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#### Who Works Longer Hours in Smart Cities?

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#### Abstract

This paper investigates how human capital concentration in cities is associated with working hours across different worker groups, an important but understudied dimension of urban agglomeration effects. Using microdata from the American Community Survey covering 240 metropolitan statistical areas in 2018, the study finds significant heterogeneous effects: a one percentage point increase in college graduate share is associated with a 0.043% increase in working hours for college graduates but a 0.023% decrease for non-college workers. The effects vary between employment types: collegeeducated paid workers work 0.054% more hours while the self-employed work 0.071% fewer hours in cities with higher human capital stocks. Through a two-step two-stage least squares approach, the study reveals that these effects operate primarily through income changes rather than non-income channels. Alternative measures of human capital stock and various robustness checks confirm the main findings. These heterogeneous labor supply responses suggest that the welfare impact of place-based development initiatives depends not only on productivity gains but also on workers' capacity to capture these benefits through skill development, highlighting the importance of complementing talent attraction policies with workforce development programs.

Keywords: hours worked; human capital externalities; income; STEM; Heckman procedure JEL codes: J22, J24, R23

#### **1** Introduction

Cities are engines of economic growth, and cities with high human capital stocks, commonly known as "smart cities" in the urban economics literature (Shapiro 2006; Winters 2011), are particularly effective at fostering productivity and innovation.<sup>1</sup> While existing literature has extensively documented that human capital externalities in smart cities enhance productivity and wages (Moretti 2004; Winters 2014), we know little about how they affect labor supply decisions. This gap limits our understanding of the overall welfare impact of human capital concentration, as output depends not only on productivity gains but also on how different worker groups adjust their working hours in response.

This paper investigates who works longer hours in smart cities and why these labor supply patterns differ across worker groups. Understanding these patterns is crucial for evaluating the welfare implications of human capital externalities in urban labor markets. The findings directly inform place-based economic development initiatives as cities compete for talent. The welfare impact of such policies depends not only on productivity gains, but critically on how different worker segments adjust their labor supply in response to changing human capital concentrations.

Previous research provides important context but leaves key questions unanswered. Studies show that localization economies can increase work hours through competition effects (Rosenthal and Strange 2008) and that self-employed workers respond

<sup>&</sup>lt;sup>1</sup> The terms "city" and "metropolitan statistical area" (MSA) are used interchangeably in this paper.

differently to agglomeration from wage workers (Cai 2019). Research on human capital externalities demonstrates positive effects on productivity and wages (Moretti 2004; Winters 2014). Some evidence suggests that less-educated workers benefit more from these spillovers (Moretti 2004; Winters 2013). However, we lack evidence on how these externalities affect labor supply decisions across worker groups.

This study uses microdata from the American Community Survey (ACS) 2018 sample to examine how city-level human capital stocks influence hours worked. The empirical strategy addresses potential endogeneity by using the locations of historical land-grant universities as instruments for current human capital levels. Through a novel two-step two-stage least squares approach, the analysis decomposes income and nonincome channels affecting work hours. The study also explores heterogeneity across education levels and between self-employed and wage workers.

The results reveal that college graduates work significantly more hours in smart cities while less educated workers work fewer hours, with these effects operating primarily through income channels. Among college graduates, employment type matters: the self-employed reduce hours while paid workers increase hours in highhuman-capital cities. Using population share of workers who hold a college degree with a major in science, technology, engineering, and mathematics (STEM) as an alternative measure of human capital yields similar patterns.

This study contributes to the literature in two ways. First, it employs a novel twostep two-stage least squares approach that demonstrates human capital externalities affect hours worked primarily through income effects rather than behavioral spillovers. Second, it documents significant heterogeneity across education and employment types, showing how workers' ability to capture benefits from human capital externalities depends on their skill levels.

These findings have important implications for place-based economic development policies. When evaluating initiatives like corporate relocations or expansions, policymakers should consider heterogeneous labor supply responses across worker groups, not just focus on attracting talent. This suggests the importance of complementing place-based development policies with workforce development initiatives to ensure existing workers can benefit from human capital spillovers in their communities.

The remainder of the paper is organized as follows: Section 2 discusses the conceptual framework, Section 3 introduces the empirical methodology and data, Section 4 presents the results, and Section 5 concludes.

## **2** Conceptual Framework

The labor supply of a worker in a city could be affected by the human capital stock through two broad mechanisms: income and non-income channels. While a higher supply of skilled workers might theoretically reduce wages, empirical evidence shows that human capital externalities increase earnings in smart cities (Moretti 2004; Winters 2013; 2014). Workers respond to these income gains through two opposing mechanisms: a substitution effect encouraging more work hours and an income effect reducing desired work hours. The net effect varies across worker groups depending on which force dominates

The human capital stock of a city may also affect hours worked through nonincome channels such as learning spillovers and role model effects. Less-educated workers can learn from their more educated counterparts through observation and interaction (Jovanovic and Rob 1989; Glaeser 1999; Glaeser and Maré 2001). In cities with high concentrations of hard-working skilled workers, this learning process can create a role model effect, influencing lower-educated workers to increase their hours worked independently of income effects. Similarly, highly educated workers often respond to the work habits of their peers through professional networks and knowledge spillovers. This study empirically distinguishes between income and non-income channels in the subsequent analysis.

Beyond these channels, sorting affects the relationship between city human capital stock and hours worked. Workers preferring longer hours may sort into cities, industries, and occupations offering additional compensation for extended work (Cai 2019). Conversely, those valuing leisure may select locations and jobs facilitating better skill-employment matches (Rosenthal and Strange 2004). Smart cities accommodate both sorting types. Consequently, unobserved factors influencing workers' location and job choices could bias estimates of human capital effects on hours worked. This study addresses this challenge using an instrumental variable estimation method detailed in

the next section.

#### **3** Empirical Framework and Data

To investigate which workers work more in cities with higher human capital stocks, I estimate the following model:

$$\ln(Hours)_{im} = \theta Share_m + X_{im}\beta + \delta_s + \varepsilon_{im}$$
(1)

where *i* indexes individual workers, and *m* indexes Metropolitan Statistical Areas (MSA).<sup>2</sup> Hours measures usual hours worked per week. For the Share<sub>m</sub>, I employ two alternative measures: (1) the share of workers with college or higher degrees in an MSA (with higher values indicating "smarter" cities), and (2) the share of workers with STEM college degrees (capturing city STEM-intensity).  $X_{im}$  includes demographic controls: a quartic of age, log commute time, gender, race (4 categories), birthplace (51 categories), and college major (37 categories).  $\delta_s$  represents state-of-workplace fixed effects, and  $\varepsilon_{im}$  is the error term.

