Not the Great Equalizer? Local Economic Mobility and Inequality Effects for the Establishment of U.S. Universities

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Not the Great Equalizer? Local Economic Mobility and Inequality Effects from the Establishment of U.S. Universities

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Abstract

We exploit historical natural experiments to test whether universities increase economic mobility and equality. We use "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. University establishment causes greater intergenerational income mobility but also increases cross-sectional income inequality. We highlight four findings to explain this seeming paradox: universities hollow out the local labor market and provide greater opportunities to achieve top incomes, both of which increase cross-sectional inequality, and increase educational attainment and connections to high-SES people, which prevent inequality from perpetuating into intergenerational immobility.

JEL Codes: J21; J62; I23; I24

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1 Introduction

Since the middle of the 20th century, intergenerational income mobility in the U.S. has fallen, while income inequality has increased. Many scholars argue that these two phenomenon are closely linked (Krueger, 2012; Chetty, Grusky, Hell, Hendren, Manduca, and Narang, 2017; Corak, 2013).[1] Given the strong link between inequality and mobility, it is widely believed that policies that reduce inequality will also increase intergenerational mobility, and vice versa. Additionally, inequality and mobility vary widely across space (Chetty, Hendren, Kline, and Saez, 2014; Chetty, Friedman, Hendren, Jones, and Porter, 2020), suggesting a role for local and regional policymakers.

Expanding educational institutions is frequently hailed as a policy that state and local policymakers can use to reduce inequality and increase mobility. Famed educator Horace Mann referred to education as "the great equalizer" (Mann, 1848).[2] Mann was referring to primary and secondary education, but many scholars point to the importance of higher education in the face of a highly skill-intensive labor market (Goldin and Katz, 2008; Autor, 2014). It is difficult to establish causal relationships between local policies that expand higher education and overall income inequality and mobility outcomes. For instance, locations with more egalitarian cultures and concern for future generations may be more likely to both have widespread access to higher education and high rates of economic mobility. Numerous studies from across the social sciences argue that reverse causality is likely to occur, with greater income inequality creating inequality in educational attainment (Bailey and Dynarski, 2011; Bloome, 2015; Jackson and Holzman, 2020; Pfeffer, 2018; Rauscher, 2016; Conley, 2001; Mettler, 2014; Armstrong and Hamilton, 2013; Kearney and Levine, 2016), which makes it

[1] Several studies provide theoretical arguments why greater inequality can cause intergenerational mobility to decrease (Solon, 2004; Durlauf and Seshadri, 2017; Becker, Kominers, Murphy, and Spenkuch, 2018). The negative relationship between inequality and intergenerational mobility holds empirically across countries (Andrews and Leigh, 2009) as well as across commuting zones within the U.S. (Chetty, Hendren, Kline, and Saez, 2014; Bradbury and Triest, 2016). It also holds over time (Chetty, Grusky, Hell, Hendren, Manduca, and Narang, 2017); intergenerational occupational mobility fell in the U.S. (Long and Ferrie, 2013; Song, Massey, Rolf, Ferrie, Rothbaum, and Xie, 2020) at the same time that U.S. inequality rose (Piketty and Saez, 2003), although some studies find that income mobility in the U.S. has remained roughly constant over the last several decades while inequality continued to increase (Chetty, Hendren, Kline, Saez, and Turner, 2014; Lee and Solon, 2009).

[2] Mann would go on to elaborate several ways through which education reduces inequality: by making the educated more charitable towards the poor, by providing all who received an education the means to provide for themselves, and by transforming the economy and culture to provide more opportunities for everyone (Mann, 1848). Notably, Mann recognized that expanding education affected more than just the people who received education.

difficult to interpret college rankings on the basis of economic mobility (Cantwell, 2022). The dearth of research on causal effects is not surprising since it is difficult to find exogenous variation in broad-based educational access.

We overcome this challenge by exploiting 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. Russell, Yu, and Andrews (2021) verify that these historical experiments still matter, with counties that won a university in the past being much more likely to have a university today, having more local colleges/universities on average, and having more years of exposure to a university over their history. We follow the approach of Russell, Yu, and Andrews (2021) to compare the winning and runner-up counties today. We find that counties that win a university have greater rates of 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. At the same time, and in contrast to conjectures in the literature, 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.

