time 0 and time 1. According to above argument, $\log w_{2,t} - \log w_{1,t}$ is equal to the difference in the amount of general human capital the two workers accumulated between time 0 and time 1 in market 2 and market 2' respectively. Consequently, $\frac{\log w_{2,t} - \log w_{1,t}}{ACS_2 - ACS_1}$ can be used as a measure of the impact of college shares on general human capital accumulation.

Following this argument, the empirical specification used in this section is

$$\log w_{i,t} = \alpha_{c,t} + X_{i,t}\delta + \beta ACS_{c'(i,t)} + \varepsilon_{i,t} \tag{7}$$

where $w_{i,t}$ is the hourly wage of worker i at time t, $\alpha_{c,t}$ is a current-market-by-time fixed effect, $X_{i,t}$ is a vector of individual characteristics, $ACS_{c'(i,t)}$ is a measure of the average college share of the worker's previous market of residence $c'(i,t) \neq c$, and $\varepsilon_{i,t}$ is the error term.

The inclusion of $\alpha_{c,t}$ implies that we are comparing workers currently in the same market facing the same price of human capital. Through the vector $X_{i,t}$ I am trying to make sure that workers in comparison had comparable stock of general human capital at the entry of the previous market $c'(i,t)$. In this case, a factor has to affect the amount of general human capital accumulated in the previous market $c'(i,t)$ in order to affect current wage $w_{i,t}$. One such factor considered in this paper is the average college share of the previous market $ACS_{c'(i,t)}$. Everything else equal, a positive

[21] Because the two workers were identical at time 0, they would also have the same amount of experience at any time in market 3. In this case, the two workers will face the same price of human capital even if the price depends explicitly on experience.

[22] The price of human capital can always be normalized to be 1.

estimate of β reflects a positive effect of college shares on general human capital accumulation.

The key assumption is that, conditional on $\alpha_{c,t}$ and $X_{i,t}$, workers were not systematically different from each other when they moved into different previous markets. This would be the case if the destinations of observationally identical movers are determined randomly through a job search process. Recent studies suggest that majority of moves are contracted in the sense that most workers move after a job has already been secured in the destination[23]. This implies that workers in one market can search remotely for jobs in other markets. If no worker moves without receiving a job offer from the destination, the distribution of destinations will be determined by the arrival of job offers, which is likely to be random across markets. Additionally, a significant fraction of workers move for family and other reasons not related to jobs (Basker (2003), Guo (2014) and Kaplan and Schulhofer-Wohl (2015)), and the distribution of these workers is likely to be random across markets. In the following, I present some evidence that, once enough information is controlled through $X_{i,t}$, workers were not systematically different when they moved into different previous markets.

5.2 Estimation

Equation (7) is estimated using the sample of movers $c \neq c'(i,t)$ in the NLSY79. Table 6 reports some summary statistics about the movers in the NLSY97. About 48% of the workers in the sample have moved at least once, and 30.5% of them have moved twice or more. On average, a mover moves about 2.2 times and lives in each market for about 4 years. Relative to those who never moved (stayers), movers are more likely to be male, less likely to be black, better-educated and performed better in AFQT. These differences suggest that estimates based on movers reported below may not be representative of the population of all workers.

As argued above, a necessary assumption for β to measure the impact of average college share on general human capital accumulation is that, workers were comparable before moving into different previous markets $c'(i,t)$. This assumption fails, for example, if the college share of the previous market is systematically correlated with the learning ability of the workers moving into that market. One way to check this is to compare the workers who moved to a market with a larger college share (moved up or an upward move) with those who moved to a market with a smaller college share (moved down or a downward move). Among all of the moves observed in the sample, 55.93% of them are upward moves. As shown in the bottom panel of table 6, workers who moved up are not significantly different from workers who moved down in terms of gender, race, education and AFQT score[24]. The evidence, although not conclusive because workers may still be different in some unobserved characteristics, is consistent with the assumption that workers moving into different

[23]Using data from the Current Population Survey on reasons of migration, Basker (2003) and Kaplan and Schulhofer-Wohl (2015) find that around 90% of interstate migrants in the US who moved for job-related reasons did so in order to take a new job or for job transfer, and only 10% of them moved in order to look for work. To address the concern that reasons people give in a survey may not be the actual reasons of moving, in Guo (2014), I use longitudinal data from the Panel Study of Income Dynamics to show that around 80% of interstate migrants were neither unemployed nor out of labor force around the time of a move, suggesting that most of them did not move to look for work.