To mitigate endogeneity concerns, I employ an instrumental variable (IV) estimation strategy using the presence of land-grant universities in an MSA as an instrument for human capital stocks. These institutions, established under the Morrill Acts of 1862 and 1890, were located primarily based on land availability and agricultural considerations rather than economic factors (Moretti 2004; Iranzo and Peri 2009; Winters 2013). Their initial placement was determined by factors unrelated to

 $<sup>^2</sup>$  This study uses the MSA where individuals work as the geographic unit of analysis. The term "MSA" is used throughout for simplicity.

current labor markets, as they predated modern human capital concentration patterns. While this historical context supports their use as instruments, I acknowledge they may have influenced local economic development over the subsequent 160 years. Therefore, I complement my analysis with two robustness checks in Section 4.2 to assess sensitivity to potential violations of the exclusion restriction.

For STEM share analysis, I modify the instrument to be the distance from an MSA's population center to its nearest land-grant university. This continuous measure provides greater variation for identification compared to the binary presence indicator, which is particularly important since STEM shares exhibit less volatility across MSAs than overall college shares, as illustrated in Figure 1.

I estimate Equation (1) for three subsamples: all workers, non-college educated workers, and college graduates, to investigate heterogeneity. Similarly, when using STEM share as the human capital stock measure, I analyze non-college educated workers, non-STEM graduates, and STEM graduates separately.

To investigate the mechanisms through which human capital stocks affect hours worked, I employ a two-step two-stage least squares approach to decompose the total effect into direct and indirect components. The direct effect operates through hourly earnings: human capital externalities increase local productivity and hourly incomes, which in turn influence labor supply decisions. The indirect effect captures any nonincome channels through which human capital concentration might affect hours worked, such as learning spillovers or role model effects. In the first step, I isolate the direct income effect by estimating:

$$\ln(Hours)_{im} = \alpha Income_m + X_{im}\beta + \delta_s + \mu_{im}$$
(2)

where  $Income_m$  is the regression-adjusted average hourly income at the MSA level.<sup>3</sup> To identify exogenous variation in local incomes, I instrument  $Income_m$  using a Bartik shift-share instrument that captures demand-driven changes in local income levels.<sup>4</sup> This approach helps ensure that the error term  $\mu_{im}$  primarily reflects supplyside variation in hours worked rather than demand-side factors.

In the second step, I test whether human capital stocks affect hours worked through non-income channels by estimating:

$$\hat{\mu}_{im} = \gamma Share_m + X_{im}\beta + \delta_s + \epsilon_{im} \tag{3}$$

where  $\hat{\mu}_{im}$  is the residual from Equation (2). Since  $\hat{\mu}_{im}$  represents the variation in hours worked that is not explained by income effects, the coefficient  $\gamma$  captures the non-income channel effects. I instrument  $Share_m$  with the land-grant university indicator as in the main analysis. This two-step approach allows me to cleanly separate income and non-income effects while addressing endogeneity concerns at each stage.

Given the inherent differences between self-employment and paid employment (Cai 2019), I further examine heterogeneity across these work arrangements. However, workers may self-select into these two groups. To address this potential selection bias,

 $<sup>^3</sup>$  The adjusted hourly incomes are computed as the MSA fixed effects of a Mincer equation.

<sup>&</sup>lt;sup>4</sup> I constructed Bartik instrumental variables at the MSA level following  $Bartik_m = \sum_k s_{km}^{2009} g_{k\bar{m}}$ . Here,  $s_{km}^{2009}$  represents the employment share of industry k in city m in 2009.  $g_{k\bar{m}}$  measures the employment growth rate in industry k from 2009 to 2018 across all cities except city m. I selected 2009 as the base year because consistent MSA workplace information only became available in the ACS from that year forward. Additionally, I utilized two-digit industry codes to calculate local industry shares and industry growth rates, excluding the public sector and military.

I employ a two-stage Heckman procedure (Heckman 1979). In the first stage, I estimate the probability of being in each employment type using a probit regression. In the second stage, I include the inverse Mills ratio from the first stage to correct for selection bias. Following Cai, Stephens, and Winters (2019) and to satisfy the exclusion restriction, I exclude the college major dummies in the second stage regression.

The data used in this study come from the 2018 American Community Survey (ACS) microdata obtained through IPUMS-USA (Ruggles et al. 2019). The analytical sample is restricted to workers aged 26–59 who work more than 35 hours weekly in MSAs. The ACS data provide comprehensive worker information spanning labor market outcomes (hours, earnings), demographics, and educational background.

The key independent variables are college and STEM shares at the MSA level, calculated using the full sample with personal survey weights and without age or working-hour restrictions. College share represents the proportion of individuals with college or higher degrees in an MSA's total population, while STEM share captures the proportion with STEM-majored undergraduate degrees. STEM majors are defined following the U.S. Immigration and Customs Enforcement classification (Cai and Winters 2017).<sup>5</sup>

As discussed above, I use the presence of at least one land-grant university in an MSA and the distance from the population center of each MSA to the nearest land-grant university as instruments for college and STEM shares, respectively. I combine the list

<sup>&</sup>lt;sup>5</sup> The STEM list is available at <u>https://www.ice.gov/sites/default/files/documents/Document/2016/stem-list.pdf</u>. The majors in the ICE list are slightly different from those in the ACS, but the difference is negligibly small. I provide the STEM list of this study in Appendix Table A1.

of land-grant universities from Nevins (1962) with the list of 1862 and 1890 land-grant colleges and universities from the National Institute of Food and Agriculture (NIFA) of the United States Department of Agriculture (USDA) to identify the land-grant universities. This yields a list of 67 land-grant universities for this study, which is available in Appendix Table A2. The official addresses of the land-grant universities were entered into GIS software to calculate distances for the STEM share instrument.<sup>6</sup>

Table 1 presents the summary statistics by educational groups. College graduates work, on average, 44.796 hours per week in MSAs, while their non-college counterparts work 43.533 hours per week on average. STEM graduates work 45.078 hours per week, while non-STEM graduates work 44.685 hours per week. Thus, on average, college-educated workers work more hours than non-college workers in MSAs, and STEM graduates work the most.

## [Please insert Table 1 here]

Figure 1 provides a visual preview of the key relationships examined in this study. The left panel shows that college graduates tend to work longer hours in MSAs with higher college shares, while non-college workers exhibit the opposite pattern. A similar divergent pattern appears when using STEM shares as an alternative measure of human capital stock (right panel). These raw correlations suggest potentially heterogeneous effects of human capital externalities on hours worked across worker types. However, these patterns may reflect various confounding factors and selection issues. The

<sup>&</sup>lt;sup>6</sup> The work described in this paragraph comes from Cai (2016).

following empirical analysis formally investigates these relationships while addressing potential endogeneity concerns.

## [Please insert Figure 1 here]

#### **4 Empirical Results**

#### 4.1 Human Capital Stocks and Hours Worked

This section begins by estimating Equation (1) to investigate the relationship between human capital stocks and hours worked by workers in cities. Panel A of Table 2 reports the ordinary least squares (OLS) estimates. Column (1) shows that a 1 percentage point increase in the share of college graduates in an MSA is correlated with a 0.002% increase in usual hours worked per week for an average worker, but the effect is not statistically significant. This implies that one standard deviation increase in college share corresponds to approximately 0.33 more hours worked per year,<sup>7</sup> which is not economically significant. Next, the analysis examines heterogeneity between non-college and college workers. Column (2) shows that lower-educated workers work statistically fewer hours in smart cities at the 10% significance level. Column (3) reveals that for college graduates, a 1 percentage point increase in college share is associated with a 0.043% increase in hours worked, significant at the 1% level. In summary, these results demonstrate that non-college workers work fewer hours in smart cities while their college-educated counterparts work significantly more hours.