To understand this seeming paradox, we investigate how winning a university affects the local economy more broadly, highlighting four channels that the literature suggests may be related to inequality or mobility. 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.

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. Several studies document correlations between greater educational attainment and both lower inequality (Abdullah, Doucouliagos, and Manning, 2015; Liu, Green, and Pensiero, 2016) and greater intergenerational mobility (Mazumder, 2015; Chetty, Friedman, Saez, Turner, and Yagan, 2018), and numerous authors have documented that higher education raises earnings for those who obtain a degree (Zimmerman, 2014, 2019; Ost, Pan, and Webber, 2018; Anelli, 2020). 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 lower high school dropout rates.

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, 2022d).

These four findings show that universities create polarization in the local labor market and more opportunities for top incomes, both of which increase local inequality, while simultaneously democratizing the opportunity to reach top incomes and hence increasing intergenerational mobility. Contrary to Horace Mann, expanding access to higher education through university establishment does not appear to be a "great equalizer," at least cross-sectionally, but 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 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 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. Appendix Table A.1 shows a list of the 61 high quality site selection experiments in our sample, and A.1 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

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

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 γ_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 report robust standard errors.

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 (2022a) 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 chances 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 chances 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.

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 become more unequal. 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 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 B 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. But even among householders over age 25, winning counties have 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 some of the low incomes at the bottom of the county-wide income distribution probably do represent college students.

As a complement to these results, Appendix Table A.3 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 partially reflects increased numbers of low-earning college students residing in university areas), 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.4). 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.

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 for 2001-2020 (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 reports results from dynamic difference-in-differences specifications:

$$Y_{ct} = \sum_{y=-5}^{12} \beta_y Winner_c \times Decade_{cy} + \sum_{y=-5}^{12} \theta_y Decade_{cy} + \gamma_c + \gamma_t + \epsilon_{ct}. \tag{2}$$

where Y is an outcome based on occupational income scores, c indexes a county, and t indexes a decade. We include county fixed effects (γ_c), census year fixed effects (γ_t), fixed effects for decades relative to the university establishment experiment year, and decade event time indicators interacted with treatment. We plot the β_y's, omitting $y = 0$.

Panel A plots the treatment effect on the county mean occupational income score. Panel B plots the variance of occupational income in the county. 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 fail to be a "great equalizer" of local incomes, even as they increase mobility to top incomes? We next present results for four ways in which university establishment affects local economies; the first two illustrate mechanisms through which university establishment increases income inequality, while the third and fourth show why university establishment does not decrease intergenerational mobility.

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. 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 two highest wage industries). 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 D 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 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).[4] 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 E 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. The decrease in high school dropout rates in winning counties suggests

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

that the presence of a university may provide opportunities for those who would otherwise obtain low levels of human capital, suggesting one channel through which a local university increases intergenerational mobility.

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%).

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, 2022d). 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 (2022a), 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, 2022b). 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 given imprecision in our estimates we are not generally able to 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.[5] 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

[5] 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.

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.

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, though point estimates are suggestive of a positive correlation.

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.

We find that public universities have not functioned as "great equalizers." Although universities democratize access to top incomes (by expanding access to human capital to those born into the bottom of the income distribution and increasing economic connectedness), the same institutions also increase inequality (through hollowing out the local labor market and providing paths to top incomes). Promoting institutions of higher education, therefore, is not a policy that will simultaneously reduce inequality and increase mobility. More broadly, our results show that when a particular policy affects the local economy through multiple channels, mechanical relationships between inequality and mobility may break down.

