Learning to Love Government? Technological Change and the Political Economy of Higher Education

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Abstract

Why do voters have divergent beliefs about the role of government in solving social problems? We study this question in the context of skill-biased technological change and investment in higher education. We document that the negative income consequences of technological change are, descriptively, mitigated in US counties with greater levels of higher education investment. We show that exposure to these conditions is, in turn, correlated with greater public support for higher education spending. We conclude that higher education investments are productive. However, we find that there is also evidence of history-dependent diverging support for such investments. We suggest that one potential explanation for these facts is differential learning given past experiences. In a context where higher education spending dampens the negative employment effects of technological change, a history of believing that education is productive may advantage local communities in learning the true productivity of higher education investments.

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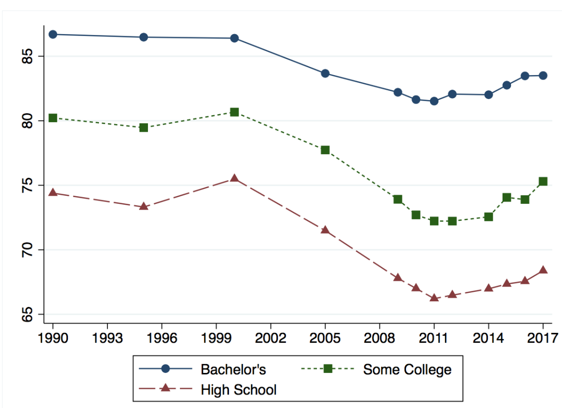
Replication files are available in the JOP Dataverse (https://dataverse.harvard.edu/dataverse/jop). The empirical analysis has been successfully replicated by the *JOP* replication analyst.

1 Introduction

Workplace automation has had well-known polarizing effects on the labor market over the last several decades in the United States. The trends in labor market outcomes by educational attainment are striking in having advantaged more educated workers and disadvantaged others. Among those of working age, a much larger portion of those with some college education or a Bachelor's degree are in employment, compared to those with only a high school education. As shown in Figure 1a, this difference has grown since 1990. In 2017, while 68% of those with a high school diploma were employed, it was 75% of those with some college and 83% of those with a Bachelor's degree. Figure 1b documents even starker increases in the differences in earnings of workers with different levels of education—showing a growing wage premium for college degree-holders.

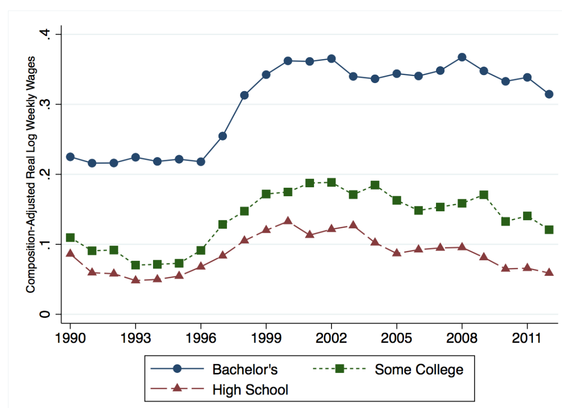
Figure 1: Evolution since 1990 in employment and earnings by education level

(a) Employment rate (percent)



Note: Outcome is share of 25-64 years old in employment. Source: US Census' Current Population Survey (CPS).

(b) Earnings

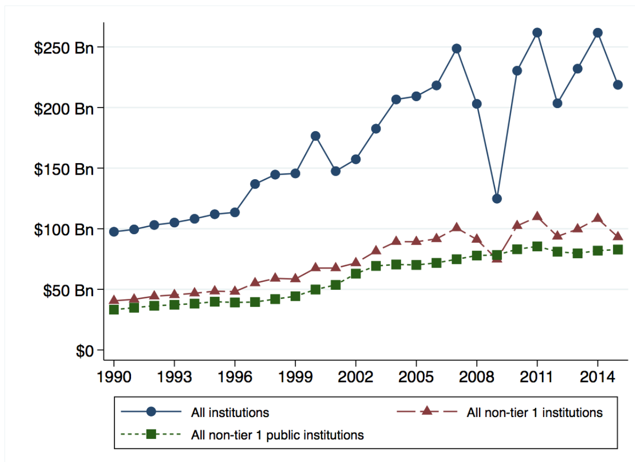


Note: Outcome is Log-weekly real wages for full-time full-year male workers. Source: March CPS.

A large literature (see e.g. Goldin and Katz, 2009; Autor, 2014; Acemoglu and Autor, 2011) has shown that skill-biased technological change is a major contributor to these trends. Since those who experience shocks may be liquidity-constrained or not choose optimally to make private investments in education, a natural policy reaction would be to invest more in higher education (HE).

However, that does not seem to have happened over the last two decades. The trajectory of U.S. public and private real spending (excluding tuition) in higher education has been flat since 2005. This is shown in Figure 2. This is particularly true in non-research universities and colleges (non-tier 1), where 67% of all students enrolled in 2015.

Figure 2: Higher education investment by type of institution



Note: Higher education investment defined as revenues from federal, state and private investment sources. Source: Integrated Postsecondary Education Data System (IPEDS).

