# Beyond Students: Effects of University Establishment on Local Economic Mobility

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**Abstract**

How does the presence of a university affect local economic mobility and inequality? Existing work on universities' role in economic mobility have focused on students but have not examined the effect on local communities. We exploit historical natural experiments to answer these questions, using "runner-up" counties that were strongly considered to become university sites but were not selected for as-good-as-random reasons as counterfactuals for university counties. We find that university establishment causes greater intergenerational income mobility but also increases cross-sectional income inequality. We highlight four channels through which these effects operate: universities "hollow-out" the local labor market and provide greater opportunities to achieve top incomes, both of which increase cross-sectional inequality, while at the same time increasing educational attainment across the income distribution and fostering social interactions to high-socioeconomic status individuals, which both prevent inequality from perpetuating into intergenerational immobility.

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# 1 Introduction

Scholars and policymakers have recently argued in favor of increased investments in higher education in order to reduce inequality and promoting local economic mobility (Austin, Glaeser, and Summers, 2018; Gruber and Johnson, 2019; Guzman, Murray, Stern, and Williams, 2023; Maxim and Muro, 2021). In spite of the policy interest in this topic, most of the existing causal work on the role of colleges in economic mobility has focused narrowly on the students who attend college (Chetty, Friedman, Saez, Turner, and Yagan, 2018, 2020) and has neglected the larger impacts universities have as they shape the areas in which they have been established (Cantwell, 2022).

We explore local externalities of universities using historical natural experiments related to the site selection decisions for U.S. colleges and universities. More specifically, we draw on the 61 public college and university site selection experiments identified in Andrews (2021a) in which public college/university locations were selected from a set of finalist locations; which of these finalist sites won was as-good-as-random. The runner-up sites therefore provide natural counterfactuals for locations that receive universities. These historical experiments still matter today: counties that won a university in the past are much more likely to have a university today, have more local colleges/universities on average, and have more years of exposure to a university over their history (Russell, Yu, and Andrews, 2021).

In this paper, we find that counties that win a university have greater rates of contemporary income mobility: children born in the bottom half of the income distribution are significantly more likely to make it into the top income percentiles in the winning counties relative to the runners-up. Counties that win a university also have a higher degree of income inequality, with a Gini coefficient about 6% higher in the winning counties relative to the runners-up. This increased inequality is due primarily to rising top incomes.

We highlight four channels through which winning a university affects the local economy broadly. First, we show that local labor markets are markedly different today in winning counties relative to the runners-up. While the overall U.S. labor market has become more polarized in recent decades (Autor, Katz, and Kearney, 2006; Autor and Dorn, 2013; Atalay, Phongthiengtham, Sotelo, and Tannenbaum, 2020), this effect is larger in the winning counties. Winning counties see an extreme "hollowing out" of the labor market, with much higher shares of employment in high-skill and high-wage sectors like IT and professional business services, as well as higher shares in low-wage service sectors like leisure and hospitality, and much smaller shares in middle wage industries like manufacturing and natural resources extraction that employ many low-skill workers. We would expect these structural changes to lead to more income variance in winning locations relative to the runners-up. Indeed, this is exactly what we observe in the distribution of household incomes. Mean earnings in the lowest quintile are 11% lower, but mean earnings in the top quintile are 14% higher in winning counties. The absolute decline in earnings at the bottom of the distribution could be driven by large numbers of university students working part-time in low-wage sectors like hospitality; we find no statistically significant differences at the bottom of the household income distribution for households with heads aged 25 and older, and there are actually fewer households earning $20,000 or below in winning areas for households with a head aged 45 to 64.

Second, we show that winning counties have higher levels of activities likely to generate top incomes, and hence increase local inequality. One such activity is innovation (Aghion, Akcigit, Bergeaud, Blundell, and Hemous, 2019). Consistent with several studies on the role of institutions of higher education in promoting innovation (Andrews, 2021a,b; Hausman, 2022; Jaffe, 1989; Aghion, Boustan, Hoxby, and Vandenbussche, 2009) and high technology startups (Zucker, Darby, and Brewer, 1998; Belenzon and Schankerman, 2009; Hausman, 2022), we find that the winning counties have much higher rates of patenting and high-growth entrepreneurship.

Third, we investigate how local universities affect local educational attainment. We show that children who grow up in winning counties (regardless of where they live as adults) are 4-5 percentage points more likely to have a four-year college degree than children who grow up in the runner-up counties for every quintile of parental income; these increases are largest in percentage terms for those born into the lowest incomes. Additionally, Russell, Yu, and Andrews (2021) find that winning counties not only have higher rates of college completion than the runner-up counties, but also higher rates of high school completion, which indicates that even for educational outcomes, universities have impacts beyond just the students who enroll in them. In this paper, we are unable to disentangle whether these effects are due to universities having causal effects on the people who live there (for instance, perhaps universities change local culture and beliefs about the value of an education) or because they attract parents who differentially promote educational attainment, but both are likely present.[1]

Fourth, winning counties have greater levels of bridging social capital, as measured by relative rates of Facebook friendship between low-SES and high-SES individuals. Recent work has pointed to this kind of social capital as one of the strongest predictors of improved local economic mobility, and preliminary analyses indicate that the relationship between economic connectedness and economic mobility is at least partially causal (Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt, 2022a).

These four findings suggest that the impact of universities on economic mobility and the local distribution of income is due both to direct effects of access to higher education and indirect effects from changes in the local economy. Universities create polarization in the local labor market and more opportunities for top incomes, both of which increase local inequality by increasing incomes at the top, while simultaneously democratizing the opportunity to reach top incomes and hence increasing intergenerational mobility. Thus, our results are consistent with higher education being both meritocratic and democratic.

Our work contributes to the developing literature on the causal mechanisms impacting intergenerational mobility (Black and Devereux, 2011) and investigates one factor that may explain persistent differences in intergenerational mobility across space (Lefgren, Pope, and

[1] In prior work, Russell, Yu, and Andrews (2021) rule out that educational impacts are driven solely by university employees.

Sims, 2019; Chetty, Hendren, Kline, and Saez, 2014; Rothstein, 2019). Our analysis is one of only a few that has examined the link between place-based investments and subsequent economic mobility using a quasi-experimental research design (Lefgren, Pope, and Sims, 2019).[2]

## 2 Empirical Strategy and Data

### 2.1 College Location Experiments

Andrews (2021a, 2022) describes the college/university establishment quasi-experiments we use in detail. We provide only a brief overview here.

During the mid-19th to mid-20th centuries, many state governments established public universities. The decision for where these universities would be located was contentious, with many localities hoping to "win" the university. Institutional histories reveal that in a non-trivial number of cases, multiple sites were seriously considered for the university, and which place ultimately won the university was as-good-as-random. We use the runner-up sites as counterfactuals for the sites that received the university.

Andrews (2021a) notes that these site-selection experiments broadly fall into four categories. Sometimes the vote among candidate locations was exceptionally close. Other times a new university had specific infrastructure needs, and only two or three sites within the state met the infrastructure requirements. In other cases, a few potential sites submitted bids that were quite similar, leaving the state legislatures or boards of trustees largely indifferent between potential locations. Finally, some universities were established in locations due to odd quirks that are orthogonal to the site's suitability. Andrews (2021a,b) shows that the winning and runner-up counties were similar to one another, in both levels and trends, in the decades before the university site selection experiments; we reproduce these results for our sample of universities in Appendix Figures A.1 and A.2. Appendix Table A.1 shows

[2] Two other recent papers also exploit quasi-random establishment of higher education institutions to examine effects on local income mobility, albeit in different settings. Howard and Weinstein (2022) compare places that get regional public universities to places that received historical insane asylums and show that social mobility of children increases more in places that receive a university. Suhonen and Karhunen (2019) use the plausibly exogenous roll-out of new universities in Finland and conclude that parental access to higher education increases children's educational attainment.

a list of the 61 high quality site selection experiments in our sample, and Appendix Table A.3 shows the locations of the winning and losing sites. Our experiments cover 185 counties in 39 states.

Higher education institutions in our site selection experiments sample tend to be larger and more research-active than institutions not in our sample (Andrews, 2021a).[3] Using Reports of the Commissioner of Education from 1870-1934, Andrews (2021a) shows that institutions in the experimental sample have higher total enrollments, greater numbers of graduate students, more faculty, and higher library volumes compared to all non-experimental institutions and are comparable to institutions with a contemporary Carnegie classification of R1 or R2 ("high" or "very high" research activity) according to these measures, indicating that they are representative of U.S. research universities. Since most establishment cases in our sample involve universities, we use the term "university" throughout to refer to any kind of institution of higher education in our sample.

Treating runner-up counties as counterfactuals for winner counties, we compare contemporary outcomes for winning and runner-up counties within each university location experiment by estimating regressions of the form

$$y_c = \alpha + \beta Winner_c + \gamma_e + \varepsilon_c, \tag{1}$$

where $y_c$ is an outcome for county $c$, $Winner_c$ is an indicator that equals 1 if this county won a university as part of the site selection experiment, and $\gamma_e$ is a set of site selection experiment fixed effects so that comparisons are between winning and runner-up counties for the same university. We stress that we estimate long-run local effects of universities, which necessarily capture both the direct effect of establishing a university and any indirect effects that result from a county having a university throughout its history. In all results we report robust standard errors.

[3]See especially the Online Appendix of (Andrews, 2021a).

## 2.2 Contemporary County-Level Measures

In addition to the aforementioned university site selection experiments data from Andrews (2021a), we use data on a variety of contemporary county-level outcomes. County-level mobility measures come from Opportunity Insights (Chetty, Friedman, Hendren, Jones, and Porter, 2021; Chetty, Hendren, Kline, and Saez, 2021) and are based on deidentified tax records for 40 million children and their parents between 1996 and 2012 (Chetty, Hendren, Kline, and Saez, 2014). The sample consists of children born between 1978 and 1983 with a valid social security number and US citizenship. Most of our outcomes of interest are measured as of 2014-2015 when the children are in their 30s. Parental income is measured between 1996 and 2000. To protect privacy, a small amount of noise is added to each estimate. County-level income and inequality measures, median earnings by education level, and labor market outcomes by education level come from the American Community Survey 2015-2019 five-year estimates (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021).

Data for private employment by industry corresponds to 2018 and comes from the Quarterly Census of Employment and Wages from US Bureau of Labor Statistics (2018). The data cover more than 95% of U.S. jobs but notably exclude proprietors, unincorporated self-employed workers, unpaid family members, certain farm and domestic workers, and railroad workers covered by the railroad unemployment insurance system. We report results for county-level location quotients which are ratios that allow an area's distribution of employment by industry to be compared to the national distribution and average wages by industry at the national level.

Patent data are from U.S. Patent and Trademark Office (2021); counts of patents awarded between 1988 and 2014 are aggregated to the county-level using the inventor's location of residence. Data on county-level start-up activity, including measures of entrepreneurial quality, are from the Startup Cartography Project (Andrews, Fazio, Guzman, Liu, and Stern, 2020) and based on business registration records from 1988 to 2014. County-level measures of social capital come from Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt (2022b) and are based on 21 billion Facebook friendships.

# 3 Effects of University Establishment on Economic Mobility and Inequality

## 3.1 Economic Mobility

Winning counties have greater rates of intergenerational mobility for children born to parents at the bottom of the income distribution. Table 1 uses Opportunity Insights data to investigate economic outcomes for children who were born between 1978 and 1983 and grew up in winning counties compared to runner-up counties by parental income percentile. University establishment more than doubles the chance that a child born to parents in the 1st or 10th percentile reaches the top 1%, although absolute rates of mobility to the top 1% are still low—only 0.1% of children born to parents at the 1st or 10th percentile will reach the top 1% in winning counties. Children born to parents in the 25th or 50th percentile of the income distribution are also more likely to reach the top 1%. The absolute magnitude of the effect is the same as for children born to poorer parents (+0.2 percentage points), though the mean rate of children reaching the top 1% is slightly higher for these groups. There is no change in upward mobility for children born to parents at the very top of the national income distribution. The mean effect (column 7) indicates that, not conditioning on parental income, children are 0.5 percentage points more likely to reach the top 1% in winning locations.