[24]None of the differences is statistically significant.

Table 6: Movers in the NLSY79

	(1)	(2)
All workers		
% Moved once		17.6
% Moved twice or more		30.5
	Moves	Stayers
% Male	50.85	45.73
% Black	26.37	30.95
Years of schooling	14.19	13.36
AFQT percentile	48.67	38.75
Movers		
Average number of moves		2.20
Average number of years in each market		3.99
% Moves involving an increase in college share		55.93
	Up	Down
% Male	51.05	52.38
% Black	25.43	25.09
Years of schooling	14.02	13.96
AFQT percentile	48.18	47.47

previous markets were not different systematically.

Table 7 reports the estimates of equation (7) using movers in the NLSY79. Besides the current-market-by-year fixed effects $\alpha_{c,t}$, variables included in all columns are gender, race, education, a quadratic in experience and AFQT. The first column uses the average college share of all previous markets, while other columns use only the average college share of the previous market. That is, if a worker is currently in the nth market, the measure in the first column is calculated from all of the first $n-1$ markets the worker has been to, while the measure in other columns is the average college share of the $(n-1)$th market during the time the worker was in that market.

The measure in all but the first column has two advantages. First, in cases where we do not know the whole history of locational choices but know the previous market, this measure is the only choice. Second, in cases where we do know the whole history of locational choices, we can use the information right before the previous market as additional controls to further make sure that workers were comparable before entering the previous market, and use only the average college share of the previous market to estimate the impact of college shares on general human capital accumulation. This is done in the last two columns of table 7.

The first column shows that, everything else equal, a one percentage point increase in the average college share of all previous markets raises the wage in the current market by about 0.441%. The estimate is statistically significant at 1% significance level. The estimate in the second column is very similar to the one in the first column, which is not surprising because most of the movers have moved only once, and for these movers, the measures in the first two columns are identical to each other. The estimate in the second column is slightly smaller, suggesting that workers can also benefit from the college share of the markets before the previous one[25]. For the purpose of comparison with the last two columns, the third column repeats the specification of the second column, using only the second to the last moves of workers who have moved twice or more. Relative to the estimate in the second column, the one in the third column is smaller. As the first move is dropped, the observations used in the third column on average have more experiences. The smaller estimate in the third column is consistent with the earlier results that the impact of college shares on the return to experience is decreasing with experience.

Table 7: Effects of the College Share of the Previous Market: Estimates from the NLSY79

	(1)	(2)	(3)	(4)	(5)
Average college share of previous markets	0.441***				
	(0.108)				
Average college share of previous market		0.415***	0.351***	0.333**	0.345*
		(0.086)	(0.116)	(0.169)	(0.189)
Hourly wage before the previous market				0.229***	0.228***
				(0.019)	(0.019)
College share before the previous market				-0.277	-0.250
				(0.232)	(0.233)
Experience before the previous market				-0.020***	-0.068
				(0.005)	(0.104)
Experience in the previous market				-0.019***	-0.043
				(0.007)	(0.052)
CZ-by-year fixed effects	Yes	Yes	Yes	Yes	Yes
First move dropped			Yes	Yes	Yes
Additional controls for the previous market					Yes
Number of workers	2631	2631	1625	923	923
Number of observations	16982	16982	9072	4139	4139

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Standard errors are in the parentheses.