<sup>&</sup>lt;sup>7</sup> I assume that workers work 48 weeks per year for simplicity.

However, these results could be biased due to the endogeneity issues discussed in Section 2.

#### [Please insert Table 2 here]

To address the endogeneity, I use the presence of at least one land-grant college in an MSA to instrument for college share. Panel B of Table 2 reports the two-stage least squares (2SLS) estimates. The estimated coefficients are larger than their OLS counterparts in absolute magnitudes and exhibit the same or higher precision, except for non-college workers. The full sample results show that one standard deviation increase in college share is associated with workers working 4.62 more hours per year at the 10% significance level. The effect for non-college workers remains negative and similar in magnitudes but becomes statistically insignificant. The coefficient for college graduates is statistically significant at the 1% level, showing that a 1 percentage point increase in college share associates with a 0.081% increase in hours worked among college graduates, or one standard deviation increase in college share leads to 13.06 additional hours worked per year. The 2SLS results display a roughly similar pattern to the OLS results. This is supported by the results of the endogeneity tests, which fail to reject the null hypothesis that college share can be treated as exogenous at conventional significance levels, suggesting OLS estimates may be more efficient.<sup>8</sup>

Nevertheless, the presence of a land-grant college proves to be a fair instrument

<sup>&</sup>lt;sup>8</sup> To test for endogeneity, I implement a robust test based on differences in Sargan-Hansen statistics. The test compares two J-statistics: one treating college share as endogenous and another treating it as exogenous. Under the null hypothesis that college share can be treated as exogenous, the test statistic follows a chi-squared distribution. While this test is numerically equivalent to a Hausman test under homoskedasticity (see Hayashi 2000, pp. 233-234), my implementation is robust to various violations of homoskedasticity. This provides a rigorous framework for evaluating the necessity of instrumental variables estimation.

for college share in this case. The first stage results show that the presence of a landgrant college significantly predicts college share at the MSA level. The first stage Fstatistics are all larger than 10, indicating the specifications are less likely to suffer from a weak instrument issue.

#### 4.2 Sensitivity Analysis of the IV Strategy

I conduct two analyses to assess the credibility of my identification strategy. First, following Conley, Hansen, and Rossi (2012), I relax the assumption that the presence of land-grant universities affects hours worked only through college share. Specifically, I allow land-grant universities to have a direct effect on hours worked by modifying the main specification to:

$$\ln(Hours)_{im} = \theta Share_m + \pi LG_m + X_{im}\beta + \delta_s + \varepsilon_{im}$$

where  $LG_m$  is a dummy variable indicating the presence of at least one land-grant university in the MSA and  $\pi$  represents its direct effect on hours worked. While  $\pi = 0$ in the baseline IV analysis, I now allow  $\pi$  to vary within [-0.001, 0.001]. Panel C of Table 2 reports these bounded estimates. For college graduates, the bounds [0.010, 0.160] exclude zero, indicating that even allowing for meaningful direct effects of landgrant university presence, the impact of college share remains significantly positive. For non-college workers, the bounds [-0.075, 0.038] include zero, consistent with the baseline results.

As a second robustness check, I implement Oster (2019)'s coefficient stability

analysis to assess the influence of selection on unobservables. Panel D of Table 2 reports two key statistics: Delta ( $\delta$ ), which indicates how strong selection on unobservables would need to be relative to selection on observables to explain away the estimated effect; and bias-adjusted treatment effects and identified sets calculated under the assumption of equal selection ( $\delta = 1$ ), using  $R_{max} = \min\{1.3\tilde{R}^2, 1\}$  as suggested by Oster (2019).

For college graduates, the bounds [0.043, 0.059] exclude zero, supporting the significant positive effect. The delta of -19.773 indicates that selection on unobservables would need to be in the opposite direction and nearly 20 times as strong as selection on observables to nullify the result. For non-college workers, the bounds [-0.023, -0.008] also exclude zero, supporting the OLS finding of a significant negative effect. The delta of 1.390 suggests selection on observables is stronger than that on unobservables, lending further credibility to these results.

Collectively, these robustness checks support the main findings while also validating the endogeneity test results from Panel B, which fail to reject exogeneity at conventional levels. This suggests that while the IV estimates provide a useful robustness check, the OLS estimates may be more efficient in this context.

## 4.3 Mechanism Tests

To investigate the mechanism through which human capital stocks affect hours worked, I use the two-step procedure from Section 3 to decompose effects into income and non-income channels. Panel A of Table 3 presents 2SLS estimates using a Bartik shift-share instrument to identify exogenous variation in local wages, ensuring residual variation reflects supply-side factors. For the full sample in Column (1), a one-unit increase in regression-adjusted income associates with a 0.017 increase in hours worked, though not statistically significant. Non-college graduates (Column 2) show a small negative effect (-0.004), also insignificant, suggesting neither the income nor substitution effect dominates. For college graduates (Column 3), the effect is positive and significant at the 1% level (0.033), implying the substitution effect dominates. These findings indicate the income channel matters primarily for college graduates, with less clear impacts on other groups.

After isolating the income channel effects, I examine whether human capital stocks affect hours worked through non-income channels by using the residuals from the second stage of the first step estimation as the dependent variable of Equation (3). I return to using the land-grant university instrument for college share to maintain consistency with the main analysis. Panel B of Table 3 shows that while point estimates suggest positive effects for college graduates (0.028) and the full sample (0.006), none are statistically significant. The estimate for non-college workers is negative (-0.012) but also insignificant. These results indicate limited evidence of human capital stocks affecting hours worked through non-income channels, though relatively large standard errors limit statistical precision.

## [Please insert Table 3 here]

#### 4.4 Heterogeneity Tests

Prior research has documented that self-employed individuals work more hours than paid employees (Baines and Gelder 2003; Cai 2019; Parker 2004), a pattern confirmed by the estimates for paid-employment dummies in Table 2 regressions (not reported). Paid employees work significantly fewer hours: 0.058 log points less in the full sample, 0.065 points less for lower-educated workers, and 0.046 points less for college graduates. These heterogeneous differences between employment types may contribute to the patterns observed in Table 2.

To investigate this heterogeneity, I split both the non-college and college samples into self-employment and paid-employment subsamples. Panel A of Table 4 presents the OLS results.<sup>9</sup> For less-educated workers, college share significantly reduces hours worked only among the self-employed, with no significant effect on paid workers. Among college graduates, a 1 percentage point increase in college share produces divergent effects: reducing self-employed hours by 0.071% (p < 0.05) while increasing paid workers' hours by 0.054% (p < 0.01).