Results for reaching the top 20% tell a similar story. Children born to parents with the median national income or below are more likely to reach the top 20% if they grow up in areas where universities were established. The absolute change is roughly equivalent across reported parental income percentiles, but in percentage terms, the effect is relatively larger for those born to parents in lower quintiles. The mean effect indicates that among all children who grow up in winning counties, the chance that the child reaches the top 20% of the income distribution increases by 2.5 percentage points or 14%.

Panels C and D of Table 1 show effects on mean income rank for children. Growing up in a winning county does not benefit children if we measure their household income at age 26 (Panel C). In fact, children born to parents at the 50th, 75th, or 100th percentile actually have lower incomes than peers who grow up in runner-up counties using household income at age 26. However, by their mid-30s children growing up in winning counties have more than caught up (Panel D). On average, children growing up in winning counties have income percentile ranks that are 1.5 higher, on average, than runner-up counties. This effect could be driven by increased average mobility in winning counties, an increased likelihood that a child is born to a high-income household, or both. Investigating effects on the rank-rank slope (Panel E) allows us to assess this first potential explanation.

The rank-rank slope comes from an OLS regression of child rank on parent rank within each county which identifies the correlation between children's and parents' positions in the national income distribution. A negative effect of university establishment on this measure would indicate less correlation between children and parental income and more economic mobility (Chetty, Hendren, Kline, and Saez, 2014). We find no statistically significant effect on the rank-rank slope, indicating that average mobility is comparable in winning and losing areas. The 95% confidence interval is fairly precise and rules out decreases in that slope larger than -0.02. Taken as a whole, our results show more mobility to the top 1% or 20% in the winning counties but little effect on average mobility.[4]

### 3.2 Income Inequality

Although university establishment does facilitate greater economic mobility to the top for children growing up in these counties in the 1980s and 1990s, counties that win universities also have more income inequality. Using five-year data from the American Community Survey (2015-2019), Table 2 Panel A examines differences in mean household income by quintile. Relative to runner-up counties, average household incomes in the bottom quintile

[4] In Appendix Table A.3, we show that these results are robust to including pre-university establishment baseline covariates.

are \$1,500 lower in winning counties. There is no statistically significant difference for the second or third quintiles, but incomes in the fourth and fifth quintiles are higher in winning areas by \$6,800 and \$23,900, respectively.

Since a household is defined as all people who occupy a single housing unit and, according to official Census rules, people should be counted as part of a residence if they live or stay at that residence most of the time, most university students would be counted at their university address. Therefore, decreasing incomes for quintile 1 in winning counties could reflect greater numbers of college students who are earning very low incomes. In Appendix C we explore effects on the county's household income distribution separately by the age of the household head. We find that the share of households where the householder is under age 25 and earns less than \$10,000 a year is 12 percentage points higher in winning counties. Among households with householders over age 25, winning counties have comparable shares of households earning incomes \$60,000 and below as losing counties but fewer households earning middle incomes and more households earning very high incomes (\$125,000+). Thus, increased income inequality is not simply driven by students themselves, although low incomes at the bottom of the county-wide income distribution probably do reflect greater numbers of young college students.

As a complement to these results, Appendix Table A.5 examines effects on incomes for parents in the core Opportunity Insights sample, whose children appear in Table 1. As was the case for the entire adult population in the county, those at the upper parts of the distribution have much higher incomes in winning counties compared to losing counties. Unlike the county-wide household distribution which could include university students, the Opportunity Insights parent sample distribution does not reveal negative effects for the lower part of the distribution.

Panel B of Table 2 reports effects on the share of aggregate income in the county that accrues to each quintile. Consistent with the income results, we find that university establishment increases contemporary inequality in the share of income across percentiles. The share of aggregate income earned by the top quintile increases by 2 percentage points or roughly 5%. Panel C, which reports effects on the county-level Gini coefficient, indicates an increase of about 6%.

We also investigate effects on economic inequality measures reported for the Opportunity Insights core parent sample (Appendix Table A.6). Every inequality measure in that data (top 1% income share, the interquartile income range, the Gini coefficient, and the fraction of parents who would be classified as middle class based on their rank in the national income distribution) indicates increasing inequality from university establishment. The only measure that is directly comparable to the ACS data (the Gini coefficient) reveals a somewhat larger effect: a 10% increase rather than the 6% in the ACS data.[5]

### 3.3 Dynamics

Data on individual income do not exist prior to 1940, and so we cannot repeat the exercises in the previous two sections in a differences-in-differences framework, comparing the winning counties to runner-up counties before and after the university was established as in Andrews (2021a,b). Instead, we proxy income using occupational income scores, which are available going back to 1850. We use individual-level occupational income scores (rather than county-level averages) from the 100% decennial population censuses for the years 1850-1940, 1% sample for 1950, 5% samples for 1960-2000, and the ACS sample for 2010 (Ruggles, Fitch, Goeken, Hacker, Nelson, Roberts, Schouweiler, and Sobek, 2021; Ruggles, Flood, Goeken, Schouweiler, and Sobek, 2022). Occupational income scores report the median income of all individuals in the same occupation, with incomes based on occupations in the 1950 census. Feigenbaum (2018) provides a detailed discussion of the strengths and weaknesses of using occupational income scores as a proxy for individual income; notably, occupational income scores do not allow us to investigate changes in within-occupation income inequality.

Figure 1 displays two event studies that plot aggregated average treatment effects for the treated subpopulations (ATTs) estimated using the Callaway and Sant'Anna (2021) estimator. Panel A plots ATTs on the county mean occupational income score while Panel

[5]In Appendix Table A.4, we show that the results reported in Table 2 are robust to including pre-university establishment baseline covariates.

B plots effects on the variance. In both cases, pretrends are parallel between the winning and runner-up counties. There is no statistically significant increase in average occupational income in the winning counties relative to the runners-up after establishing the university. The variance does increase in the winning counties relative to the runners-up, consistent with increasing income inequality as documented using the ACS data in the cross sectional regression results. Results using other occupation-based measures of earnings and education produce similar results.

# 4 Channels

Why does the establishment of a university increase inequality and mobility to top incomes? We next present results for four ways in which university establishment affects local economies.

## 4.1 Local Labor Market Effects

Figure 2 shows that relative to runner-up counties, winning counties experience a "hollowing out" of the local labor market, with dramatic declines in employment in middle income sectors.[6] The results plotted in this figure are from regressions where the dependent variable is the private employment location quotient for a particular industry. Location quotients are ratios of a county's share of employment in a particular industry to the national share of employment in the same industry. We order the nine different industries by the average national wage in that industry in 2018. Leisure & hospitality has the lowest average wage at $24,087 while information has the highest average wage at $113,781.

Winning a university lowers the location quotients for natural resources & mining and manufacturing (middle wage industries) and raises the location quotients for leisure & hospitality, professional and business services, and information (the lowest wage industry and the

[6] In results available upon request, we have investigated whether the large estimated impact on the Natural Resources & Mining location quotient is due to outliers. Specifically, we re-estimate that effect leaving out one of the experiments each time and then plot the distribution of the coefficients. The estimated effects all fall between -1.14 and -1.44, indicating that the large impact we estimate with the full set of experiments cannot be attributed to a large outlier.

two highest wage industries).[7] Winning counties thus have more employment opportunities in both high and low wage industries. This "hollowing out" mirrors the income inequality results for household income shown in Table 2 Panel A. Winning areas see a "hollowing out" of those at the middle of the income distribution and have a greater spread of household incomes.

Given the observed differences in labor market opportunities, it is natural to test whether differences in returns to education in winning counties relative to the runners-up drive these results. In Appendix E we show that median earnings are between 3 and 5% lower for non-college-educated men in winning counties. This is consistent with the disappearance of jobs in the middle wage industries (manufacturing and natural resources & mining) that overwhelmingly employ low-skill men. We do not find a similar difference in median earnings for low-skill women, nor do we find any difference in the college premia overall. We lack sufficiently disaggregated data to directly test whether the variance of income is greater at each level of educational attainment, but the mobility results indicate that this is likely. Since people who grow up in winning counties are more likely to reach the top 20% or top 1% of income earners as adults, but there are no statistically significant effects on the income ranks of children at the reported percentiles, there must be offsetting effects where children who grow up in winning areas are also more likely to end up in the left tail of the national income distribution.

## 4.2 Top Incomes

The presence of a local university may be especially effective at promoting activities that lead to top incomes, which in turn increase cross sectional income inequality. Innovation is one such activity; Aghion, Akcigit, Bergeaud, Blundell, and Hemous (2019) find that highly innovative locations have both higher income inequality and more income mobility, and they argue this relationship is causal. Using data from U.S. Patent and Trademark Office (2021), we find that the total number of patents granted to county residents between

[7] In Appendix Figure A.4, we show that these results are robust to including pre-university establishment baseline covariates.

1988 and 2014 is 380% higher ($e^{1.568} - 1 = 3.80$) in the winning counties relative to the runners-up (Table 3 Panel A).[8] These patents also tend to be higher quality, receiving 509% more citations ($e^{1.806} - 1 = 5.09$) than patents in the runner-up counties; in Appendix F we use an alternate measure of patent quality from Kogan, Papanikolaou, Seru, and Stoffman (2017) that is based on how firms' stock prices change in narrow event windows after patent issuance and likewise find that patents in winning counties are more valuable. Using data from Andrews, Fazio, Guzman, Liu, and Stern (2020), we also find that winning counties have 132% ($e^{0.841} - 1 = 1.32$) more startups between 1988 and 2014 and that these startups are on average of higher expected quality, as measured using the Entrepreneurial Quality Index (EQI) that is constructed using observable information about each startup at the time of its founding to predict the probability that the startup will have a liquidity event (Guzman and Stern, 2015, 2020). In Appendix F we additionally show that winning counties have more realized liquidity events and that the entrepreneurial ecosystem in winning counties is more conducive to startup success than in runner-up counties.

### 4.3 Educational Attainment

Russell, Yu, and Andrews (2021) show that winning counties have higher levels of educational attainment than runner-up counties. This holds for all levels of schooling: winning counties have lower rates of high school dropouts, as well as higher rates of bachelor and advanced degree attainment. In Table 3 Panel B we extend those results to show that a local university increases four-year college degree attainment even for children born to parents with low incomes. We use the Opportunity Insights data that report educational attainment by parent's percentile in the national income distribution. The effect size of winning a university on degree completion is about 5 percentage points for children born to parents at every percentile; this is a larger percentage increase for children born to parents at the first percentile (about 45%) or 25th percentile (28%) than for those born at the 50th percentile (18%), 75th percentile (11%), or 100th percentile (4.5%). These effects could reflect both causal effects

[8] Results are nearly identical if we use ln(y+1) as the outcome instead of the inverse hyperbolic sine.

universities on the people who grow up near them and sorting. For instance, universities may change local culture and beliefs about the value of an education, so children who grow up in this environment may be more likely to enroll in a university and obtain a degree. In addition, since proximity influences college enrollment, access itself promotes educational attainment (Card, 1995; Kane and Rouse, 1995; Kling, 2001; Do, 2004; Frenette, 2009; Jepsen and Montgomery, 2009; Doyle and Skinner, 2016). On the other hand, university counties could also attract parents who differentially facilitate the educational attainment of their children.

### 4.4 Social Capital

Recent work has shown that "bridging social capital," in which individuals are connected to people with different characteristics than their own, is one of the strongest predictors of local upward economic mobility, even stronger than local predictors commonly cited in the literature such as median income, the poverty rate, and racial segregation (Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt, 2022a). We use estimates of county-level bridging social capital from Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt (2022b), which they term "economic connectedness." Economic connectedness is measured as two times the share of high-SES friends among low-SES individuals, averaged over all low-SES individuals in the county. Establishing a local university could increase economic connectedness by fostering cross-SES interactions among university students and employees, as well as by changing the composition of the local labor market to bring together high and low SES occupations (Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt, 2022c). Table 3 Panel C shows that winning counties do indeed have significantly more economic connectedness than the runners-up counties.