In the fourth column, I use the sample of workers who have moved twice or more and thus have been to at least three markets. For the third to the last market these workers have been to, we know not only the previous market but also the market before the previous one and other labor market information right before the worker entered the previous market. We can control for this labor market information to further make sure that workers were comparable before entering the previous market. Specifically, I control for the log hourly wage, the college share and experience in the year before the worker moved into the previous market. I also control for the experience accumulated in the previous market. Because these additional controls are not always available, the sample size in the fourth column is substantially smaller than the third column[26].

[25]As shown earlier in this paper, the impact of college share is decreasing in experience. Consequently, the impact of the market in the more distant past should be larger than the impact of the market in the recent past, explaining the larger estimate in the first column.

[26]When I estimate the specification in column 3 using the same observations as in column 4, the estimated impact

Not surprisingly, the wage before entering the previous market is positively related to the current wage. The college share before entering the previous market is negatively related to the current wage. This is expected because, as college share is positively related to the price of human capital, conditional on the wage before entering the previous market, workers in markets with a larger college share on average have a lower stock of human capital. In fact, the exact reason that I control for both the wage and the college share before entering the previous market is to make sure that workers have the same amount of general human capital before entering the previous market. Both the experience before entering the previous market and the experience accumulated in the previous market are negatively related to the current wage. This is expected because these two experiences affect current wage only through general human capital, while experience in the current labor market affects wage through both general and market-specific human capital. Conditional on total experiences, more experiences in the previous markets imply fewer experiences in the current market, a smaller return from market-specific human capital, and a lower wage.

With these additional controls, the estimated impact of average college share of the previous market is slightly smaller but not very different from the estimate in the third column. Everything else equal, a one percentage point increase in the average college share of the previous market raises the wage in the current market by about 0.333%. The estimate is significant at 5% significance level.

Finally, in the last column of table 7, I repeat the exercise in the fourth column with additional controls for the previous market to confirm that the estimated effect of college share is not driven by other characteristics of the previous market. Three controls of the previous market are included: the population of workers, the shock index for workers with college education and the shock index for workers without college education. These variables are constructed as explained in section 4. With these additional controls, the college share of the previous market still has a significant effect on the current wage.

5.3 Discussion of Assumption

In order to check of the assumption that, conditional on the current market of residence and other observables, workers from different previous markets were comparable to each other before entering the previous market, I regress measures of average college share of the previous market(s) used in table 7 on AFQT and other controls. Table 8 reports the results. Except for the fact that the dependent variable is not log hourly wage but relevant measures of average college share of the previous market(s), the specifications for table 8 are the same as those in table 7.

In the first three columns of table 8, ability as measured by AFQT is significantly positively correlated with the average college share of the previous market(s), suggesting that workers from a previous market with a larger college share also have higher learning ability on average. The estimated impact of the average college share of the previous market(s) is likely to be biased without

of the average college share of the previous market is 0.393 with a standard error of 0.171, statistically significant at 5% significance level.

appropriate control of individual learning ability. As AFQT is included in all specifications reported in table 7, this potential bias is reduced. In the last two columns of table 8, with the additional controls of relevant labor market information before entering the previous market, AFQT is no longer significantly correlated with the average college share of the previous market, suggesting that workers from different previous markets were comparable to each other before entering the previous market and the estimated impact of the average college share of the previous market is not biased.

Table 8: Ability and College Share of the Previous Market(s)

	(1)	(2)	(3)	(4)	(5)
AFQT percentile/100000	17.009***	21.202***	18.622***	1.810	5.092
	(1.929)	(2.430)	(3.742)	(6.333)	(5.688)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are in the parentheses. Specifications are the same as those in table 7 except that the dependent variable in all columns is the college share of the previous market(s).

Overall, the results in this section imply that workers can accumulate more general human capital in markets with a larger college share. The preferred estimate suggests that a one percentage point increase in the college share of the previous market raises the amount of general human capital accumulated there by about 0.345%. As the average amount of time spent in the previous market is about 3.99 years, a one percentage point increase in the college share of the previous market raises the amount of general human capital accumulated there by about 0.086%.