The results in Panel A of Table 4 may be biased due to non-random selection into self-employment and paid employment. Following Heckman (1979) and Cai, Stephens, and Winters (2019), I apply a two-stage Heckman selection correction procedure to account for potential selection bias. To satisfy the exclusion restriction, I use college

<sup>&</sup>lt;sup>9</sup> The 2SLS results, which display a similar pattern, are provided in Appendix Table A3.

major dummies as exclusion variables. Panel B of Table 4 reports these results.

Comparing results between Panel B and Panel A reveals subtle pattern changes. For college-educated workers, higher college share still reduces hours worked among the self-employed and increases hours for paid workers. The self-employment effect is smaller in magnitude but more precise, while the paid employment effect is larger with similar precision. These findings suggest differing leisure preferences between employment types among college graduates. For self-employed college graduates, the income effect dominates the substitution effect, while the opposite occurs for those in paid employment.

A noteworthy difference between Panels B and A is that for lower educated workers, the effects of college share on hours worked become highly significant and larger in magnitude for both employment types, suggesting that the income effect dominates the substitution effect for both self-employed and paid non-college workers. This difference from Panel A results from selection bias, as evidenced by the statistically significant coefficients on the inverse Mills ratios in Panel B, particularly for paid employment.

## [Please insert Table 4 here]

Panel B of Table 4 also reports the marginal effects for the first stage probit estimates of the Heckman procedure. The results show that college share is significantly associated with employment decisions for both education groups. Non-college workers are more likely to be self-employed (by 0.037 percentage points) and therefore less likely to be paid workers in cities with higher college shares. This selection pattern explains why the negative effect of college share on hours worked among lowereducated paid workers is underestimated in Panel A. In contrast, for college graduates, a 1 percentage point increase in college share reduces the probability of being selfemployed by 0.072 percentage points, and increases the probability of being a paid worker by the same magnitude.

These findings partially align with existing literature. Sousa (2013) shows human capital spillovers increase self-employment among less-educated immigrants in ethnic enclaves, consistent with my results, while Acs, Braunerhjelm, Audretsch, and Carlsson (2009) demonstrate knowledge spillovers enhance entrepreneurship nationally. The literature on educational attainment and self-employment shows mixed results: some studies find educated workers more likely to be self-employed given sufficient wealth (Robinson and Sexton 1994; Greene and Saridakis 2008), while others suggest education is not a strong determinant (Bates 1995). Dawson, Henley, and Latreille (2009) connect higher education with "opportunity" entrepreneurship, and Baumann and Brändle (2012) find education explains self-employment when considering employment protection. My MSA-level results show college graduates gravitate toward paid employment while less-educated workers favor self-employment in smart cities, likely reflecting the earning opportunity differentials described in Cai and Winters (2017).

#### 4.5 Alternative Measure for Human Capital Stocks: STEM Shares

Previous research has shown that STEM graduates play a particularly important role in generating income externalities (Winters 2014). To further check the robustness of the findings above, I use the share of STEM-educated workers instead of college share as an alternative measure for human capital stock. Table 5 shows the estimated effects of STEM share on hours worked by different types of workers.

The OLS results (Panel A of Table 5) show a highly significant and positive effect of STEM share on hours worked by college graduates (Column 2), while the effect on non-college workers is not significant (Column 1). These results align with the previous findings using college share as the measure of human capital. For STEM graduates specifically (Column 4), a 1 percentage point increase in STEM share is associated with 0.082% more hours worked. This translates to approximately 8.16 additional hours worked per year given a one standard deviation increase in STEM share. Similarly, Column (3) shows that non-STEM graduates work 4.96 more hours per year with a one standard deviation increase in STEM share. Setablished in the mechanism analysis, income appears to be the primary channel through which human capital affects labor supply. The positive effect on working hours among STEM graduates appears to "spills over" to non-STEM graduates through income externalities, suggesting that the substitution effect dominates the income effect for both groups.

Panel B of Table 5 reports the 2SLS results. All estimates increase in magnitude but decrease in precision. Instead of the land-grant university indicator used in Table 2, I use log distance from each MSA's population center to the nearest land-grant university as an instrument for STEM share. This choice aligns with the 1862 Act's mandate for land-grant universities to teach "practical agriculture, science, military science, and engineering"<sup>10</sup> – subjects that largely overlap with today's STEM fields. The instrument's validity is supported by the first stage results and F statistics reported at the bottom of Table 5.

## [Please insert Table 5 here]

Following the approach in Table 4, I separate non-STEM and STEM samples into self-employment and paid-employment subsamples to investigate heterogeneous effects. Panel A of Table 6 presents the OLS results for these subsamples.<sup>11</sup> The findings show that an increase in STEM share is associated with paid employees working significantly more hours, regardless of whether they are non-STEM or STEM workers, while the estimates for self-employed workers are both negative and statistically insignificant. These differential responses suggest that for self-employed workers, the income effect approximately balances the substitution effect, whereas for paid employees, the substitution effect clearly dominates the income effect.

To control for potential selection bias, I apply the Heckman procedure as in Table 4. The results shown in Panel B of Table 6 are consistent with those in Panel A. The main difference is that the magnitudes of the estimates for paid employment are larger, as college graduates are more likely to select into paid employment when STEM share

<sup>&</sup>lt;sup>10</sup> See <u>https://en.wikipedia.org/wiki/Land-grant\_university</u>

<sup>&</sup>lt;sup>11</sup> The 2SLS results display a similar pattern and are provided in Appendix Table A4.

increases. This finding aligns with Cai and Winters (2017), who show that foreign STEM graduates prefer paid employment due to potential earning advantages. Additionally, as STEM share increases, non-STEM graduates are also more likely to enter paid employment.

#### [Please insert Table 6 here]

#### 4.6 Sensitivity Analysis

To verify result robustness, I conduct several sensitivity analyses based on the preferred specifications in Tables 2, 4, 5, and 6. Table 7 reports the estimated coefficients of college and STEM shares. Panels A to D present results controlling for ten dummy variables for education attainment, one indicator for marital status, and one indicator for children at home. Despite these variables' potentially endogeneity to local economic conditions (hence their exclusion from main analyses), the results remain consistent with earlier findings.

Immigrants may differ from natives in hours worked due to cultural differences and language proficiency. Panels E to H of Table 7 report the results after controlling for citizenship status, duration of residence in the United States (using five interval categories), and English language proficiency (using four categories). These additional controls do not substantially alter the main findings, confirming the robustness of the results.

Working hours in different industries and occupations may inherently vary.

However, hours worked, industries, and occupations may be jointly determined due to unobserved worker heterogeneity. Therefore, I do not control for these variables in the main analyses.

Panels I to L report the results including industry and occupation dummies for sensitivity analysis. Most results remain robust compared to the main findings. In Panel I, the significance levels switch in Columns (1) and (2) compared to Table 2, but this does not qualitatively change the pattern. In Panel J, the income effect slightly dominates the substitution effect for the self-employed. However, caution is warranted when interpreting these results since workers jointly choose their occupations, industries, and places of work.