### 4.5 Other Channels

We also conduct heterogeneity analyses where we test whether mobility and inequality effects are larger for more research-intensive universities. This analysis is only suggestive because unlike the university location experiments themselves, the type of university established is not necessarily exogenous. The full set of results appears in Appendix G. Point estimates tend to be larger for doctoral R1 universities compared to non-doctoral colleges, consistent with research-related activities leading to high incomes and greater inequality, but estimates are imprecise and generally we cannot reject the null hypothesis of homogeneous inequality and mobility effects.

In Appendix H, we limit our analysis to the set of 12 university establishment experiments that involve counties with consolation prizes to test whether counties that received alternative public institutions (a penitentiary, asylum, or capital) have economic mobility rates and levels of inequality comparable to counties that received a university. When these institutions were established, the alternative public investments were highly coveted, sometimes even more than a university, because they could serve as anchor institutions to attract people and firms. Historical experience accords with this view; Andrews (2021a) shows that areas that received one of these alternative institutions experienced population growth similar to areas that received universities.[9] We then compare counties that win the university to counties that win a consolation prize. The point estimates are similar in magnitude to those from the analysis using all losing counties as the comparison group, though the standard errors are larger due to the smaller sample sizes, and many of the effects are no longer statistically significant. Because these other types of public investments do not appear to generate increases in inequality and intergernational mobility, we interpret these results as being broadly suggestive that activities specific to universities generate the effects that we observe.

[9] All consolation prizes are listed in Appendix Table A.2. See also Howard, Weinstein, and Yang (2022), who argue that locations that received state insane asylums are good counterfactuals for locations with regional universities.

In Appendix I, we test whether the intergenerational income mobility rate for those who attend the experiment universities, using Mobility Report Cards data from Chetty, Friedman, Saez, Turner, and Yagan (2017), correlates with income mobility rates and inequality in the county more broadly. In particular, we estimate models where we add an interaction term for university establishment times the university-specific mobility rate, where that rate is the probability that a student with parents in the bottom 20% of the national income distribution ends up in the top 1%. The direction of the interaction coefficients indicates that these rates do correlate (more bottom-to-top university mobility correlates with both more bottom-to-top county mobility and more county inequality), but the standard errors are quite large, and the effects are not statistically significant. In a similar fashion, we test whether college-specific economic connectedness rates correlate with income mobility rates and inequality in the county (Appendix J). The confidence intervals for the interaction effect are large, so we are unable to draw definitive conclusions.

## 5 Conclusion

Existing work on the role of education in economic mobility has tended to focus on the students who attend (e.g., Chetty, Friedman, Saez, Turner, and Yagan (2018, 2020)). Our study takes a more holistic view and assesses the impact of university establishment on all those who grow up or live near a university. Our results show that public universities shape the areas in which they are located through many channels, affecting even those who do not enroll in the university.

Our results underscore the danger in relying on existing social-mobility rankings of universities to judge institutional success in promoting economic mobility. Cantwell (2022) has adeptly pointed out that, "...social mobility might depend more on what's happening off campus than what's happening on campus. Political economy and economic geography confound the rankings, and factors outside the control of individual institutions shape the extent to which their excellent work results in upward social mobility." We take this claim one step further and document that universities themselves have shaped the economic geography in nuanced ways which feedback into economic outcomes for students but also other residents.

Prior work has suggested that growing up in a more unequal place leads to less economic mobility (Kearney and Levine, 2016; Chetty and Hendren, 2018; Corak, 2013). However, in our setting of university counties, we find that increased mobility and increased inequality go hand in hand. Although universities increase inequality, they also democratize access to top incomes by expanding access to human capital to those born into the bottom of the income distribution and by increasing economic connectedness. More broadly, our results show that when a particular local public investment affects the local economy through multiple channels, mechanical relationships between increased mobility and decreased inequality may break down.

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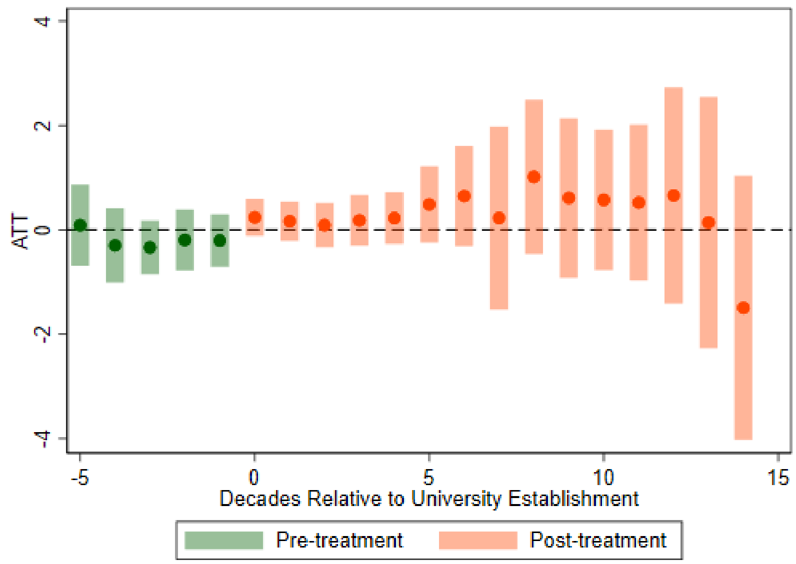
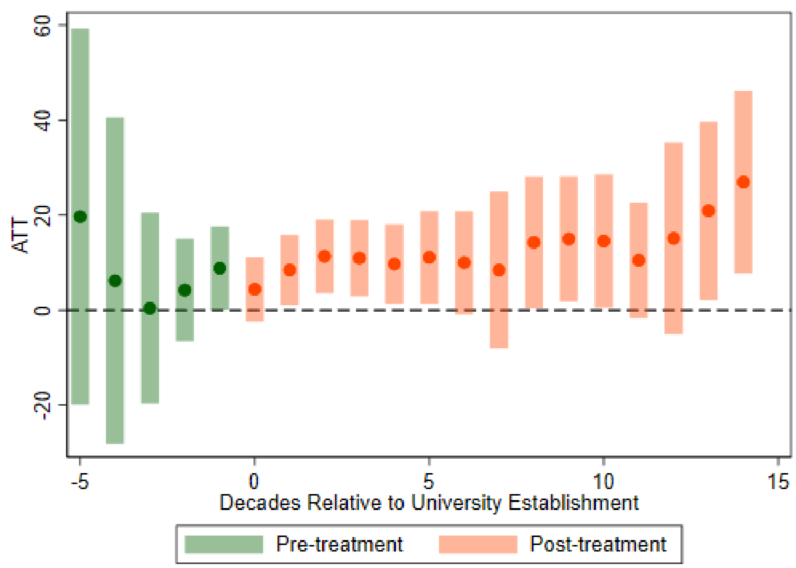
# Figures

Figure 1: Difference-in-Differences for Occupational Income Scores

(a) Mean



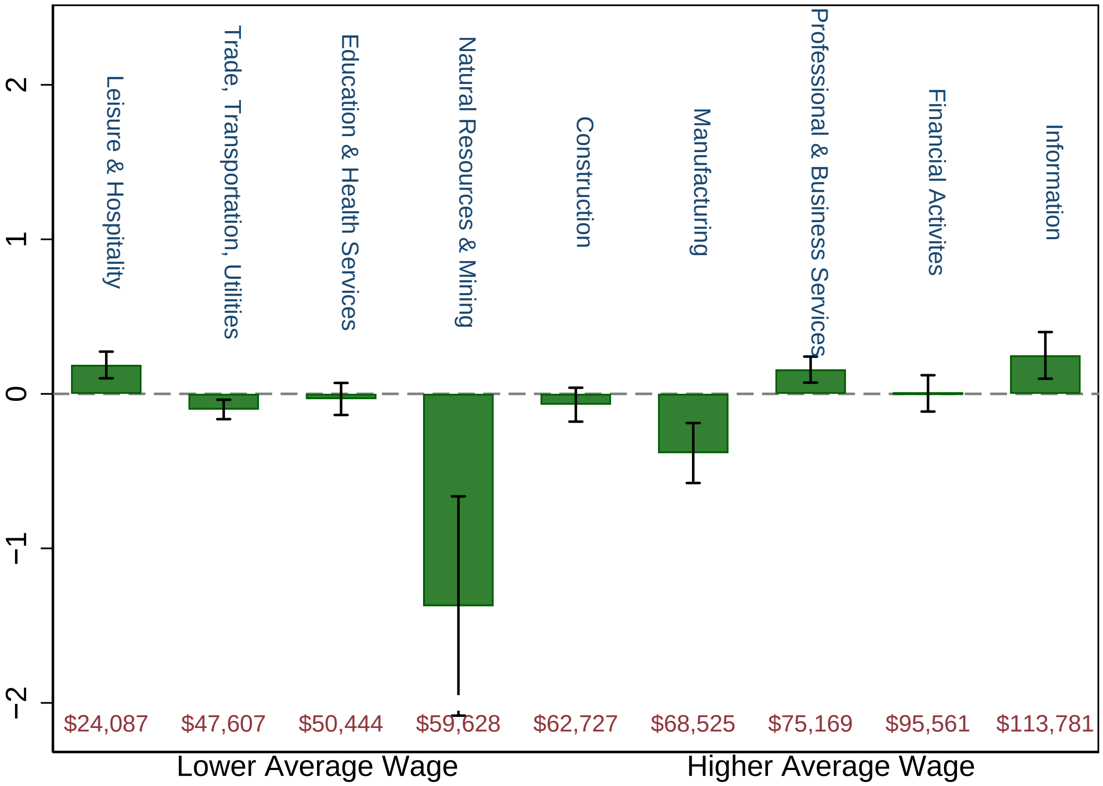

(b) Variance




Source: Ruggles, Fitch, Goeken, Hacker, Nelson, Roberts, Schouweiler, and Sobek (2021)

Notes: Occupational scores are based on occupations reported by prime age adults (age 18-55) and reflect the median income of all people in the same occupation (based on 1950s incomes) in hundreds of dollars. The event study window is from 6 decades prior to university establishment to 15 decades after; panel is unbalanced. DiD specifications are estimated using the Callaway and Sant'Anna (2021) estimator. Standard errors are clustered at the county level. Bars show 95% confidence intervals.

Figure 2: Effects on Private Employment by Industry Location Quotients




Source: Quarterly Census of Employment and Wages, US Bureau of Labor Statistics (2018)

Notes: Location quotients are ratios that allow an area's distribution of employment by industry to be compared to the national distribution. If a location quotient is equal to 1, then the industry has the same share of its area employment as it does in the nation. Industries are ordered from lowest average (national) wage to highest average (national) wage. The height of each bar is the point estimate for the effect of winning the university on the employment location quotient for the county. The black error bars show the 95% confidence interval. Data plotted correspond to 2018.

# Tables

Table 1: Economic Mobility for Children by Parental Income Percentile

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.001* | -0.007 | 0.005*** |
| | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.001) | (0.007) | (0.001) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.007* | 0.007** | 0.007** | 0.006** | 0.006* | 0.004 | 0.025*** |
| | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.006) | (0.005) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Winning Location | 0.003 | 0.000 | -0.002 | -0.006*** | -0.010*** | -0.013*** | 0.004 |
| | (0.003) | (0.003) | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Winning Location | 0.003 | 0.003 | 0.002 | 0.002 | 0.001 | -0.000 | 0.015*** |
| | (0.003) | (0.003) | (0.003) | (0.002) | (0.002) | (0.004) | (0.003) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel E: Effect on Rank-Rank Slope*** | | | | | | | |
| Winning Location | -0.008 | | | | | | |
| | (0.006) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 184 | | | | | | |
| Experiments | 61 | | | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021)

Notes: The sample consists of data for children born between 1978 and 1983. The outcome for Panel C is the mean percentile rank relative to other children in the same year in the national distribution of household income measured at age 26. The outcome for Panel D is the mean percentile rank relative to other children born in the same year using average household income in 2014-2015.