6 Instrumental Variable Estimates with the 2000 Census

The previous sections have shown that markets with larger college shares have a positive effect on the return to experience and human capital accumulation. While I have controlled for the population of workers and measures of labor demand shocks for each labor market, it's still possible that the positive effect is due to other characteristics of the labor markets as opposed to the college share. To rule out this possibility and get an estimate of the causal effect of the college share, this section exploits the exogenous variation in college shares using an instrumental variable (IV). Following Moretti (2004a) and Shapiro (2006), the instrument used in this section is the presence of land-grant colleges in a labor market.

6.1 Land-grant Colleges

In 1862, the US Congress passed the first Morrill Act, and a second act was passed later in 1890. As the first major federal program to support higher education in the United States, the acts funded educational institutions by granting federally controlled land to the states for them to sell to raise funds to establish and endow "land-grant" colleges. The mission of these institutions as set forth in the 1862 Act is to focus on the teaching of practical agriculture, science, military science and engineering (though "without excluding ... classical studies"), as a response to the industrial revolution and changing social class. Altogether, 75 land-grant colleges and universities were founded, with each state having at least one[27]. Most of these land-grant colleges have grown into large public universities that offer a full spectrum of educational opportunities and have educated almost one-fifth of all students seeking degrees in the United States.

The presence of colleges in a labor market is likely to raise the college share of the labor market because (1) having a local college could raise the college enrollment by lowering the cost of going to college for local residents[28], and (2) college graduates are more likely to stay and work in the labor market where they were educated[29]. Empirically, I show in the next subsection that the presence of land-grant colleges has a significantly positive effect on the college share of a labor market.

Using the presence of colleges as an instrumental variable for the college share may be problematic if their locations are not random. For example, colleges and universities may be more likely to be located in wealthy areas or areas where the industries require more college-educated workers. In both cases the exogeneity of the instrument may be in question.

Although many CZs have colleges, only 67 of them have land-grant colleges. The key assumption for the presence of land-grant colleges to be a valid instrument is that unobservable determinants of returns to experience in CZs with a land-grant college are not systematically different from those in CZs without a land-grant college. Because the program that established land-grant colleges was federal and took place more than 100 years ago, the presence of a land-grant college is unlikely to be correlated directly with unobservable determinants of the return to experience around the year 2000. Actually, as argued in Moretti (2004a), land-grant colleges were often established in rural areas, and their locations were not dependent on natural resources or other factors that could make an area wealthier. Judged from today's point of view, the geographical location of land-grant colleges seems close to being random. Cities with land-grant colleges are as diverse as Ames, IA; Baton Rouge, LA; Cambridge, MA; Knoxville, TN; and Reno, NV.

Shapiro (2006) shows that the geographic distribution of land-grant colleges is quite even. More importantly, using a human capital index based on the distribution of occupations[30] within a labor market[31], Shapiro (2006) compares the difference in human capital stock between markets with and without land-grant colleges over time. There was essentially no difference between the two types of markets at the end of 19th century when many of the land-grant institutions had not yet been established. In the first few decades of the 20th century, when these institutions had been established but rates of college graduation were still very low, the differences were larger but not significant. The difference became significant since 1940 when the land-grant colleges were of significant size. The fact that the difference in human capital stock between the two types of markets became significant

[27] A complete list of land-grant colleges can be found in the appendix of Nervis (1962). The list is a little bit different from other sources like the Integrated Postsecondary Education Data System (IPEDS). Following Moretti (2004a) and Shapiro (2006), this paper uses the list from Nervis (1962). The results are similar when the list from IPEDS is used instead.

[28] Among others, Card (1995), Rouse (1995) and Long (2004) all find that proximity to a college is an important determinant of college enrollment, although its importance may have been declining over time.

[29] For evidence on this link, see, for example, Bound et al. (2004), Groen (2004) and Kennan (2015).

[30] Direct measures of educational attainment can not be used because it was not available until the 1940 census.

[31] Labor markets in Shapiro (2006) are defined as MSAs.

only after land-grant colleges could have played a significant causal role leads Shapiro (2006) to conclude that the presence of land-grant colleges is exogenous to preexisting differences across labor markets.