Panels M to P report the results controlling for Bartik shift-share instruments constructed using two-digit industry codes to account for local labor demand shocks. These results also remain robust.

## [Please insert Table 7 here]

#### **5** Conclusions

This paper uses the ACS microdata to examine how human capital stocks are associated with the hours worked by different types of workers in MSAs. The results show that less-educated workers work marginally fewer hours and college-educated workers work significantly longer hours in smart cities. The effects primarily stem from income gains in smart cities. For non-college workers, the income effect weakly dominates the substitution effect, while for college graduates, the substitution effect strongly dominates the income effect.

After applying the Heckman correction, the results show that non-college workers work significantly fewer hours regardless of whether they are self-employed or in paid employment. Among college graduates, those who are self-employed work significantly fewer hours while those in paid employment work significantly more hours in smart cities. The findings remain robust when using STEM share as an alternative proxy for human capital stocks and when conducting several sensitivity tests.

These findings have important implications for several pressing policy challenges in the U.S. First, the results provide new insights for place-based development initiatives, which have gained prominence with high-profile cases like Amazon's HQ2 selection. While these initiatives often emphasize attracting talent, the findings on heterogeneous labor supply responses suggest the need for a more nuanced approach. Cities competing for corporate relocations or expansions should consider how the influx of high-skilled workers might affect their entire labor market, including existing low-skilled workers' employment patterns.

Second, the finding that human capital externalities primarily operate through income channels highlights the importance of skill development. This is particularly relevant for regions experiencing industrial transitions, where federal and state job training programs, including the workforce development initiatives through community colleges, play a crucial role in helping workers capture the benefits of human capital spillovers.

Lastly, the results help explain the declining business dynamism in American cities. College graduates increasingly prefer paid employment in smart cities, consistent with observed trends in tech hubs like Silicon Valley and Boston where high-skilled workers join established firms rather than start new businesses. This suggests policies promoting entrepreneurship must address not just the general business environment but also specific challenges faced by high-skilled entrepreneurs in high-cost, talentconcentrated cities.

Several limitations should be noted. First, focusing exclusively on U.S. metropolitan areas limits generalizability to cities in countries with different labor market institutions, work cultures, and economic development levels. Future research could test whether these relationships between human capital stocks and working hours persist across diverse institutional contexts. Second, workers' self-selection into occupations, industries, and cities complicates causal interpretation. Despite employing various strategies to address endogeneity, the cross-sectional nature of the data constrains causal inference. These findings should be viewed as descriptive evidence of important associations warranting further investigation.

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Figure 1: Hours Worked by Education Type and Human Capital Stock

Notes: The figure shows the relationship between average log weekly hours worked and human capital stocks (measured by college and STEM shares) across MSAs. Point sizes are weighted by MSA population. Solid and dashed lines show fitted linear relationships for college graduates and non-college workers, respectively. Data source: 2018 ACS.

	Mean	Std. Dev.	Min	Max
Full sample (N=572,536)				
Usual hours worked per week	44.026	8.096	35.000	99.000
College share	0.373	0.078	0.163	0.567
STEM share	0.096	0.035	0.023	0.297
Age	41.573	10.297	25.000	60.000
Commute time	28.499	23.898	0.000	188.000
Female	0.419		0.000	1.000
Self-employment	0.092		0.000	1.000
White	0.563		0.000	1.000
Black	0.120		0.000	1.000
Hispanic	0.214		0.000	1.000
Asian	0.080		0.000	1.000
Other races	0.023		0.000	1.000
	Mean	Std. Dev.	Min	Max
<u>Non-college (N=331,339)</u>				
Usual hours worked per week	43.533	7.970	35.000	99.000
College share	0.361	0.077	0.163	0.567
STEM share	0.091	0.032	0.023	0.297
Age	42.052	10.379	25.000	60.000
Commute time	28.436	24.073	0.000	188.000
Female	0.395		0.000	1.000
Self-employment	0.094		0.000	1.000
White	0.503		0.000	1.000
Black	0.142		0.000	1.000
Hispanic	0.286		0.000	1.000
Asian	0.046		0.000	1.000
Other races	0.022		0.000	1.000
	Mean	Std. Dev.	Min	Max
<u>College (N=241,197)</u>				
Usual hours worked per week	44.796	8.230	35.000	99.000
College share	0.391	0.075	0.163	0.567
STEM share	0.102	0.038	0.023	0.297
Age	40.826	10.123	25.000	60.000
Commute time	28.597	23.623	0.000	188.000
Female	0.457		0.000	1.000
Self-employment	0.090		0.000	1.000
White	0.656		0.000	1.000
Black	0.085		0.000	1.000
Hispanic	0.100		0.000	1.000
Asian	0.133		0.000	1.000

## **Table 1: Summary Statistics**

Other races	0.025		0.000	1.000
	Mean	Std. Dev.	Min	Max
<u>Non-STEM (N=172,128)</u>				
Usual hours worked per week	44.685	8.113	35.000	99.000
College share	0.388	0.074	0.163	0.567
STEM share	0.099	0.034	0.023	0.297
Age	40.778	10.144	25.000	60.000
Commute time	28.337	23.499	0.000	188.000
Female	0.527		0.000	1.000
Self-employment	0.095		0.000	1.000
White	0.684		0.000	1.000
Black	0.094		0.000	1.000
Hispanic	0.105		0.000	1.000
Asian	0.093		0.000	1.000
Other races	0.024		0.000	1.000
	Mean	Std. Dev.	Min	Max
<u>STEM (N=69,069)</u>				
Usual hours worked per week	45.078	8.511	35.000	99.000
College share	0.398	0.078	0.163	0.567
STEM share	0.109	0.046	0.023	0.297
Age	40.944	10.070	25.000	60.000
Commute time	29.252	23.920	0.000	188.000
Female	0.281		0.000	1.000
Self-employment	0.076		0.000	1.000
White	0.587		0.000	1.000
Black	0.062		0.000	1.000
Hispanic	0.090		0.000	1.000
Asian	0.236		0.000	1.000
Other races	0.026		0.000	1.000

Notes: This table provides the summary statistics for the variables used in the main analysis. Dummy variables for majors of study and states of workplace are omitted to conserve space. The sample is restricted to workers employed in Metropolitan Statistical Areas. Personal survey weights are used.