Table 2: Household Incomes and Inequality

| | (1) Quintile 1 | (2) Quintile 2 | (3) Quintile 3 | (4) Quintile 4 | (5) Quintile 5 |
|---|---|---|---|---|---|
| ***Panel A: Mean Household Income*** | | | | | |
| Winning Location | -1512*** | -322 | 2088 | 6759*** | 23934*** |
| | (500) | (1022) | (1493) | (2037) | (4970) |
| Control Mean | 13413 | 33702 | 55376 | 84921 | 177120 |
| Counties | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel B: Share of Aggregate Income by Quintile*** | | | | | |
| Winning Location | -0.663*** | -0.795*** | -0.640*** | -0.099 | 2.197*** |
| | (0.092) | (0.123) | (0.132) | (0.131) | (0.392) |
| Control Mean | 3.674 | 9.217 | 15.168 | 23.329 | 48.613 |
| Counties | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel C: Gini Coefficient*** | | | | | |
| Winning Location | 0.027*** | | | | |
| | (0.004) | | | | |
| Control Mean | 0.450 | | | | |
| Counties | 185 | | | | |
| Experiments | 61 | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Community Survey 2015-2019 (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021)

Notes: Panel A reports effects on mean household income by quintile in the county. Panel B reports effects on the share of aggregate household income in the county by quintile. Panel C reports effects on the county's Gini coefficient.

Table 3: Mobility and Inequality Channels

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| ***Panel A: Economic Innovation*** | | | | | |
| | IHS(Patents) | IHS(Cites) | IHS(Total Ventures) | IHS(EQI) | |
| Winning Location | 1.568*** | 1.806*** | 0.841*** | 0.00007** | |
| | (0.208) | (0.234) | (0.229) | (0.00003) | |
| Control Mean | 5.796 | 8.527 | 8.645 | .0004 | |
| Counties | 185 | 185 | 185 | 185 | |
| Experiments | 61 | 61 | 61 | 61 | |
| ***Panel B: Children's College Attainment by Parental Income Percentile*** | | | | | |
| | p1 | p25 | p50 | p75 | p100 |
| Winning Location | 0.05*** | 0.05*** | 0.05*** | 0.05*** | 0.04*** |
| | (0.01) | (0.01) | (0.01) | (0.01) | (0.01) |
| Control Mean | .11 | .18 | .28 | .46 | .88 |
| Counties | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel C: Social Capital*** | | | | | |
| | Econ Connectedness | | | | |
| Winning Location | 0.106*** | | | | |
| | (0.017) | | | | |
| Control Mean | .788 | | | | |
| Counties | 185 | | | | |
| Experiments | 61 | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: U.S. Patent and Trademark Office (2021), the Startup Cartography Project (Guzman, Andrews, Stern, Fazio, and Liu, 2022), The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021), and Social Capital Data by County (Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt, 2022b)

Notes: IHS(Patents) is the inverse hyperbolic sine of the total patents issued to those in the county between 1988 and 2014. IHS(Cites) is the inverse hyperbolic sine of citations to all patents issued to those in those in the county between 1988 and 2014. Total ventures is the number of startups in the county between 1988 and 2014. EQI is an "entrepreneurship quality index" created by Guzman, Andrews, Stern, Fazio, and Liu (2022). Economic Connectedness is a measure of social capital from Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt (2022a)'s analysis of Facebook data and is calculated as two times the share of high-SES friends among low-SES individuals, averaged over all low-SES individuals in the county.

# Online Appendixes

# A Details on the Colleges Sample

Table A.1: List of College Site Selection Experiments

| | College | County | State | Runner-Up Counties | Experiment Year | College Type | Consolation Prize |
|---|---|---|---|---|---|---|---|
| 1 | University of Missouri | Boone | Missouri | SALINE; COOPER; COLE; CALLAWAY; HOWARD | 1839 | Land Grant | |
| 2 | University of Mississippi | Lafayette | Mississippi | MONROE; WINSTON; RANKIN; HARRISON; ATTALA; MONTGOMERY | 1841 | Land Grant | |
| 3 | Eastern Michigan University | Washtenaw | Michigan | JACKSON | 1849 | Normal School | |
| 4 | Pennsylvania State University | Centre | Pennsylvania | BLAIR | 1855 | Land Grant | |
| 5 | The College of New Jersey | Mercer | New Jersey | MIDDLESEX; ESSEX; BURLINGTON | 1855 | Normal School | |
| 6 | University of California Berkeley | Alameda | California | CONTRACOST; NAPA | 1857 | Land Grant | |
| 7 | Iowa State University | Story | Iowa | TAMA; POLK; JEFFERSON; MARSHALL; HARDIN | 1859 | Land Grant | |
| 8 | University of South Dakota | Clay | South Dakota | BONHOMME; YANKTON | 1862 | Land Grant | YES |
| 9 | University of Kansas | Douglas | Kansas | SHAWNEE | 1863 | Land Grant | YES |
| 10 | Lincoln College (IL) | Logan | Illinois | EDGAR; WARRICK; MACON | 1864 | Other Private | |
| 11 | Cornell University | Tompkins | New York | SENECA; SCHUYLER; ONONDAGA | 1865 | Land Grant | YES |
| 12 | University of Maine | Penobscot | Maine | SAGADAHOC | 1866 | Land Grant | |
| 13 | University of Wisconsin | Dane | Wisconsin | FONDDULAC | 1866 | Land Grant | |
| 14 | University of Illinois | Champaign | Illinois | MCLEAN; MORGAN | 1867 | Land Grant | |
| 15 | West Virginia University | Monongalia | West Virginia | GREENBRIER; KANAWHA | 1867 | Land Grant | YES |
| 16 | Oregon State University | Benton | Oregon | MARION | 1868 | Land Grant | YES |
| 17 | Purdue University | Tippecanoe | Indiana | MARION; HANCOCK | 1869 | Land Grant | |
| 18 | Southern Illinois University | Jackson | Illinois | WASHINGTON; MARION; CLINTON; JEFFERSON; PERRY | 1869 | Normal School | |
| 19 | University of Tennessee | Knox | Tennessee | RUTHERFORD | 1869 | Land Grant | |
| 20 | Louisiana State University | Eastbatonr | Louisiana | BIENVILLE; EASTFELICI | 1870 | Land Grant | |
| 21 | Missouri University of Science and Technology | Phelps | Missouri | IRON | 1870 | Technical School | |
| 22 | Texas A and M University | Brazos | Texas | GRIMES; AUSTIN | 1871 | Land Grant | |
| 23 | University of Arkansas | Washington | Arkansas | INDEPENDEN | 1871 | Land Grant | |
| 24 | Auburn University | Lee | Alabama | LAUDERDALE; TUSCALOOSA | 1872 | Land Grant | |
| 25 | University of Oregon | Lane | Oregon | LINN; POLK; WASHINGTON | 1872 | Land Grant | |
| 26 | Virginia Polytechnic Institute | Montgomery | Virginia | ROCKBRIDGE; ALBEMARLE | 1872 | Land Grant | |
| 27 | University of Colorado | Boulder | Colorado | FREMONT | 1874 | Land Grant | YES |
| 28 | University of Texas Austin | Travis | Texas | SMITH | 1881 | Land Grant | |
| 29 | University of Texas Medical Branch | Galveston | Texas | HARRIS | 1881 | Technical School | |
| 30 | North Dakota State University | Cass | North Dakota | STUTSMAN | 1883 | Land Grant | YES |
| 31 | University of North Dakota | Grandforks | North Dakota | BURLEIGH | 1883 | Land Grant | YES |
| 32 | University of Arizona | Pima | Arizona | PINAL | 1885 | Land Grant | YES |
| 33 | University of Nevada | Washoe | Nevada | CARSONCITY | 1885 | Land Grant | |
| 34 | Georgia Institute of Technology | Fulton | Georgia | GREENE; BIBB; BALDWIN; CLARKE | 1886 | Technical School | |
| 35 | Kentucky State University | Franklin | Kentucky | DAVIESS; CHRISTIAN; FAYETTE; WARREN; BOYLE | 1886 | HBCU | |
| 36 | North Carolina State University | Wake | North Carolina | LENOIR; MECKLENBUR | 1886 | Land Grant | |
| 37 | University of Wyoming | Albany | Wyoming | UINTA; LARAMIE | 1886 | Land Grant | YES |
| 38 | Utah State University | Cache | Utah | WEBER | 1888 | Land Grant | YES |
| 39 | Clemson University | Pickens | South Carolina | RICHLAND | 1889 | Land Grant | |
| 40 | New Mexico State University | Donaana | New Mexico | SANMIGUEL | 1889 | Land Grant | YES |
| 41 | University of Idaho | Latah | Idaho | BONNEVILLE | 1889 | Land Grant | |
| 42 | Alabama Agricultural and Mechanical University | Madison | Alabama | MONTGOMERY | 1891 | HBCU | |
| 43 | University of New Hampshire | Strafford | New Hampshire | BELKNAP | 1891 | Land Grant | |
| 44 | Washington State University | Whitman | Washington | YAKIMA | 1891 | Land Grant | |
| 45 | North Carolina A and T University | Guilford | North Carolina | FORSYTH; NEWHANOVER; DURHAM; ALAMANCE | 1892 | HBCU | |
| 46 | Northern Illinois University | Dekalb | Illinois | WINNEBAGO | 1895 | Normal School | |
| 47 | Western Illinois University | Mcdonough | Illinois | WARREN; ADAMS; MERCER; SCHUYLER; HANCOCK | 1899 | Normal School | |
| 48 | University of Nebraska at Kearney | Buffalo | Nebraska | CUSTER; VALLEY | 1903 | Normal School | |
| 49 | Western Michigan University | Kalamazoo | Michigan | BARRY; ALLEGAN | 1903 | Normal School | |
| 50 | University of Florida | Alachua | Florida | COLUMBIA | 1905 | Land Grant | |
| 51 | Georgia Southern College | Bulloch | Georgia | EMANUEL; TATTNALL | 1906 | Other Public | |
| 52 | University of California Davis | Yolo | California | SOLANO | 1906 | Land Grant | |
| 53 | East Carolina University | Pitt | North Carolina | BEAUFORT; EDGECOMBE | 1907 | Normal School | |
| 54 | Western State Colorado University | Gunnison | Colorado | GARFIELD; MESA | 1909 | Normal School | |
| 55 | Arkansas Tech University | Pope | Arkansas | SEBASTIAN; CONWAY; FRANKLIN | 1910 | Technical School | |
| 56 | Bowling Green State University | Wood | Ohio | VANWERT; SANDUSKY; HENRY | 1910 | Normal School | |
| 57 | Kent State University | Portage | Ohio | MEDINA; TRUMBULL | 1910 | Normal School | |
| 58 | Southern Arkansas University | Columbia | Arkansas | HEMPSTEAD; POLK; OUACHITA | 1910 | Other Public | |
| 59 | Southern Mississippi University | Forrest | Mississippi | HINDS; JONES | 1910 | Normal School | |
| 60 | Southern Methodist University | Dallas | Texas | TARRANT | 1911 | Other Private | |
| 61 | Texas Tech | Lubbock | Texas | SCURRY; NOLAN | 1923 | Technical School | |
| 62 | US Merchant Marine Academy | Nassau | New York | BRISTOL | 1941 | Military Academy | |
| 63 | US Air Force Academy | Elpaso | Colorado | MADISON; WALWORTH | 1954 | Military Academy | |

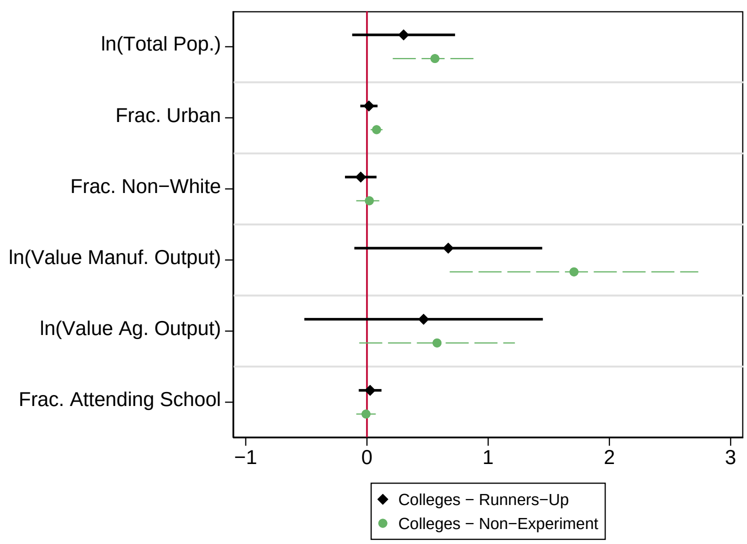
Notes: List of university site selection experiments used in the sample in chronological order by the experiment date. The experiment date refers to the date at which uncertainly over the site location was resolved. The experiment year does not necessarily coincide with the establishment year of the institution.