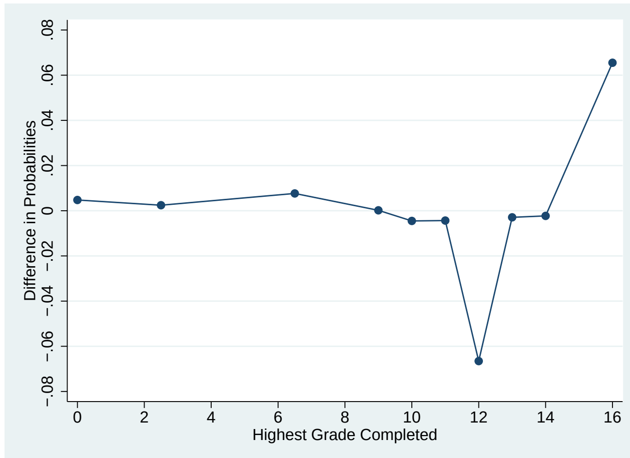

Figure 5: Difference in the Distribution of Schooling Between CZs with and without a Land-grant College in 2000 Census

Figure 5 plots the difference in the distribution of schooling for CZs with and without a land-grant college in the 2000 census. Relative to CZs without a land-grant college, the fraction of college graduates is larger while the fraction of high school graduates is smaller in CZs with a land-grant college. This suggests that some high school graduates would only choose to attend and finish college if there is a land-grant college nearby. Note that there is not much difference between the two types of labor markets in the fractions of workers with other levels of schooling. Figure 5 is consistent with the assumption that the presence of a land-grant college increases the probability of college education, and not vice versa. If the presence of a land-grant college captures unobservable characteristics of the area, such as a larger demand for education either from the industry or due to a higher taste, we would expect that in CZs with a land-grant college not only the fraction of college graduates, but also the fraction of high school graduates and college dropouts, would be higher.

6.2 OLS and IV Estimates

I use the following empirical specification to estimate the effect of college share on the return to experience with the 2000 census

$$RE_c = \beta CS_c + Z_c\Gamma + \alpha_{div} + \xi_c \tag{8}$$

where RE_c, as defined in equation (4), is the return to the first 10 years of experience in labor market c. Z_c is a vector of observable characteristics of the labor market. α_{div} is a fixed effect for each of the nine census divisions, and ξ_c is the error term.

The variables included in the vector Z are the (log) population of workers, the share of workers with 11-20 years of experience, and the share of workers with more than 20 years of experience. The shares of experienced workers are included for two reasons. First, to the extent that experienced workers are more likely to be of high skills, the shares of experienced workers serve as alternative measures of average human capital. Secondly, because educational attainment has been increasing over time, the share of college graduates is negatively related to experience. Because of this correlation, the estimated effect of college shares will be biased if shares of experienced workers have a direct effect on the return to experience and are not included in the regression.

One important labor market characteristic that is omitted from equation (8) is the industry structure. It's not clear whether we should control for the industry structure of a labor market. On one hand, both the college share and the return to experience may vary across industries, omitting the industry structure could potentially bias the estimated effect of college share on the return to experience. On the other hand, industry structure of a labor market is endogenous and could potentially be affected by the college share of the labor market, in which case it would make no sense to control for it. In the following I proceed with no controls for the industry structure, but note that the results are similar when the industry structure of each labor market is controlled through the shares of workers employed in each of the two-digit industry. As a check for the robustness of the results, I estimate in the next subsection the effect of college share on the return to experience by industry.

The first column of table 9 reports the OLS estimates of equation (8). A one percentage point increase in the college share of a labor market is associated with a 0.127 percentage point increase in the return to the first 10 years of experience. The estimate is statistically significant at 1% significance level.