Table 2: Hours Worked and College Share							
	(1)	(2)	(3)				
	Full	Non-college	College				
A. OLS results:							
College share	0.002	-0.023*	0.043***				
conege share	(0.002)	(0.013)	(0.012)				
<b>B. 2SLS results:</b>	(0.011)	(0.013)	(0.012)				
College share	$0.028^*$	-0.016	$0.081^{***}$				
	(0.016)	(0.021)	(0.030)				
First Stage results							
Land grant	$0.068^{***}$	$0.068^{***}$	0.066***				
	(0.019)	(0.018)	(0.019)				
Underidentification	6.706	7.648	5.658				
	{0.010}	{0.006}	{0.017}				
Weak identification	13.177	13.828	11.739				
Endogeneity	2.473	0.148	2.159				
	{0.116}	$\{0.700\}$	{0.142}				
C. Conley et al. (2012) boun	<u>ds:</u>						
College share	[-0.021 0.075]	[-0.075 0.038]	[0.010 0.160]				
D. Oster (2019) bounds:							
College share	[-0.004 0.002]	[-0.023 -0.008]	[0.043 0.059]				
Delta	0.373	1.390	-19.773				
Ν	572,536	331,339	241,197				
N The state of the state	11	1 551 / 11 1					

Notes: The dependent variable is log usual hours worked per week. The table only reports the estimates for the coefficients of interest due to space constraints. The regressions also control for age, log commute time, a gender dummy, a work type dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Standard errors in parentheses are clustered at the MSA level. Values in curly brackets represent p-values. Panel C reports bounds following Conley et al. (2012) assuming the presence of at least one land-grant university in an MSA as the instrument, with its direct effect on hours worked bounded between -0.001 and 0.001. Panel D reports coefficient bounds following Oster (2019) assuming  $R_{max} = \min\{1.3\tilde{R}^2, 1\}$ , where  $\tilde{R}^2$  is the R-squared from the controlled regression, with "Delta" representing the ratio of selection on unobservables to selection on observables that would reduce the estimated effect to zero. Personal survey weights are used. \* denotes significance at the 10% level; \*\*\* significance at the 1% level.

Table 3: Mechanism Test							
	(1)	(2)	(3)				
	Full	Non-college	College				
A. First step 2SLS results:							
Regression-adjusted income	0.017	-0.004	0.033***				
	(0.010)	(0.020)	(0.011)				
<b>B. Second step 2SLS results:</b>							
College share	0.006	-0.012	0.028				
	(0.016)	(0.021)	(0.025)				
Ν	572,536	331,339	241,197				

Notes: The dependent variable of Panel A is log usual hours worked per week. The dependent variable of Panel B is the residual of the second stage regression in Panel A. The instrumental variable for Panel A is a Bartik shift-share constructed using two-digit industry codes. The instrument for Panel B is a dummy for the presence of at least one land-grant university in an MSA. The first-stage F statistics are larger than 10 in all specifications. The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, a work type dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Standard errors in parentheses are clustered at the MSA level. Personal survey weights are used. \*\*\* denotes significance at the 1% level.

	Table 4: Self-employment vs. Paid employment										
	Non-college College										
	(1)	(2)	(3)	(4)							
	Self-	Paid	Self-	Paid							
	employment	employment	employment	employment							
A. OLS res	ults										
College	-0.051**	-0.020	-0.071**	$0.054^{***}$							
share	(0.022)	(0.013)	(0.035)	(0.011)							
B. Heckman	n procedure resu	ılts									
College	-0.073***	-0.029***	-0.063***	$0.082^{***}$							
share	(0.027)	(0.005)	(0.023)	(0.006)							
Coefficient	-0.096	0.159***	-0.019*	0.110***							
on the	(0.107)	(0.012)	(0.010)	(0.006)							
inverse											
Mills ratio											
First Stage	Marginal Effects										
College	$0.037^{***}$	-0.037***	-0.072***	$0.072^{***}$							
share	(0.008)	(0.008)	(0.010)	(0.010)							
Ν	32,319	299,020	22,362	218,835							

Notes: The dependent variable is log usual hours worked per week. The dependent variable for the first stage of the Heckman procedure is a dummy variable for self-employment (Columns 1 and 3) and paid employment (Columns 2 and 4). The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Personal survey weights are used. \* denotes significance at the 10% level; \*\* significance at the 1% level.

Table 5: Hours worked and STEM Share									
	(1)	(2)	(3)	(4)					
	Non-college	College	Non-STEM	STEM					
A. OLS results:									
STEM share	-0.025	$0.070^{***}$	$0.068^{***}$	$0.082^{***}$					
	(0.019)	(0.015)	(0.017)	(0.019)					
<b>B. 2SLS results:</b>									
STEM share	0.025	$0.091^{**}$	0.078	0.126**					
	(0.043)	(0.043)	(0.048)	(0.053)					
First Stage results									
Log distance to land	-0.015***	-0.018***	-0.017***	-0.020***					
grant	(0.003)	(0.004)	(0.003)	(0.006)					
Underidentification	6.901	7.287	6.574	6.708					
	[0.009]	[0.007]	[0.010]	[0.010]					
Weak identification	20.897	22.212	33.923	10.099					
Endogeneity	1.405	0.320	0.067	0.764					
	[0.236]	[0.571]	[0.796]	[0.382]					
Ν	331,339	241,197	172,128	69,069					

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Notes: The dependent variable is log usual hours worked per week. The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, a work type dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Standard errors in parentheses are clustered at the MSA level. The numbers in brackets are p-values. Personal survey weights are used. \*\* denotes significance at the 5% level; \*\*\* significance at the 1% level.

Table 6: Self-employment vs. Paid employment									
Non-STEM STEM									
	(1)	(2)	(3)	(4)					
	Self-	Paid	Self-	Paid					
	employment	employment	employment	employment					
A. OLS res	ults								
STEM	-0.038	$0.078^{***}$	-0.098	$0.094^{***}$					
share	(0.078)	(0.020)	(0.141)	(0.015)					
B. Heckman	n procedure resu	ılts							
STEM	-0.034	$0.125^{***}$	-0.065	$0.179^{***}$					
share	(0.053)	(0.014)	(0.090)	(0.023)					
Coefficient	-0.012	$0.077^{***}$	-0.027	0.222***					
on the	(0.015)	(0.009)	(0.017)	(0.016)					
inverse									
Mills ratio									
First Stage	Marginal Effects								
STEM	-0.122***	0.122***	-0.297***	0.297***					
share	(0.024)	(0.024)	(0.028)	(0.028)					
Ν	16,918	155,210	5,444	63,625					

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Notes: The dependent variable is log usual hours worked per week. The dependent variable for the first stage of the Heckman procedure is a dummy for being self-employed (Columns 1 and 3) and paid employment (Columns 2 and 4). The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Personal survey weights are used. \*\*\* denotes significance at the 1% level.