Table A.2: List of Consolation Prizes

| | College | State | College County | Consolation Prize County | Consolation Prize Type |
|---|---|---|---|---|---|
| 1 | University of Colorado | Colorado | Boulder | Fremont | Penitentiary |
| 2 | University of Kansas | Kansas | Douglas | Shawnee | Capital |
| 3 | New Mexico State University | New Mexico | Donaana | San Miguel | Asylum |
| 4 | Cornell University | New York | Tompkins | Seneca | Asylum |
| 5 | North Dakota State University | North Dakota | Cass | Stutsman | Asylum |
| 6 | University of North Dakota | North Dakota | Grandforks | Burleigh | Capital, Penitentiary |
| 7 | Oregon State University | Oregon | Benton | Marion | Capital |
| 8 | University of South Dakota | South Dakota | Clay | Yankton | Capital |
| 9 | University of South Dakota | South Dakota | Clay | Bon Homme | Penitentiary |
| 10 | Utah State University | Utah | Cache | Weber | Penitentiary |
| 11 | West Virginia University | West Virginia | Monongalia | Kanawha | Capital |
| 12 | University of Wyoming | Wyoming | Albany | Uinta | Asylum |
| 13 | University of Wyoming | Wyoming | Albany | Laramie | Capital |

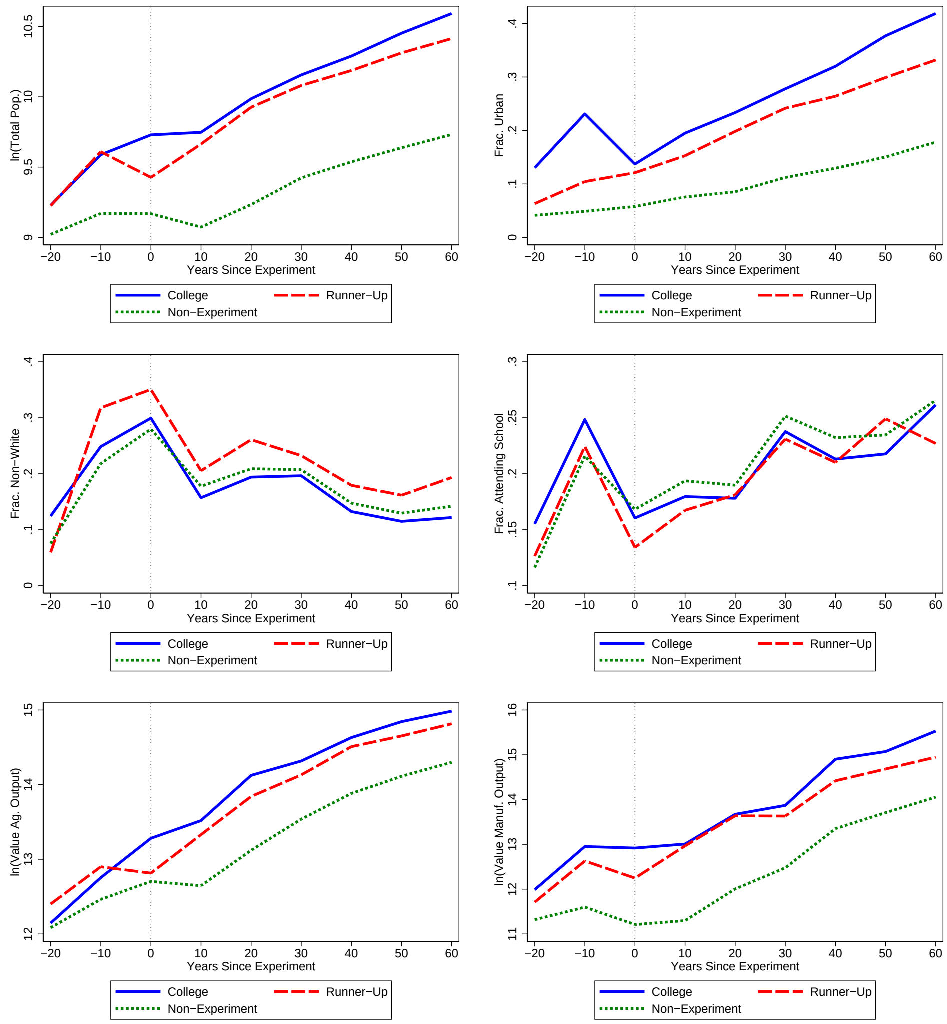
Notes: List of the universities in which a runner-up county received a consolation prize, along with details about the consolation prize.

Figure A.1: Balance Checks Comparing Universities to Runner-Up Counties in the Last Census Before the Universities Were Established



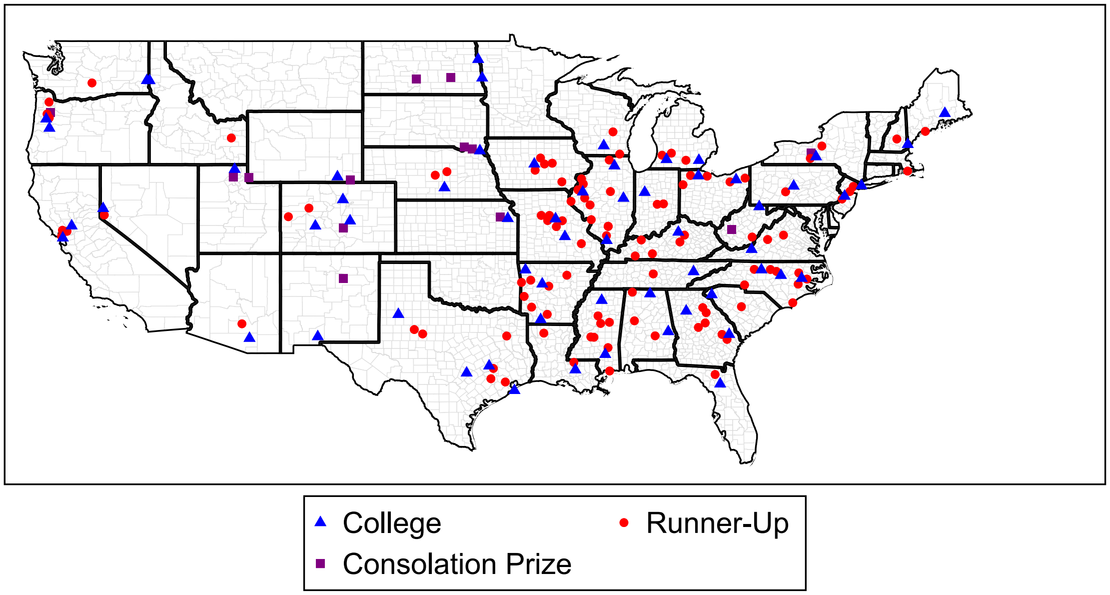

Notes: Black diamonds show the difference in means between university and runner-up counties in the last census year before each site selection experiment for various demographic and economic variables. Green circles show the difference in means between the university counties and all other non-runner-up counties in the same state in the last census before each site selection experiment. 95% confidence intervals are displayed. Demographic and economic data are from the National Historical GIS (Manson, Schroeder, Riper, Kugler, and Ruggles, 2022). In some cases, NHGIS data for a particular demographic or economic variable is not available in the last census before a college was established; in these cases we use data from the next earlier census. Even after this correction, not all variables are available for years before the college is established for all of the colleges, and so the sample is not balanced across rows.

Figure A.2: Trends in University and Runner-Up Counties for Selected Observable Characteristics




Notes: Time series for various demographic and economic variables. Blue solid lines plot time series for the university counties. Red dotted lines plot time series for the runner-up counties. Green dashed lines plot time series for non-university, non-runner-up counties in the same state. The x-axis plots years since the university site selection experiment occurred. Demographic and economic data are from the National Historical GIS (Manson, Schroeder, Riper, Kugler, and Ruggles, 2022).

Figure A.3: Map of College and Runner-Up Counties in the Sample




Notes: College locations are shown by diamonds. Runner-up locations that do not receive a consolation prize are shown by circles. Runner-up locations that do receive a consolation prize are shown by squares.

# B Robustness Checks: Controlling for Baseline Covariates

For these specifications, regressions include controls for the following county-level baseline covariates: fraction urban, ln of total population, ln value of manufacturing product, and ln value of agricultural product. Covariates are from most recent pre-establishment census. When data is missing for particular years, we pull in data from the next prior census. The census of manufacturing did not collect manufacturing data in 1850, and many counties were not established in 1840, making it impossible to pull in manufacturing data from the previous census for a large fraction of our university establishment experiments. The fraction attending school is missing for most years, so we have not included this is the list of baseline covariates used. Additionally, race data is often missing (and even if provided, we suspect unreliable) in the years before the Civil War, so we have not included it in our baseline covariates list for these robustness checks.

Table A.3: Economic Mobility for Children by Parental Income Percentile, Robustness to Baseline Covariates Inclusion

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.001 | -0.007 | 0.004*** |
| | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.001) | (0.009) | (0.001) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 113 | 113 | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.007* | 0.007* | 0.007* | 0.006* | 0.005 | 0.003 | 0.026*** |
| | (0.004) | (0.004) | (0.003) | (0.003) | (0.004) | (0.009) | (0.005) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 113 | 113 | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Winning Location | 0.001 | -0.001 | -0.002 | -0.005* | -0.007** | -0.009** | 0.007* |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.003) | (0.004) | (0.004) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 113 | 113 | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Winning Location | -0.002 | -0.001 | -0.000 | 0.001 | 0.002 | 0.004 | 0.016*** |
| | (0.004) | (0.003) | (0.003) | (0.003) | (0.003) | (0.005) | (0.004) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 113 | 113 | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 | 38 | 38 |
| ***Panel E: Effect on Rank-Rank Slope*** | | | | | | | |
| Winning Location | -0.002 | | | | | | |
| | (0.007) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 112 | | | | | | |
| Experiments | 38 | | | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021)

Notes: These specifications include controls for baseline covariates (fraction urban, ln of total population, ln value of manufacturing product, and ln value of agricultural product). The sample consists of data for children born between 1978 and 1983. The outcome for Panel C is the mean percentile rank relative to other children in the same year in the national distribution of household income measured at age 26. The outcome for Panel D is the mean percentile rank relative to other children born in the same year using average household income in 2014-2015.