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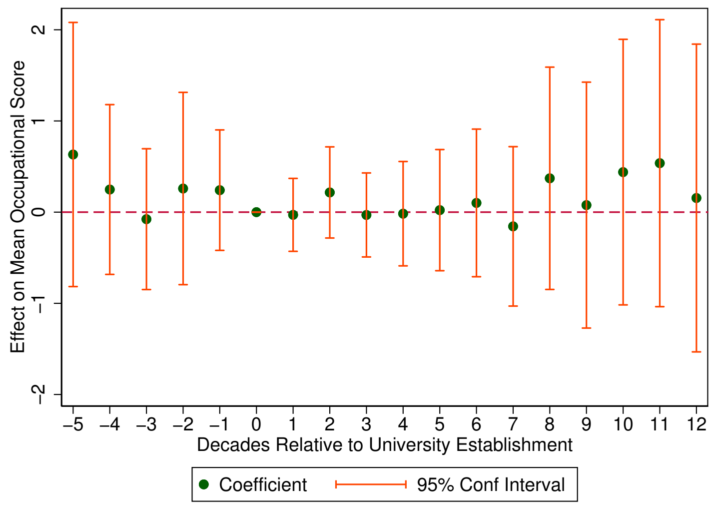
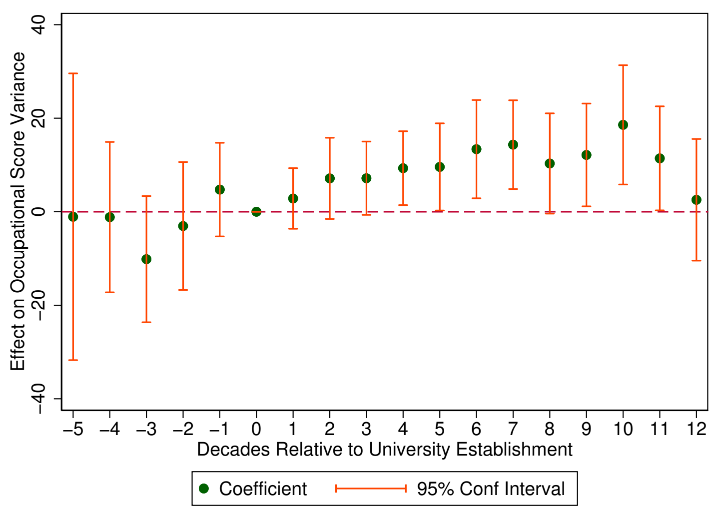
Figures