			Tab	ole 7: Sensitiv	ity Analysis			
A. Table 2:	: OLS inclu	ding controls for e	ducation, marria	ige, and child	ren			
	(1)	(2	2)			(3)		
	Full	Non-c	ollege			College		
College	-0.001	-0.0	)24*			0.035***		
share	(0.011)	(0.0	)13)			(0.011)		
B. Table 4:	: Heckman J	orocedure includi	ng controls for ed	lucation, mar	riage, and children			
		Non-c	ollege			College		
		(1)	(2)		(3)	C	(4)	
		Self-	Paid		Self-employment		Paid employment	
		employment	employment					
College	-	-0.071**	-0.032***		-0.065***		0.073***	
share		(0.029)	(0.005)		(0.023)		(0.006)	
Coefficient		-0.065	0.161***		-0.018*		0.112***	
on the		(0.103)	(0.011)		(0.010)		(0.006)	
inverse								
Mills ratio								
C. Table 5:	: OLS inclu	ding controls for e	education, marria	ige, and child	ren			
		(1	1)	(2)	(3)		(4)	
		Non-c	ollege	College	Non-STEM		STEM	
STEM	-	-0.0	027	0.052***	$0.058^{***}$		0.055***	
share		(0.0	)19)	(0.015)	(0.018)		(0.020)	
D. Table 6:	: Heckman	procedure includi	ng controls for ed	lucation, mai	riage, and children			

				Non-S	STEM	ST	STEM	
				(1)	(2)	(3)	(4)	
				Self-	Paid	Self-	Paid	
				employment	employment	employment	employment	
STEM				-0.039	0.116***	-0.077	0.128***	
share				(0.053)	(0.014)	(0.092)	(0.018)	
Coefficient				-0.013	$0.084^{***}$	-0.023	0.168***	
on the				(0.014)	(0.008)	(0.018)	(0.013)	
inverse								
Mills ratio								
E. Table 2:	OLS includ	ling controls for <b>c</b>	titizenship, years in the	United States, and Engl	lish-speaking abili	ty		
	(1)	(2	2)		(3)	_		
	Full	Non-c	ollege		College			
College	0.001	-0.0	)24*		0.042***			
share	(0.011)	(0.0	)13)		(0.012)			
F. Table 4:	Heckman p	procedure includi	ng controls for citizensl	hip, years in the United	States, and Englis	n-speaking ability		
		Non-c	ollege		College			
		(1)	(2)	(3)		(4)		
		Self-	Paid	Self-employmen	ıt	Paid emplo	oyment	
		employment	employment					
College	-	-0.071***	-0.029***	-0.063***		$0.080^{*}$	***	
share		(0.026)	(0.005)	(0.023)		(0.006	6)	
Coefficient		-0.087	0.153***	-0.018*		$0.104^{*}$	***	

on the		(0.104)	(0.011)		(0.010)		(0.006)	
inverse								
Mills ratio								
<b>G. Table 5:</b>	OLS includir	ng controls for ci	tizenship, year	s in the Unite	d States, and Eng	lish-speaking abili	<u>ty</u>	
		(1)	)	(2)	(2	3)	(+	4)
		Non-co	ollege	College	Non-S	STEM	ST	EM
STEM		-0.0	28	$0.068^{***}$	0.06	56***	0.08	33***
share		(0.01	(9)	(0.016)	(0.0	018)	(0.0	020)
<u>H. Table 6:</u>	Heckman pro	ocedure includin	g controls for a	<mark>citizenship, ye</mark>	ears in the United	States, and English	h-speaking ability	
					Non-S	STEM	ST	EM
					(1)	(2)	(3)	(4)
					Self-	Paid	Self-	Paid
				_	employment	employment	employment	employment
STEM					-0.037	$0.122^{***}$	-0.077	$0.168^{***}$
share					(0.053)	(0.014)	(0.090)	(0.021)
Coefficient					-0.011	$0.074^{***}$	-0.024	$0.202^{***}$
on the					(0.014)	(0.008)	(0.017)	(0.014)
inverse								
Mills ratio								
<u>I. Table 2: (</u>	OLS including	g controls for inc	lustry and occu	upation fixed	<u>effects</u>			
	(1)	(2)	)			(3)		
	Full	Non-co	ollege			College		
College	$0.016^{*}$	-0.0	01			$0.042^{***}$		
share	(0.008)	(0.00	)9)			(0.012)		

J. Table 4: Heckman	procedure includin	ng controls for inc	dustry and o	ccupation fixed e	<u>ffects</u>				
	Non-college College								
	(1)	(2)	(2) (3)			(4)			
	Self-	Paid		Self-employmen	ıt	Paid emplo	yment		
	employment	employment							
College	-0.033*	0.001		-0.045*		$0.074^{*}$	**		
share	(0.019)	(0.004)		(0.023)		(0.006	5)		
Coefficient	0.113***	0.062***		-0.026* 0.074***					
on the	(0.039)	(0.005)		(0.014)		(0.006	5)		
inverse									
Mills ratio									
K. Table 5: OLS inclu	uding controls for i	ndustry and occu	pation fixed	l effects					
	()	1)	(2)	(1	3)	(4	(4)		
	Non-c	college	College	Non-S	STEM	ST	EM		
STEM	0.0	)12	$0.072^{***}$	0.05	54***	0.10	)6***		
share	(0.0	)18)	(0.015)	(0.0	)17)	(0.0	)15)		
L. Table 6: Heckman	procedure includi	ng controls for in	dustry and o	occupation fixed e	<u>effects</u>				
				Non-S	STEM	ST	EM		
				(1)	(2)	(3)	(4)		
				Self-	Paid	Self-	Paid		
			_	employment	employment	employment	employment		
STEM				-0.014	$0.080^{***}$	-0.073	$0.141^{***}$		
share				(0.053)	(0.013)	(0.102)	(0.016)		

Coefficient					-0.025	0.021***	-0.017	$0.055^{***}$
on the					(0.019)	(0.007)	(0.043)	(0.010)
inverse								
Mills ratio								
M. Table 2:	: OLS inclu	ding control for B	artik shift share					
	(1)	(2	2)			(3)		
	Full	Non-c	ollege			College		
College	-0.005	-0.0	30**			$0.041^{***}$		
share	(0.013)	(0.0	)14)			(0.013)		
<u>N. Table 4:</u>	Heckman p	orocedure includi	ng controls for B	<mark>artik shift sha</mark> i	<u>re</u>			
		Non-c	ollege			College		
		(1)	(2)		(3)		(4)	
		Self-	Paid		Self-employment		Paid emplo	yment
	_	employment	employment					
College		-0.069***	-0.034***		-0.053*		$0.091^{*}$	**
share		(0.026)	(0.006)		(0.028)		(0.007	7)
Coefficient		-0.101	$0.159^{***}$		-0.019*		$0.110^{*}$	**
on the		(0.107)	(0.012)		(0.010)		(0.006	<b>5</b> )
inverse								
Mills ratio								
<b>O. Table 5:</b>	OLS inclu	ling control for B	<u>artik shift share</u>					
		(1	l)	(2)	(3)		(4	4)
	_	Non-c	ollege	College	Non-STEN	Л	ST	EM
STEM		-0.0	030	$0.061^{***}$	$0.046^{**}$		0.09	<b>99</b> ***

share	(0.020)	(0.018)	(0.022)		(0.020)	
P. Table 6: Heckman proce	edure including control for	r Bartik shift-sha	re			
			Non-STEM		STEM	
			(1)	(2)	(3)	(4)
			Self-	Paid	Self-	Paid
			employment	employment	employment	employment
STEM			0.012	$0.108^{***}$	-0.006	$0.209^{***}$
share			(0.062)	(0.016)	(0.105)	(0.027)
Coefficient			-0.013	0.075***	-0.027	0.221***
on the			(0.015)	(0.009)	(0.017)	(0.016)
inverse						
Mills ratio						

Notes: The dependent variable is log usual hours worked per week. The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for the same set of variables as in the indicated tables. Personal survey weights are used. \* denotes significance at the 10% level; \*\* significance at the 5% level; \*\*\* significance at the 1% level.