The second column of table 9 reports the IV estimates. Consistent with figure 5, the presence of land-grant colleges has a significantly positive effect on the college share, and on average it raises the college share of a labor market by about 2.6 percentage points. The estimated effect of college share on the return to experience is about 0.5, much larger than the OLS estimate. There are two possible explanations for the larger IV estimate. First, because of the imperfect assignment of workers across CZs mentioned earlier, college shares of the labor markets are measured with error, leading to a downward bias in the OLS estimate and a larger IV estimate which is free from this measurement error. Secondly, the OLS estimate is likely to be biased downward even without the measurement error. For example, one factor included in the error term ξ_c of equation (8) is the demand of young workers relative to that of old workers in a market. A larger relative demand for young workers is likely to raise the wage of young workers relative to old workers, leading to a smaller estimate of the return to experience RE_c. On the other hand, a larger relative demand for young workers in a market may attract young workers from other markets to move into this market, leading to a larger college share because young workers are more likely to be college graduates. Because of its negative effect on the return to experience and positive effect on the college share, the relative demand of young workers in a market induces a downward bias in the OLS estimate of the effect of college share on the return to experience. The IV estimate is larger because it corrects

Table 9: Effects of College Shares on Returns to Experience: Estimates from 2000 Census

	All CZs		Large CZs	
	OLS	IV	OLS	IV
College share	0.127***	0.504***	0.122***	0.508***
	(0.021)	(0.105)	(0.024)	(0.120)
Log population of workers	0.013***	0.004	0.014***	0.004
	(0.001)	(0.003)	(0.001)	(0.003)
Share of workers with				
11-20 years of experience	0.626***	0.038	0.637***	0.053
	(0.145)	(0.233)	(0.165)	(0.265)
$>$ 20 years of experience	0.181***	0.353***	0.181***	0.364***
	(0.061)	(0.086)	(0.069)	(0.099)
First stage		0.026***		0.026***
		(0.004)		(0.004)
Census division fixed effects	Yes	Yes	Yes	Yes
Sample size	741	741	562	562

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Standard errors are in the parentheses.

this downward bias.

The effect of land-grant colleges on the college share and the return to experience can be seen visually in figure 6, which is a replication of figure 1 where the markets with land-grant colleges are shown with solid circles and markets without land-grant colleges are shown with hollow circles. Markets with land-grant colleges tend to be concentrated in the upper-right corner with both larger college shares and higher returns to experience. The average college share across markets with and without land-grant colleges are 31.05% and 24.54%, and the average return to experience for the two types of markets are 52.88% and 49.66%, resulting in a Wald estimate of 0.495 ($\frac{52.88-49.66}{31.05-24.54}$).

To check the robustness of the IV estimate, I re-estimate equation (8) by dropping many of the small CZs. Specifically, as shown in figure 7, land-grant colleges tend to be in larger labor markets, and many of the small markets do not have land-grant colleges. I drop all of the markets with a population smaller than the smallest market with a land-grant college, which are the markets on the left of the vertical line in figure 7, and the relevant estimates are reported in the third and fourth columns of table 9. The estimates with and without those small markets are very similar, suggesting that the results are not affected by the presence of land-grant colleges in relatively large markets.

Another way to check the robustness of the IV estimates is to find, for each labor market with a land-grant college, a similar market without any land-grant college, and then relate the difference in the return to experience to the difference in the college share between the two markets. While markets are different in many dimensions, I consider two markets to be similar if they are in the