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

(a) Mean



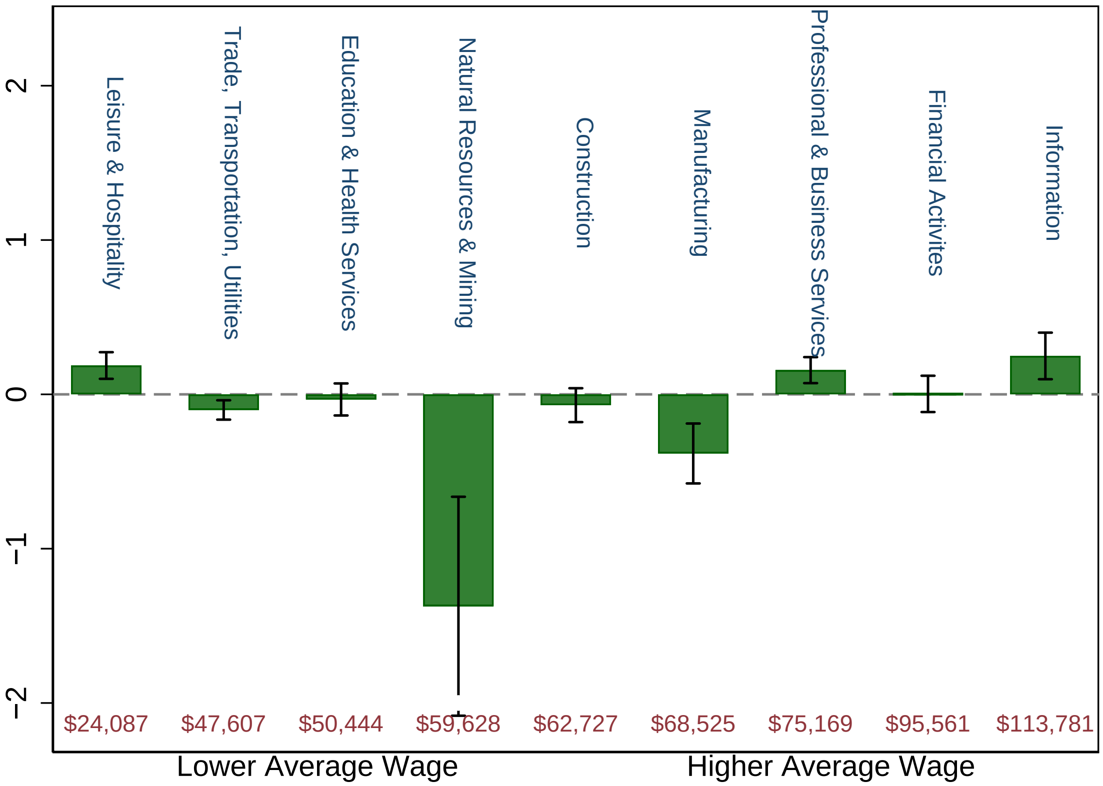
(b) Variance



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 5 decades prior to university establishment to 12 decades after; panel is unbalanced. Dynamic DiD specifications include county fixed effects, census year fixed effects, fixed effects for decades relative to university establishment, and decade event time indicators interacted with treatment. Standard errors are clustered at the county level.

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, 2022a)

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 (2022d)'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.

Appendix Materials

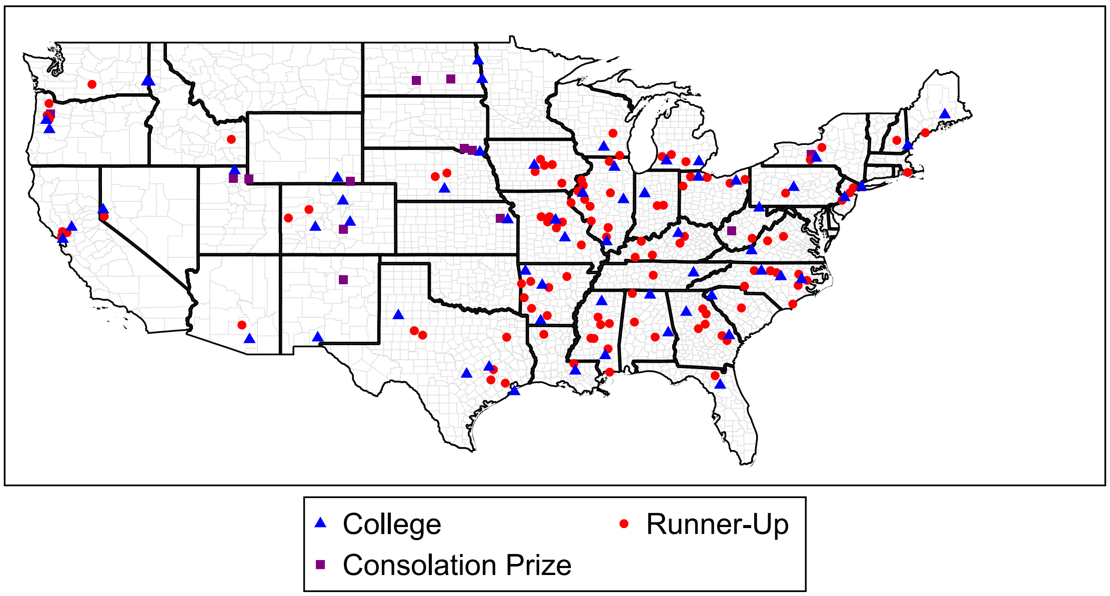
A Details on the Colleges Sample

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.

Figure A.1: 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.