Table A.4: Household Incomes and Inequality, Robustness to Baseline Covariates Inclusion

| | (1) Quintile 1 | (2) Quintile 2 | (3) Quintile 3 | (4) Quintile 4 | (5) Quintile 5 |
|---|---|---|---|---|---|
| ***Panel A: Mean Household Income*** | | | | | |
| Winning Location | -1367* | -44 | 2270 | 5958** | 19426*** |
| | (697) | (1253) | (1796) | (2425) | (5983) |
| Control Mean | 13413 | 33702 | 55376 | 84921 | 177120 |
| Counties | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 |
| ***Panel B: Share of Aggregate Income by Quintile*** | | | | | |
| Winning Location | -0.606*** | -0.636*** | -0.416** | -0.023 | 1.682*** |
| | (0.147) | (0.184) | (0.201) | (0.197) | (0.606) |
| Control Mean | 3.674 | 9.217 | 15.168 | 23.329 | 48.613 |
| Counties | 113 | 113 | 113 | 113 | 113 |
| Experiments | 38 | 38 | 38 | 38 | 38 |
| ***Panel C: Gini Coefficient*** | | | | | |
| Winning Location | 0.021*** | | | | |
| | (0.007) | | | | |
| Control Mean | 0.450 | | | | |
| Counties | 113 | | | | |
| Experiments | 38 | | | | |

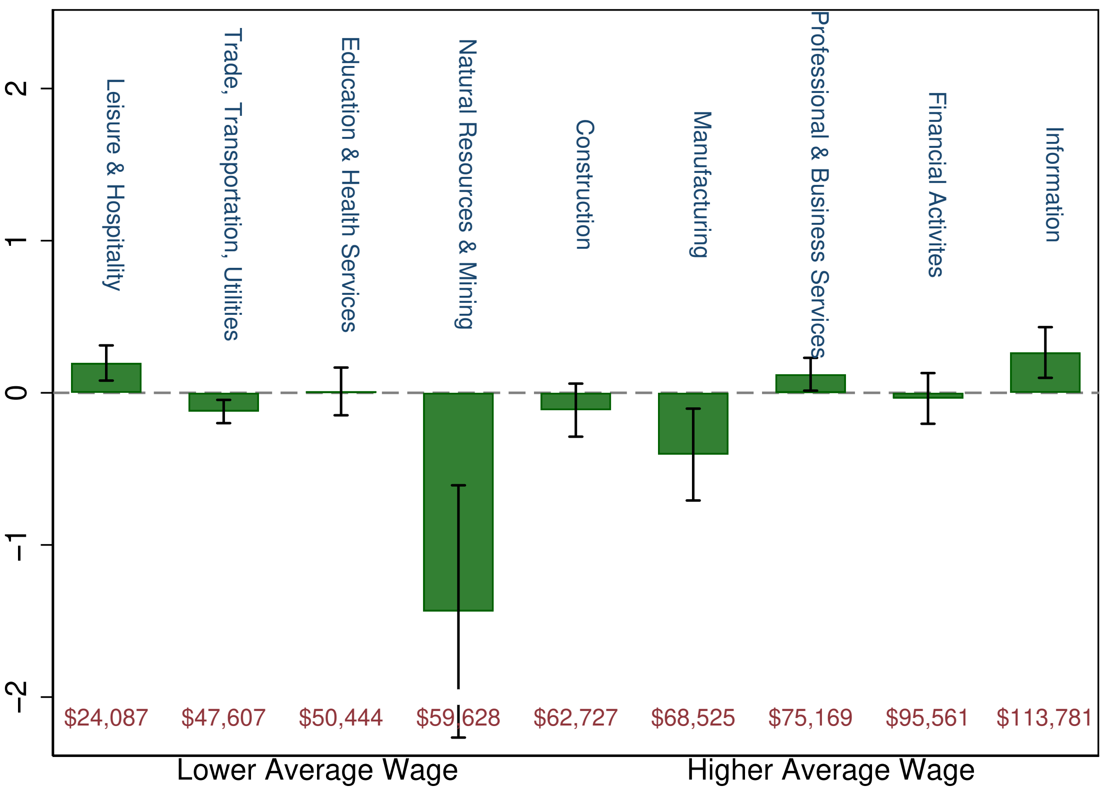
Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Community Survey 2015-2019 (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021)

Notes: These specifications include controls for baseline covariates (fraction urban, ln of total population, ln value of manufacturing product, and ln value of agricultural product). Panel A reports effects on mean household income by quintile in the county. Panel B reports effects on the share of aggregate household income in the county by quintile. Panel C reports effects on the county's Gini coefficient.

Figure A.4: Effects on Private Employment by Industry Location Quotients, Robustness to Baseline Covariates Inclusion

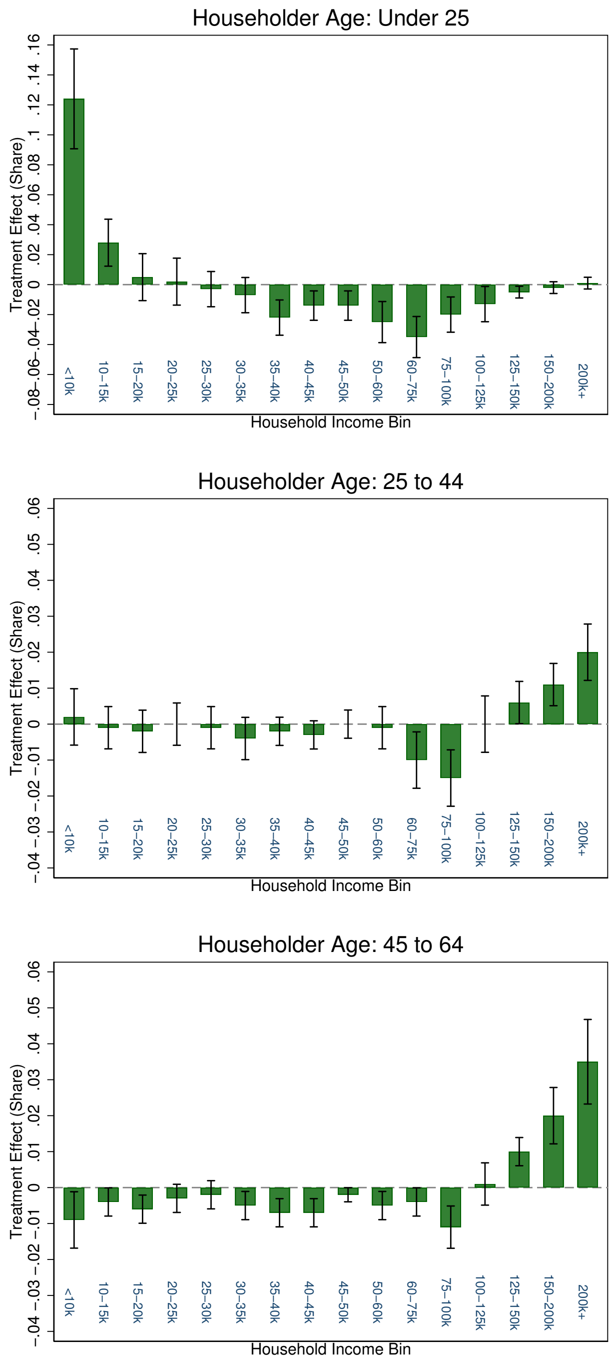



Source: Quarterly Census of Employment and Wages, US Bureau of Labor Statistics (2018)

Notes: These specifications include controls for baseline covariates (fraction urban, ln of total population, ln value of manufacturing product, and ln value of agricultural product). Location quotients are ratios that allow an area's distribution of employment by industry to be compared to the national distribution. If a location quotient is equal to 1, then the industry has the same share of its area employment as it does in the nation. Industries are ordered from lowest average (national) wage to highest average (national) wage. The height of each bar is the point estimate for the effect of winning the university on the employment location quotient for the county. The black error bars show the 95% confidence interval. Data plotted correspond to 2018.

# C Effects on Household Income Distributions by Age of Householder

Figure A.5: Effects on Household Income Distribution by Age of Householder




Source: ACS 5-Year Estimates 2015-2019

Notes: Incomes are in 2019 dollars. The height of each bar shows the estimated effect of university establishment on the share of households in the county that fall in that income bin among the universe of households with the householder of the indicated age. The bars plot 95% confidence intervals.

# D Income and Inequality Effects Using the Opportunity Insights Sample

Table A.5: Income Distributions (Opportunity Insights Sample)

| | (1)<br>Mean Parental Income | (2)<br>Income p25 | (3)<br>Income p75 | (4)<br>Income p90 | (5)<br>Income p99 |
|---|---|---|---|---|---|
| Winning Location | 14489*** | 2432** | 12592*** | 26249*** | 128004*** |
| | (2299) | (950) | (1892) | (3677) | (27558) |
| Control Mean | 73139 | 32316 | 87528 | 124838 | 380032 |
| Counties | 184 | 184 | 184 | 184 | 184 |
| Experiments | 61 | 61 | 61 | 61 | 61 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Online Data Table III, Intergenerational Mobility Statistics and Selected Covariates by County (Chetty, Hendren, Kline, and Saez, 2021)

Notes: All income outcomes reported are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). These parents have children born between 1980 and 1982, and household income is measured between 1996 and 2000.

Table A.6: Economic Inequality (Opportunity Insights Sample)

| | (1)<br>Top 1% Income Share | (2)<br>Difference P75-P25 | (3)<br>Gini Coefficient | (4)<br>Fraction Middle Class |
|---|---|---|---|---|
| Winning Location | 0.023*** | 1.0e+04*** | 0.045*** | -0.034*** |
| | (0.006) | (1324.844) | (0.011) | (0.007) |
| Control Mean | 0.103 | 55212 | 0.399 | 0.543 |
| Counties | 184 | 184 | 184 | 184 |
| Experiments | 61 | 61 | 61 | 61 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Online Data Table III, Intergenerational Mobility Statistics and Selected Covariates by County (Chetty, Hendren, Kline, and Saez, 2021)

Notes: All outcomes reported in this table are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). The top 1% income share is the share of parent income within the county accruing to the county's top 1 percent of tax filers. The interquartile income range (Difference P75-P25) is the difference between the 75th and 25th percentile of parent income within the county. The Gini coefficient is based on parents' family income within the county. The fraction middle class is the share of parents in the county who have an income rank between the 25th and 75th percentile in the national income distribution.

# E Returns to Education

Based on our previous work, we know that rates of educational attainment are higher in winning counties (Russell, Yu, and Andrews, 2021). The share of the over 25 population that has a Bachelor's degree or higher is 14 percentage points greater in winning areas. Since there are positive returns to education, and because public universities may be particularly important "engines of upward mobility," differences in educational attainment rates can at least partially explain the differences in upward mobility we see (Chetty, Friedman, Saez, Turner, and Yagan, 2018).

Given the "hollowing out" of the local labor market described earlier, it is also possible that returns to education are differentially greater in winning areas. We use county-level median earnings by educational attainment level information from IPUMS-NHGIS Manson, Schroeder, Van Riper, Kugler, and Ruggles (2021) to investigate whether highly educated workers earn more in winning areas. In the county-level ACS we only know median earnings in the past 12 months by education level for those over age 25 who have positive earnings. Since we do not know if each person is a full-time, full-year worker, comparing earnings across counties may be complicated by the fact that people with different levels of education could have different work intensities.

We do not find a statistically significant difference in median earnings for any level of educational attainment when we look at the whole sample of male and female workers (Panel A of Table A.7). Those with college degrees do earn more, on average, than workers without these credentials but not differentially moreso in areas where universities were established. Our data do not allow us to estimate returns to education that control for demographics, innate ability, and other factors that might be relevant, but if areas where universities are established attract higher quality college graduates than areas without universities, this type of geographic migration would make it more likely that we would find greater returns to education in winning areas. The fact that we do not find this even using aggregate data is notable.

Another limitation of these data is that we are unable to investigate whether the variance of earnings is higher for the college educated in winning areas. It is possible that college establishment causes changes in the tails of education-level specific income distributions. For instance, among the college educated, those in the top percentiles of the county-specific income distribution could be earning more in winning counties while those at the lower end could be earning less; the county-wide household income results suggest that this is likely the case.

Given the "hollowing out" of the local labor market discussed in section 4.1, it is particularly insightful to look separately at earnings for men. Winning areas experienced particularly strong declines in natural resources and mining and manufacturing, two male-dominated industries. As of 2021, 85% of workers employed in natural resources & mining and 70% of workers employed in manufacturing were male (US Bureau of Labor Statistics, 2021). Looking separately by level of educational attainment is also informative since less than a quarter of individuals working in natural resources & mining or manufacturing have a bachelor's degree or higher, and manufacturing and other non-manufacturing production industries are the largest employers of blue-collar men (Bureau of Labor Statistics, U.S. Department of Labor, 2018; Rose, 2018).

Panel B of Table A.7 shows that earnings are lower for low-skill men in winning areas. The estimates are negative but imprecisely estimated for high school dropouts and those with only a high school degree. The effect for those with only some college is statistically significant at the 5% level and indicates that median earnings are 5% lower for men working in winning counties. At a national level, middle-skill production and operative positions have declined, leading to declining wages of low-education males as they have been forced to move into lower-paying occupations (Autor and Wasserman, 2013). Our results indicate that this has occurred to a greater extent in counties where universities were established.

Since the previous earnings by education results condition on having positive earnings, it is also worth investigating whether labor force participation and employment rates differ between winning and losing areas. Publicly available data do not allow us disaggregate data by gender, but we find that those with lower levels of educational attainment (some college or less) are more likely to be in the labor force in winning counties. Conditional on labor force participation, unemployment rates are comparable. (See Panels D and E of Table A.7.)