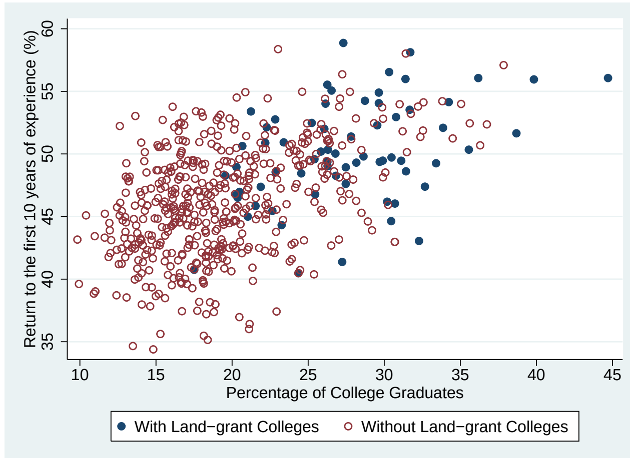

Figure 6: College Shares and Returns to Experience by Land-Grant Status

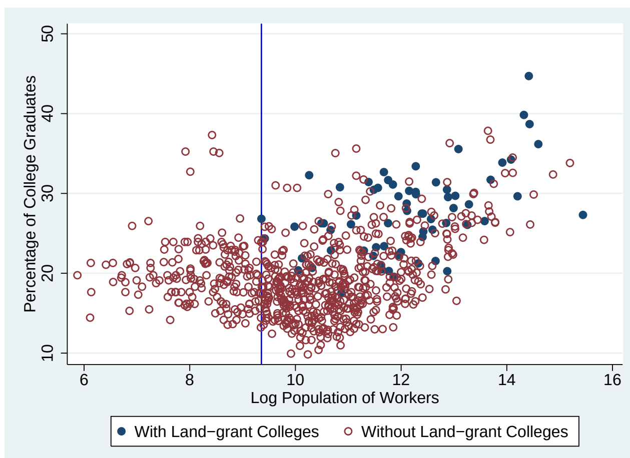

Figure 7: College Shares and the Population of Workers by Land-Grant Status

same census division with similar populations. This gives me 67 pairs of markets, where each pair consists of one market with a land-grant college and another one that is closest to the first one in population among all markets without land-grant colleges in the same census division. For each pair, I can calculate the differences in the college share and the return to experience between the market with a land-grant college and the one without, and this is shown in figure 8.

Ideally, if (1) the only difference between the two markets in each pair is the presence of land-grant colleges; (2) the presence of land-grant colleges has a positive effect on college share; and (3) college share has a positive effect on the return to experience, all of the dots on figure 8 will be in the first quadrant. In practice, 42 out of 67 of them are in the first quadrant. This is not a surprise because, in the real world, the two markets in each pair are different in many other dimensions even if they are similar in population[32]. Actually, the fact that majority of them are in the first quadrant suggests that the presence of land-grant colleges has a positive effect on college share and college

[32] The difference in population between the two markets is less than 10% for 49 pairs.

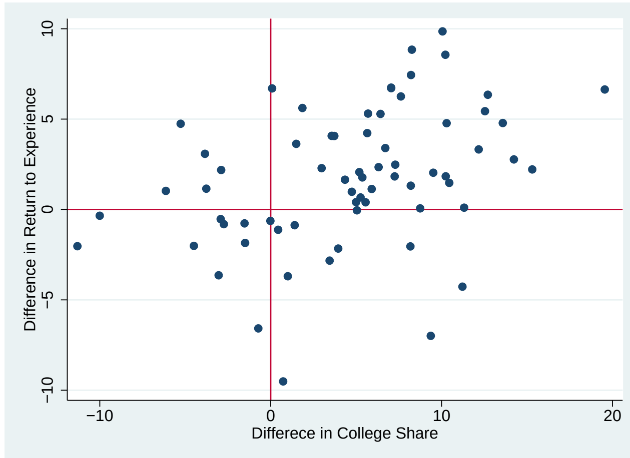

Figure 8: Differences between CZs with and without Land-Grant Colleges

share has a positive effect on the return to experience.

Formally, I run the following regression using the 67 pairs of markets

$$RE_c = \kappa_0 + \kappa_1 CS_c + \alpha_p + \nu_c$$

where α_p is an indicator for each pair of markets, and ν_c is the error term. When college share CS_c is instrumented with the presence of land-grant colleges, the estimated effect of college share on the return to experience is $\hat{\kappa_1} = 0.376$ with a standard error of 0.067. This estimate, although smaller than the IV estimates in table 9, is consistent with a positive effect of college shares on returns to experience.