## Appendix Tables Table A1: STEM majors

**Animal Sciences** Food Science Plant Science and Agronomy Soil Science **Environmental Science** Forestry **Communication Technologies Computer and Information Systems** Computer Programming and Data Processing **Computer Science Information Sciences** Computer Information Management and Security **Computer Networking and Telecommunications** General Engineering Aerospace Engineering **Biological Engineering** Architectural Engineering **Biomedical Engineering Chemical Engineering Civil Engineering Computer Engineering Electrical Engineering Engineering Mechanics Environmental Engineering** Geological and Geophysical Engineering Industrial and Manufacturing Engineering Materials Engineering and Materials Science Mechanical Engineering Metallurgical Engineering Mining and Mineral Engineering Naval Architecture and Marine Engineering Nuclear Engineering Petroleum Engineering Miscellaneous Engineering **Engineering Technologies Engineering and Industrial Management Electrical Engineering Technology** Industrial Production Technologies Mechanical Engineering Related Technologies Miscellaneous Engineering Technologies Biology **Biochemical Sciences** 

Botany Molecular Biology Ecology Genetics Microbiology Pharmacology Physiology Zoology Neuroscience Miscellaneous Biology **Mathematics Applied Mathematics** Statistics and Decision Science Military Technologies Nutrition Sciences Mathematics and Computer Science Cognitive Science and Biopsychology **Physical Sciences** Astronomy and Astrophysics Atmospheric Sciences and Meteorology Chemistry Geology and Earth Science Geosciences Oceanography Physics Materials Science Multi-Disciplinary or General Science Nuclear Transportation Sciences and Technologies Health and Medical Preparatory Programs Pharmacy **Actuarial Science** Management Information Systems and Statistics

Notes: The STEM majors are defined following the definition of the U.S. Immigration and Customs Enforcement (ICE). Some small adjustments are made to match the ACS data.

University	Year
Alabama A&M University	1890
Auburn University	1862
University of Arizona	1862
University of Arkansas at Pine Bluff	1890
University of Arkansas	1862
University of California	1862
Colorado State University	1862
University of Connecticut	1862
Delaware State University	1890
University of Delaware	1862
Florida A&M University	1890
University of Florida	1862
Fort Valley State University	1890
University of Georgia	1862
University of Idaho	1862
University of Illinois	1862
Purdue University	1862
Iowa State University	1862
Kansas State University	1862
Kentucky State University	1890
University of Kentucky	1862
Louisiana State University	1862
Southern University and A&M College	1890
University of Maine	1862
University of Maryland	1862
University of Maryland Eastern Shore	1890
Massachusetts Institute of Technology	1862
University of Massachusetts	1862
Michigan State University	1862
University of Minnesota	1862
Alcorn State University	1890
Mississippi State University	1862
Lincoln University	1890
University of Missouri	1862
Montana State University	1862
University of Nebraska	1862
University of Nevada	1862
University of New Hampshire	1862
Rutgers University, The State University of N	lew
Jersey	1862
New Mexico State University	1862

## Table A2: Land-Grant Universities

Cornell University	1862
North Carolina A&T State University	1890
North Carolina State University	1862
North Dakota State University	1862
Ohio State University	1862
Langston University	1890
Oklahoma State University	1862
Oregon State University	1862
Pennsylvania State University	1862
University of Rhode Island	1862
Clemson University	1862
South Carolina State University	1890
South Dakota State University	1862
Tennessee State University	1890
University of Tennessee	1862
Texas A&M University	1862
Prairie View A&M University	1890
Utah State University	1862
University of Vermont	1862
Virginia Tech	1862
Virginia State University	1890
Washington State University	1862
West Virginia University	1862
West Virginia State University	1890
University of Wisconsin	1862
University of Wyoming	1862
University of the District of Columbia	1862

Notes: This list combines the list of land-grant universities from Nevins (1962) and the list of 1862 and 1890 land-grant colleges and universities from the National Institute of Food and Agriculture of the United States Department of Agriculture.

	employment v	5. I alu-employin			
	Non-college		Col	lege	
	(1)	(2)	(3)	(4)	
	Self-	Paid	Self-	Paid	
	employment	employment	employment	employment	
College share	-0.131*	-0.006	$-0.108^{*}$	$0.104^{***}$	
	(0.067)	(0.021)	(0.063)	(0.031)	
First Stage results					
Land grant	$0.072^{***}$	$0.068^{***}$	$0.074^{***}$	$0.065^{***}$	
	(0.021)	(0.018)	(0.022)	(0.019)	
Underidentification	5.969	7.853	4.666	5.769	
	[0.015]	[0.005]	[0.031]	[0.016]	
Weak	11.449	14.095	11.150	11.753	
identification					
Endogeneity	2.414	0.658	0.308	3.358	
	[0.120]	[0.417]	[0.579]	[0.067]	
Ν	32,319	299,020	22,362	218,835	

## Table A3: 2SLS Estimates of Hours Worked and College Share - Selfemployment VS, Paid-employment

Notes: The dependent variable is log usual hours worked per week. The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Standard errors in parentheses are clustered at the MSA level. The numbers in brackets are p-values. Personal survey weights are used. \* denotes significance at the 10% level; \*\*\* denotes significance at the 1% level.

employment vS. raid-employment					
	Non-STEM		ST	EM	
	(1)	(2)	(3)	(4)	
	Self-	Paid	Self-	Paid	
	employment	employment	employment	employment	
STEM share	-0.109	$0.099^*$	-0.350**	0.173***	
	(0.127)	(0.057)	(0.171)	(0.063)	
First Stage results					
Log distance to	-0.017***	-0.017***	-0.019***	-0.020***	
land grant	(0.003)	(0.003)	(0.003)	(0.006)	
Underidentification	5.376	6.736	6.300	6.604	
	[0.020]	[0.009]	[0.012]	[0.010]	
Weak	35.537	33.653	29.384	9.461	
identification					
Endogeneity	0.379	0.195	2.304	1.893	
	[0.538]	[0.659]	[0.129]	[0.169]	
Ν	16,918	155,210	5,444	63,625	

#### Table A4: 2SLS Estimates of Hours Worked and STEM Share - Selfemployment VS\_Paid-employment

Notes: The dependent variable is log usual hours worked per week. The table only reports the estimates for the coefficients of interest for space conservation. The regressions also control for age, log commute time, a gender dummy, 4 race/ethnic group dummies, 51 birthplace dummies, 37 major of degree dummies, and state of workplace fixed effects. Standard errors in parentheses are clustered at the MSA level. The numbers in brackets are p-values. Personal survey weights are used. \* denotes significance at the 10% level; \*\* significance at the 5% level; \*\*\* significance at the 1% level.