Table A.7: Labor Market Outcomes by Education Group

| | (1) HS Dropout | (2) HS | (3) Some College | (4) BA | (5) Grad |
|---|---|---|---|---|---|
| ***Panel A: Ln Median Earnings (All)*** | | | | | |
| Winning Location | -0.022 | -0.005 | -0.029* | -0.003 | 0.011 |
| | (0.026) | (0.016) | (0.015) | (0.021) | (0.021) |
| Control Mean | 10.072 | 10.318 | 10.456 | 10.754 | 11.003 |
| Counties | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel B: Ln Median Earnings (Men)*** | | | | | |
| Winning Location | -0.040 | -0.030 | -0.047** | -0.021 | 0.020 |
| | (0.026) | (0.019) | (0.019) | (0.028) | (0.027) |
| Control Mean | 10.237 | 10.515 | 10.683 | 10.97 | 11.181 |
| Counties | 181 | 185 | 185 | 184 | 183 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel C: Ln Median Earnings (Women)*** | | | | | |
| Winning Location | -0.014 | 0.028* | -0.011 | -0.011 | -0.025 |
| | (0.052) | (0.016) | (0.017) | (0.020) | (0.018) |
| Control Mean | 9.754 | 10.052 | 10.262 | 10.603 | 10.908 |
| Counties | 178 | 185 | 185 | 185 | 184 |
| Experiments | 61 | 61 | 61 | 61 | 61 |
| ***Panel D: Labor Force Participation (All)*** | | | | | |
| Winning Location | 0.051*** | 0.037*** | 0.016** | 0.005 | |
| | (0.014) | (0.009) | (0.007) | (0.005) | |
| Control Mean | .545 | .700 | .78 | .856 | |
| Counties | 185 | 185 | 185 | 185 | |
| Experiments | 61 | 61 | 61 | 61 | |
| ***Panel E: Unemployment Rates (All)*** | | | | | |
| Winning Location | 0.006 | 0.003 | 0.002 | 0.001 | |
| | (0.008) | (0.003) | (0.003) | (0.001) | |
| Control Mean | .089 | .052 | .04 | .023 | |
| Counties | 185 | 185 | 185 | 185 | |
| Experiments | 61 | 61 | 61 | 61 | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: American Community Survey 2015-2019 (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021)

Notes: For Panels A-C, median earnings are measured among the over 25 population of the county who have positive earnings. Panel D reports effects on the share of the indicated education group who are in the labor force. Panel E reports effects on the unemployment rate for the indicated education group. For Panels D and E the BA group includes those with a Bachelor's degree or higher because data do not allow disaggregation into those with just a BA versus those with a graduate degree.

# F Alternative Measures of Innovation and Entrepreneurship

In the main body of the paper, we use data on patents issued between 1988 and 2014; we use these dates so that the patent data is consistent with entrepreneurship data from Guzman, Andrews, Stern, Fazio, and Liu (2022). Results are similar when using different time windows of patenting.

In the main body of the paper, we proxy patent quality using patent citations. While patent citations are probably the most widely used measure of patent quality in the literature, they have potential downsides. In particular, because they count how often others are able to build on a particular patent, citations are measure of the social value of a patent. If we are interested in how innovation can lead to top incomes, it may be more relevant to investigate the private value of patents, that is, what is the present discounted monetary value of a patent to its owner. Here, we use a measure of private patent value from Kogan, Papanikolaou, Seru, and Stoffman (2017), who observe how firms' stock prices change in narrow event windows around the issuance of a patent and use this to infer the present discounted value of each patent. Private patent values are in millions of 1982 dollars. Because this measure is based on changes in stock prices, it is only available for patents that issue to publicly traded firms. We aggregate the private patent values for all patents issued to firms in each county and year.

In the main body of the paper, we report effects on two measures of entrepreneurial quality. First, we use the Startup Formation Rate, calculated as the count of ventures divided by the count of all new business registrants in the county. Second, we use the Entrepreneurial Quality Index (EQI), which is constructed by first estimating the probability that a particular venture experiences a growth event based on early firm choices and then averaging the probability over all firms in a region and year. Here we also show effects on other county-level measures of entrepreneurial ecosystem quality from the Startup Cartography Project (Guzman, Andrews, Stern, Fazio, and Liu, 2022). Note that the data cover 1988 to 2014.

Table A.8: Effects on Alternative Measures of Patents and Entrepreneurship Firm

| | (1)<br>IHS(Patent Values) | (2)<br>IHS(Total RECPI) | (3)<br>IHS(Liq Growth Events) | (4)<br>IHS(Avg REAI) |
|---|---|---|---|---|
| Winning Location | 2.163*** | 0.598*** | 0.767*** | 0.226** |
| | (0.327) | (0.182) | (0.217) | (0.094) |
| Control Mean | 6.267 | 1.275 | 1.109 | .513 |
| Counties | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: Kogan, Papanikolaou, Seru, and Stoffman (2017); The Startup Cartography Project (Guzman, Andrews, Stern, Fazio, and Liu, 2022)

Notes: The outcome in column 1 is the inverse hyperbolic sine of the sum of private patent values for all patents issued to publicly traded firms in each county and year in millions of 1982 dollars, from Kogan, Papanikolaou, Seru, and Stoffman (2017) and based on changes in each firm's stock market price in narrow event windows around patent issuance. The Regional Entrepreneurship Cohort Potential Index (RECPI) (column 2) is the number of startups within a particular location or region expected to later achieve a significant growth outcome (SFR*EQI). Liquidity growth events are measured within six years of the entrepreneurial venture's founding. The Regional Entrepreneurship Acceleration Index (REAI) is the ability of a region to convert entrepreneurial potential into realized growth (# of Growth Outcomes / RECPI).

# G Heterogeneity by Research Intensity

Table A.9: Economic Mobility by Research Intensity of Established Institution

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Doctoral - R1 | 0.002*** | 0.002*** | 0.002*** | 0.002*** | 0.002*** | -0.004 | 0.005*** |
| | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.001) | (0.006) | (0.001) |
| Doctoral - R2 | 0.002** | 0.002** | 0.002*** | 0.002*** | 0.001 | -0.004 | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.020) | (0.001) |
| Non-Doctoral Colleges | 0.002 | 0.001 | 0.001 | 0.001 | -0.000 | -0.019 | 0.003* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.018) | (0.002) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Doctoral - R1 | 0.012*** | 0.012*** | 0.011*** | 0.009** | 0.007 | -0.000 | 0.030*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.008) | (0.007) |
| Doctoral - R2 | 0.003 | 0.003 | 0.004 | 0.005 | 0.006 | 0.011 | 0.020** |
| | (0.006) | (0.006) | (0.006) | (0.005) | (0.005) | (0.012) | (0.008) |
| Non-Doctoral Colleges | -0.000 | -0.000 | 0.000 | 0.001 | 0.002 | 0.006 | 0.020* |
| | (0.010) | (0.009) | (0.009) | (0.009) | (0.010) | (0.017) | (0.011) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Doctoral - R1 | 0.006 | 0.003 | -0.000 | -0.004* | -0.008*** | -0.012*** | 0.007 |
| | (0.004) | (0.004) | (0.003) | (0.002) | (0.003) | (0.004) | (0.004) |
| Doctoral - R2 | -0.000 | -0.002 | -0.004 | -0.007 | -0.010* | -0.013* | -0.001 |
| | (0.008) | (0.006) | (0.006) | (0.005) | (0.006) | (0.008) | (0.007) |
| Non-Doctoral Colleges | -0.000 | -0.003 | -0.005 | -0.009* | -0.012* | -0.015* | 0.003 |
| | (0.008) | (0.006) | (0.005) | (0.005) | (0.006) | (0.008) | (0.006) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Doctoral - R1 | 0.008* | 0.007* | 0.005* | 0.004 | 0.002 | -0.001 | 0.019*** |
| | (0.004) | (0.004) | (0.003) | (0.003) | (0.003) | (0.004) | (0.005) |
| Doctoral - R2 | -0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.001 | 0.010 |
| | (0.007) | (0.006) | (0.005) | (0.005) | (0.005) | (0.007) | (0.006) |
| Non-Doctoral Colleges | -0.004 | -0.003 | -0.003 | -0.002 | -0.001 | -0.000 | 0.013** |
| | (0.009) | (0.007) | (0.006) | (0.006) | (0.007) | (0.011) | (0.006) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 185 | 185 | 185 | 185 | 185 | 185 | 185 |
| Experiments | 61 | 61 | 61 | 61 | 61 | 61 | 61 |
| ***Panel E: Income Rank-Rank Slope*** | | | | | | | |
| Doctoral - R1 | -0.003 | | | | | | |
| | (0.007) | | | | | | |
| Doctoral - R2 | -0.014 | | | | | | |
| | (0.013) | | | | | | |
| Non-Doctoral Colleges | -0.014 | | | | | | |
| | (0.014) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 184 | | | | | | |
| Experiments | 61 | | | | | | |

Standard errors in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Source: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021)

Table A.10: Economic Inequality by Research Intensity of Established Institution

| | (1) Top 1% Income Share | (2) Diff P75-P25 | (3) Gini | (4) Fraction Middle Class |
|---|---|---|---|---|
| Doctoral - R1 | 0.022*** | 1.0e+04*** | 0.046*** | -0.035*** |
| | (0.008) | (2064.108) | (0.017) | (0.010) |
| Doctoral - R2 | 0.034*** | 8548.455*** | 0.058*** | -0.033* |
| | (0.011) | (2323.372) | (0.016) | (0.017) |
| Non-Doctoral Colleges | 0.012 | 1.1e+04*** | 0.024 | -0.031** |
| | (0.015) | (2300.011) | (0.027) | (0.013) |
| Control Mean | .103 | 55211.637 | .399 | .543 |
| Counties | 184 | 184 | 184 | 184 |
| Experiments | 61 | 61 | 61 | 61 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Online Data Table III, Intergenerational Mobility Statistics and Selected Covariates by County (Chetty, Hendren, Kline, and Saez, 2021)

Notes: All outcomes reported in this table are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). The top 1% income share is the share of parent income within the county accruing to the county's top 1 percent of tax filers. The interquartile income range (Difference P75-P25) is the difference between the 75th and 25th percentile of parent income within the county. The Gini coefficient is based on parents' family income within the county. The fraction middle class is the share of parents in the county who have an income rank between the 25th and 75th percentile in the national income distribution. Institutions' research intensity is based on their 2018 Carnegie classifications.

# H Effects Relative to Establishment of Other Public Institutions

Table A.11: Economic Mobility for Children by Parental Income Percentile Relative to Establishment of Other Public Institutions

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.002 | 0.002 | 0.002* | 0.001 | 0.000 | -0.021 | 0.005*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) | (0.037) | (0.002) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.003 | 0.002 | 0.002 | 0.002 | 0.002 | 0.000 | 0.023 |
| | (0.011) | (0.010) | (0.010) | (0.009) | (0.009) | (0.016) | (0.013) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Winning Location | 0.013 | 0.006 | -0.001 | -0.012* | -0.022*** | -0.032*** | -0.003 |
| | (0.011) | (0.009) | (0.008) | (0.007) | (0.006) | (0.006) | (0.007) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Winning Location | 0.013 | 0.009 | 0.004 | -0.002 | -0.009 | -0.020** | 0.011 |
| | (0.012) | (0.011) | (0.009) | (0.007) | (0.006) | (0.007) | (0.009) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 25 | 25 | 25 | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| ***Panel E: Income Rank-Rank Slope*** | | | | | | | |
| Winning Location | -0.036** | | | | | | |
| | (0.012) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 25 | | | | | | |
| Experiments | 12 | | | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021)

Notes: Other public institutions include state penitentiaries, capitals, and asylums.

Table A.12: Economic Inequality Relative to Establishment of Other Public Institutions

| | (1)<br>Top 1% Income Share | (2)<br>Difference P75-P25 | (3)<br>Gini Coefficient | (4)<br>Fraction Middle Class |
|---|---|---|---|---|
| Winning Location | 0.031 | 9013.367** | 0.038 | -0.031 |
| | (0.020) | (3425.151) | (0.024) | (0.020) |
| Control Mean | .103 | 55211.637 | .399 | .543 |
| Counties | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: Online Data Table III, Intergenerational Mobility Statistics and Selected Covariates by County (Chetty, Hendren, Kline, and Saez, 2021)

Notes: All outcomes reported in this table are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). The top 1% income share is the share of parent income within the county accruing to the county's top 1 percent of tax filers. The interquartile income range (Difference P75-P25) is the difference between the 75th and 25th percentile of parent income within the county. The Gini coefficient is based on parents' family income within the county. The fraction middle class is the share of parents in the county who have an income rank between the 25th and 75th percentile in the national income distribution.