If workers with different levels of experience are imperfect substitutes, other things equal, a larger share of experienced workers in a labor market will drive down the wage of experienced workers relative to that of young workers and lead to a smaller return to experience in a model without knowledge spillovers. With knowledge spillovers, however, young workers can learn from the experienced workers, and it will be possible for the return to experience to be increasing in the share of experienced workers in a labor market. Consistent with the existence of knowledge spillovers, table 9 shows that the share of experienced workers is positively correlated with the return to experience across markets. Population is also positively correlated with the return to experience in the OLS regressions, however, this correlation becomes insignificant in IV estimations.

6.3 Separate Estimates by Education, Gender and Industry

This subsection estimates the effect of college shares on returns to experience for subgroups of workers. I start with education. Workers are divided into four groups according to years of schooling s: high school dropouts $s < 11$, high school graduates $s = 12$, college dropouts $12 < s < 16$, and college graduates $s \geq 16$. The top panel of table 10 presents the estimated effect of college share for each of the four groups of workers. The effect tends to be hump-shaped in education. While it is not significant and even negative for high school dropouts, it's significantly positive for other three groups of workers, and the effect is largest for college dropouts. This is likely to be the results of two competing forces. On the one hand, better-educated workers are more likely to meet college-educated workers either at work or in everyday life and learn from them, which increases the effect of college share for better-educated workers. On the other hand, better-educated workers, given their higher stock of human capital, probably have less to learn from college-educated workers, which reduces the effect of college share on them.

Table 10: Effects of College Share on Return to Experience by Education, Gender and Industry

	OLS	IV
By Education		
High school dropouts	-0.009	-0.258
	(0.058)	(0.238)
High school graduates	0.163***	0.573***
	(0.027)	(0.121)
College dropouts	0.261***	0.584***
	(0.034)	(0.164)
College graduates	0.082**	0.293**
	(0.035)	(0.131)
By Gender		
Men	0.136***	0.370***
	(0.029)	(0.122)
Women	0.149***	0.739***
	(0.025)	(0.129)
By Industry		
Manufacturing	0.144***	1.221***
	(0.049)	(0.306)
Professional and related services	0.114**	0.361***
	(0.034)	(0.131)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Standard errors are in the parentheses.

Next I estimate the effect of college shares for workers in two industries: manufacturing and professional and related services[33]. These two industries are chosen because, (1) they each employ a relatively large share of the population of workers[34], resulting in a relatively large sample size, and (2) the college share for these two industries are dramatically different[35], allowing me to check the robustness of the results to the level of college share in an industry. As shown in the bottom panel of table 10, college share has a significantly positive effect on the return to experience for workers

[33]Examples of subcategories in the professional and related services industry include health services; legal services; educational services; engineering, architectural and surveying services; accounting, auditing and bookkeeping services; research, development, and testing services; management and public relations services.
[34]The share of workers employed by the two industries are 16.81% and 24.98% respectively.
[35]The college share for the two industries are 18.99% and 47.33% respectively.

in both industries, suggesting that the effect of college shares on returns to experience is not due to the geographic distribution of some specific industries.

Overall, the results in this section suggest a causal effect of college share on the return to experience across labor markets. A one percentage point increase in college share raises the return to the first ten years of experience by about 0.5 percentage point.

7 Conclusion

This paper documents a positive correlation between college shares and the returns to experience across local labor markets in the US, and provide evidence that this correlation reflects a causal effect of college share on individual human capital accumulation. The estimates suggest that a one percentage point increase in the college share of a labor market raises the return to the first ten years of experience by about 0.5 percentage point.

The results are consistent with the idea that, through knowledge spillovers, workers can learn more in markets with a larger fraction of skilled workers, and it provides an explanation for the higher returns to experience in large cities and rich countries documented recently in the literature. The positive effects of college shares on both the level and the growth of individual wages provide a justification for subsidizing higher education.

Future work can build on the results of this paper to estimate the optimal level of public subsidies to higher education and quantify the effect of geographic variation in wage growth and human capital accumulation on individual migration decisions.

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