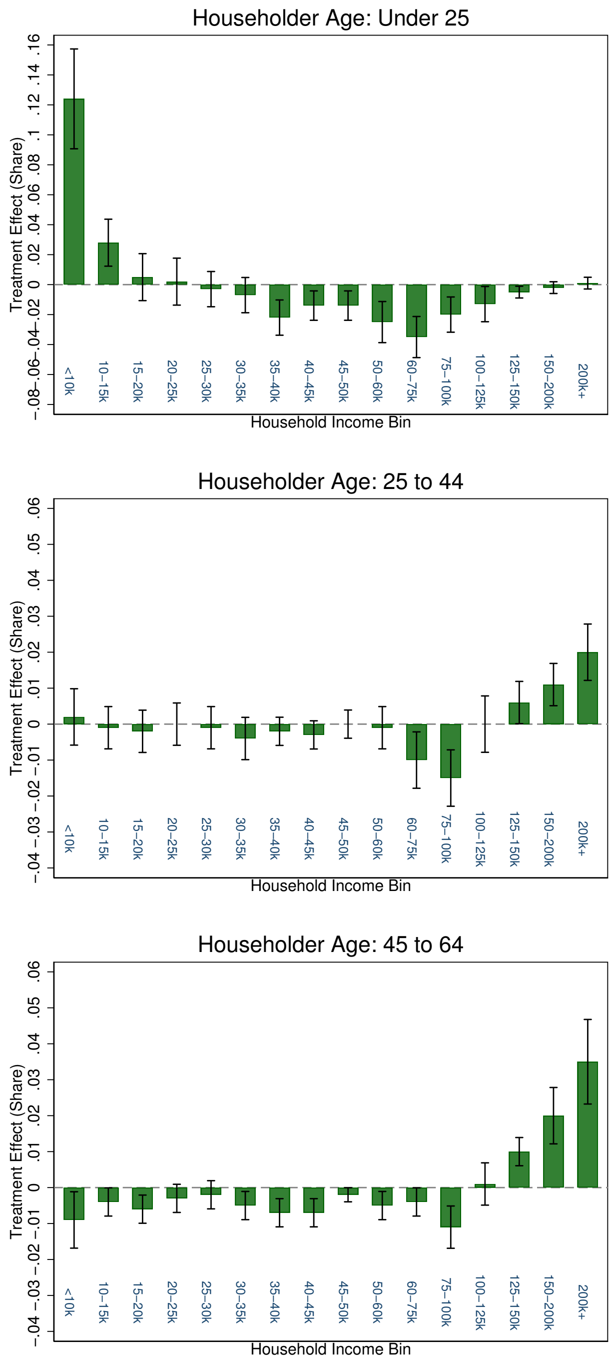
Table A.2: List of Consolation Prizes

	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.

B Effects on Household Income Distributions by Age of Householder

Figure A.2: 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.

C Income and Inequality Effects Using the Opportunity Insights Sample

Table A.3: Income Distributions (Opportunity Insights Sample)

	(1) Mean Parental Income	(2) Income p25	(3) Income p75	(4) Income p90	(5) 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.4: Economic Inequality (Opportunity Insights Sample)

	(1) Top 1% Income Share	(2) Difference P75-P25	(3) Gini Coefficient	(4) 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.

D 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.5). 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.5 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.5.)

Table A.5: 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.

E Alternative Measures of Quality-Adjusted Patents

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.

Table A.6: Effects on Total Value of Patents Assigned to a Publicly Traded Firm

	(1) IHS(Patent Values)
Winning Location	2.163***
	(0.327)
Control Mean	6.267
Counties	185
Experiments	61

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

Sources: Kogan, Papanikolaou, Seru, and Stoffman (2017)

Notes: The outcome 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.

F Alternative Measures of Entrepreneurship

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.7: Effects on Alternative Measures of Entrepreneurship

	(1) IHS(Total RECPI)	(2) IHS(Liq Growth Events)	(3) IHS(Avg REAI)
Winning Location	0.598***	0.767***	0.226**
	(0.182)	(0.217)	(0.094)
Control Mean	1.275	1.109	.513
Counties	185	185	185
Experiments	61	61	61

Standard errors in parentheses

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

Sources: The Startup Cartography Project (Guzman, Andrews, Stern, Fazio, and Liu, 2022)

Notes: The Regional Entrepreneurship Cohort Potential Index (RECPI) 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.8: 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.9: 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.10: 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.11: Economic Inequality Relative to Establishment of Other Public Institutions

	(1) Top 1% Income Share	(2) Difference P75-P25	(3) Gini Coefficient	(4) 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.12: Measures of Innovation and Entrepreneurship Relative to Establishment of Other Public Institutions

	(1) IHS(Patents)	(2) IHS(Cites)	(3) IHS(Total Ventures)	(4) 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.13: 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.14: County Economic Inequality by College Bottom 20% to Top 1% Mobility Rate

	(1) Top 1% Income Share	(2) Diff P75-P25	(3) Gini	(4) 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.15: 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 (2022c)

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.16: 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 (2022c)

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.