Table A.13: Measures of Innovation and Entrepreneurship Relative to Establishment of Other Public Institutions

| | (1)<br>IHS(Patents) | (2)<br>IHS(Cites) | (3)<br>IHS(Total Ventures) | (4)<br>IHS(EQI) |
|---|---|---|---|---|
| Winning Location | 1.480** | 1.508** | 0.350 | 0.00004 |
| | (0.510) | (0.563) | (0.512) | (0.00003) |
| Control Mean | 5.796 | 8.599 | 8.645 | .0004 |
| Counties | 25 | 25 | 25 | 25 |
| Experiments | 12 | 12 | 12 | 12 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: Bureau of Economic Analysis (2020) and American Community Survey 2015-2019 (Manson, Schroeder, Van Riper, Kugler, and Ruggles, 2021)

Notes: County-level GDP is unavailable for Albemarle, Montgomery, and Rockbridge counties in Virginia, so there are fewer counties and experiments in the specifications for county-level GDP.

# I Heterogeneity by College Scorecard Mobility Measures

Table A.14: County Economic Mobility by College Bottom 20% to Top 1% Mobility Rate

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.002*** | 0.002*** | 0.002*** | 0.001*** | 0.000 | -0.013 | 0.004*** |
| | (<0.001) | (<0.001) | (<0.001) | (<0.001) | (0.001) | (0.010) | (0.001) |
| Winning X College Mobility Rate | 0.019 | 0.020 | 0.021 | 0.025* | 0.034 | 0.182 | 0.045 |
| | (0.013) | (0.013) | (0.013) | (0.014) | (0.021) | (0.197) | (0.032) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Experiments | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.004 | 0.004 | 0.004 | 0.003 | 0.002 | 0.000 | 0.022*** |
| | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) | (0.009) | (0.006) |
| Winning X College Mobility Rate | 0.057 | 0.061 | 0.067 | 0.080 | 0.098 | 0.155 | 0.080 |
| | (0.158) | (0.151) | (0.143) | (0.136) | (0.154) | (0.310) | (0.228) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Experiments | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Winning Location | 0.000 | -0.002 | -0.004 | -0.007** | -0.010*** | -0.013*** | 0.003 |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.004) | (0.005) | (0.004) |
| Winning X College Mobility Rate | 0.117 | 0.104 | 0.089 | 0.069 | 0.050 | 0.030 | 0.024 |
| | (0.180) | (0.140) | (0.102) | (0.081) | (0.112) | (0.168) | (0.136) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Experiments | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Winning Location | 0.000 | 0.000 | 0.000 | 0.000 | -0.000 | -0.000 | 0.014*** |
| | (0.005) | (0.004) | (0.003) | (0.003) | (0.003) | (0.005) | (0.004) |
| Winning X College Mobility Rate | 0.087 | 0.078 | 0.067 | 0.051 | 0.035 | 0.006 | 0.011 |
| | (0.130) | (0.114) | (0.099) | (0.087) | (0.090) | (0.128) | (0.144) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 168 | 168 | 168 | 168 | 168 | 168 | 168 |
| Experiments | 55 | 55 | 55 | 55 | 55 | 55 | 55 |
| ***Panel E: Rank-Rank Slope*** | | | | | | | |
| Winning Location | -0.013 | | | | | | |
| | (0.008) | | | | | | |
| Winning X College Mobility Rate | 0.392 | | | | | | |
| | (0.341) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 167 | | | | | | |
| Experiments | 55 | | | | | | |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility, All Outcomes by County, Race, Gender, and Parental Income Percentile (Chetty, Friedman, Hendren, Jones, and Porter, 2021); Table 2: Baseline Cross-Sectional Estimates by College, Mobility Report Cards (Chetty, Friedman, Saez, Turner, and Yagan, 2017)

Notes: The university mobility rate is defined as the probability that someone who attends the university reaches the top 1% of the national income distribution conditional on the parent's being in the bottom quintile of the parental income distribution. Not all established universities have this mobility rate reported in the College Scorecard data which is why we report results that use data for 55 of the 61 experiments.

Table A.15: County Economic Inequality by College Bottom 20% to Top 1% Mobility Rate

| | (1)<br>Top 1% Income Share | (2)<br>Diff P75-P25 | (3)<br>Gini | (4)<br>Fraction Middle Class |
|---|---|---|---|---|
| Winning Location | 0.020** | 9352.759*** | 0.029* | -0.030*** |
| | (0.009) | (1765.320) | (0.016) | (0.011) |
| Winning X College Mobility Rate | 0.198 | 1.9e+04 | 0.858 | -0.063 |
| | (0.333) | (6.8e+04) | (0.626) | (0.329) |
| Control Mean | .103 | 55211.637 | .399 | .543 |
| Counties | 167 | 167 | 167 | 167 |
| Experiments | 55 | 55 | 55 | 55 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: Online Data Table III, Intergenerational Mobility Statistics and Selected Covariates by County (Chetty, Hendren, Kline, and Saez, 2021); Table 2: Baseline Cross-Sectional Estimates by College, Mobility Report Cards (Chetty, Friedman, Saez, Turner, and Yagan, 2017)

Notes: All outcomes reported in this table are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). The top 1% income share is the share of parent income within the county accruing to the county's top 1 percent of tax filers. The interquartile income range (Difference P75-P25) is the difference between the 75th and 25th percentile of parent income within the county. The Gini coefficient is based on parents' family income within the county. The fraction middle class is the share of parents in the county who have an income rank between the 25th and 75th percentile in the national income distribution. The university mobility rate is defined as the probability that someone who attends the university reaches the top 1% of the national income distribution conditional on the parent's being in the bottom quintile of the parental income distribution. Not all established universities have this mobility rate reported in the College Scorecard data which is why we report results that use data for 55 of the 61 experiments.

# J Heterogeneity by College's Economic Connectedness

Table A.16: County Economic Mobility by College's Economic Connectedness

| | (1) p1 | (2) p10 | (3) p25 | (4) p50 | (5) p75 | (6) p100 | (7) Mean |
|---|---|---|---|---|---|---|---|
| ***Panel A: Probability of Reaching Top 1% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | -0.000 | -0.000 | -0.000 | -0.002 | -0.004 | -0.039 | -0.004 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.003) | (0.048) | (0.003) |
| Winning X College Econ Connectedness | 0.001 | 0.001 | 0.002 | 0.002 | 0.003 | 0.022 | $0.006^{**}$ |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (0.031) | (0.002) |
| Control Mean | 0.001 | 0.001 | 0.002 | 0.004 | 0.009 | 0.095 | 0.008 |
| Counties | 177 | 177 | 177 | 177 | 177 | 177 | 177 |
| Experiments | 58 | 58 | 58 | 58 | 58 | 58 | 58 |
| ***Panel B: Probability of Reaching Top 20% in 2014-15 National Income Distribution*** | | | | | | | |
| Winning Location | 0.001 | 0.001 | 0.001 | -0.000 | -0.001 | -0.005 | 0.022 |
| | (0.019) | (0.019) | (0.018) | (0.019) | (0.024) | (0.048) | (0.029) |
| Winning X College Econ Connectedness | 0.004 | 0.004 | 0.004 | 0.004 | 0.005 | 0.006 | 0.003 |
| | (0.014) | (0.013) | (0.013) | (0.013) | (0.015) | (0.030) | (0.019) |
| Control Mean | 0.060 | 0.077 | 0.102 | 0.155 | 0.234 | 0.472 | 0.178 |
| Counties | 177 | 177 | 177 | 177 | 177 | 177 | 177 |
| Experiments | 58 | 58 | 58 | 58 | 58 | 58 | 58 |
| ***Panel C: Effect on Mean Income Rank Measured at Age 26*** | | | | | | | |
| Winning Location | 0.001 | 0.001 | 0.002 | 0.002 | 0.002 | 0.002 | $0.031^{*}$ |
| | (0.023) | (0.018) | (0.013) | (0.014) | (0.020) | (0.029) | (0.017) |
| Winning X College Econ Connectedness | 0.001 | -0.000 | -0.002 | -0.005 | -0.007 | -0.010 | -0.017 |
| | (0.015) | (0.012) | (0.009) | (0.009) | (0.013) | (0.018) | (0.011) |
| Control Mean | 0.344 | 0.386 | 0.432 | 0.498 | 0.558 | 0.620 | 0.499 |
| Counties | 177 | 177 | 177 | 177 | 177 | 177 | 177 |
| Experiments | 58 | 58 | 58 | 58 | 58 | 58 | 58 |
| ***Panel D: Effect on Mean Income Rank in 2014-15 Relative to Other Children*** | | | | | | | |
| Winning Location | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | 0.002 | $0.031^{*}$ |
| | (0.021) | (0.017) | (0.013) | (0.012) | (0.019) | (0.035) | (0.018) |
| Winning X College Econ Connectedness | 0.001 | 0.001 | 0.000 | -0.000 | -0.001 | -0.002 | -0.010 |
| | (0.014) | (0.011) | (0.009) | (0.008) | (0.012) | (0.021) | (0.012) |
| Control Mean | 0.340 | 0.380 | 0.425 | 0.491 | 0.558 | 0.675 | 0.498 |
| Counties | 177 | 177 | 177 | 177 | 177 | 177 | 177 |
| Experiments | 58 | 58 | 58 | 58 | 58 | 58 | 58 |
| ***Panel E: Rank-Rank Slope*** | | | | | | | |
| Winning Location | -0.036 | | | | | | |
| | (0.043) | | | | | | |
| Winning X College Econ Connectedness | 0.018 | | | | | | |
| | (0.027) | | | | | | |
| Control Mean | 0.342 | | | | | | |
| Counties | 176 | | | | | | |
| Experiments | 58 | | | | | | |

Standard errors in parentheses

$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Sources:Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt (2022d)

Notes: The definition of economic connectedness is two times the share of high-SES friends within three birth cohorts among low-SES individuals, averaged over all low-SES individuals in the college. Not all established universities have economic connectedness data which is why we report results that use data for 58 of the 61 experiments.

Table A.17: County Economic Inequality by College's Economic Connectedness

| | (1) Top 1% Income Share | (2) Diff P75-P25 | (3) Gini | (4) Fraction Middle Class |
|---|---|---|---|---|
| Winning Location | -0.005 | 1.3e+04 | -0.001 | 0.053 |
| | (0.051) | (8563.507) | (0.095) | (0.045) |
| Winning X College Econ Connectedness | 0.020 | -1.9e+03 | 0.031 | -0.055* |
| | (0.032) | (5527.417) | (0.059) | (0.029) |
| Control Mean | .103 | 55211.637 | .399 | .543 |
| Counties | 176 | 176 | 176 | 176 |
| Experiments | 58 | 58 | 58 | 58 |

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sources: Chetty, Jackson, Kuchler, Stroebel, Hendren, Fluegge, Gong, Gonzalez, Grondin, Jacob, Johnston, Koenen, Laguna-Muggenburg, Mudekereza, Rutter, Thor, Townsend, Zhang, Bailey, Barbera, Bhole, and Wernerfelt (2022d)

Notes: All outcomes reported in this table are based on parents in the core sample of Chetty, Hendren, Kline, and Saez (2014). The top 1% income share is the share of parent income within the county accruing to the county's top 1 percent of tax filers. The interquartile income range (Difference P75-P25) is the difference between the 75th and 25th percentile of parent income within the county. The Gini coefficient is based on parents' family income within the county. The fraction middle class is the share of parents in the county who have an income rank between the 25th and 75th percentile in the national income distribution. The definition of economic connectedness is two times the share of high-SES friends within three birth cohorts among low-SES individuals, averaged over all low-SES individuals in the college. Not all established universities have economic connectedness data which is why we report results that use data for 58 of the 61 experiments.