One possibility is that even if there there is a consensus that more investment is an optimal policy response, the political process does not deliver it. For example, the policy process may be captured by wealthy groups wanting to minimize tax costs. Some of the barriers to increases in higher education spending are discussed by Goldin and Katz (2009, ch.9), who emphasize the limited support for new programs for poorer youths (not currently attending college due to financial constraints) that the United States' political system fosters. They also highlight the lack of college-preparedness stemming from inequalities in funding and provision from a decentralized school system.

A different possibility is that voters do not agree that higher spending is the correct policy response. This view is consistent with the ambivalent perceptions in survey evidence.

Pew (Parker, 2019) has asked since 2012 a question on whether colleges and universities "are having a positive effect on the way things are going in this country today". 50% of those surveyed (and only 33% of Republicans) in 2019 thought that colleges and universities have a positive effect on the country, compared to 60% in 2012.[1]

But why would voters hold persistently disparate views in a world in which technological change seems to have raised the value of higher education? And where do voters' views about the role of government in solving these sorts of social problems come from?

There are at least two salient answers to these questions in the literature. The first is a self-interested one. Individuals will support the policies they stand to benefit the most from. When confronted with the the risk of automation, groups whose jobs may be automated away will support more welfare or protectionist policies that slow down technological change, while college graduates may prefer greater investments in higher education, each more targeted to their socioeconomic group (Busemeyer and Tober, 2022; Busemeyer et al., 2022; Gallego et al., 2022; Thewissen and Rueda, 2019). Relatedly, the latter group is more likely to support traditional conservative parties, who favor a smaller welfare state (Gallego, Kurer and Schöll, 2022).[2] The beliefs about and theories of policy that individuals adopt will ultimately justify their underlying interests. For example, a high income person may rationalize a preference for low taxes by adopting a belief that the government is inefficient in producing a given public good from taxes.

The second answer highlights the importance of early socialization into partisan identities associated with beliefs about the effectiveness of government (Meredith, 2009; Mullainathan and Washington, 2009; Prior, 2018). Partisans have a standing positive or negative view of the proper role of government in solving social problems and altering that view takes much contradictory evidence.

[1]Some of this effect could be attributable to perceptions of universities' prevalent ideology. Still, in the same 2018 survey 65% said that students are not receiving the skills they require to succeed in the workplace (Parker, 2019). There are no time trends for this item.

[2]For a recent and excellent review of this literature see Gallego and Kurer (2022).

In this paper, we explore the empirical evidence and suggest that a third type of answer is that divergent beliefs about the effectiveness of public higher education spending are in part due to diverging experiences with government.

We first investigate what voters may have learned about the effectiveness of higher education investment simply by having lived in places with high or low levels of investment, at the time of a sharp increase in the need for higher education. We use the case of workplace automation from the 1980s. We construct new measures of county-level higher education investments for every county in the United States and estimate the effect of technological change, as measured by the routine share of employment, on county decadal changes in real per capita income. We then look at whether these estimates vary by pre-period levels of county higher education investment. We show that places with greater investments in higher education succeed at mitigating the negative economic effects of technological change.

We next investigate whether individuals exposed to environments where negative effects of technological change were mitigated by past HE investments preferred more HE spending –a proxy for the perceived effectiveness of those investments. Following our logic, we would expect individuals exposed to automation shocks as well as high levels of HE investment to internalize the value of certain types of government spending more than those who are not exposed to automation shocks or, alternatively, do not experience high levels of government investment. We use individual-level survey evidence from California to show that individuals in counties with both greater technological shocks and greater initial levels of higher education investment were more supportive of spending. Given the place of higher education investments in the middle of causal chains where several other factors may be linked with this mitigation, our goal for both types of analyses is to characterize a heterogeneity among different types of counties that experience automation shocks.

One may expect respondents from counties with lower investment levels to demand more of it, particularly if they are effective elsewhere. However, the opposite is the case, and this is independent of partisan identification. One possible explanation is that individuals become more supportive of higher education investments only when they are in a place conducive to learning about its effectiveness. They do not "learn" about the effectiveness of higher education from experiences elsewhere, perhaps because they do not think it would be effective in their own context, or they have few connections in places with high investments in higher education so as to obtain such information. Because effects of educational investments today will mostly have effects on the labor force within a generation or longer, attitudes towards such investments are also unlikely to be solely the result of calculations based on own benefits.

In Appendix C, we introduce a model of incomplete learning that is consistent with this explanation. People in places with high initial HE spending are more likely to have high priors for the effectiveness of education and they become more likely to learn the true—high—productivity of educational investments. People in places with low initial spending are more likely to have the "wrong" priors and their learning is capped, so they settle on a lower preferred level of higher education investment. In the model, there is not enough information in observed success and failure for learners to make up for their original differences in beliefs.

Our findings suggest that those who posit an unstoppable negative effect of technological change on the economic prosperity of large fractions of the population (Brynjolfsson and McAfee, 2014; Ford, 2015) may be mistaken since there are some policy interventions that have been effective in mitigating the negative effects of technology and these interventions can receive wide support. Equally mistaken, however, are those who believe that interventions that soften the negative effects of technology will automatically come to pass (Boix, 2019). We suggest that successful interventions will be more likely in areas where government intervention has been successful to date.

We also complement the view that Republicans and Democrats may be increasingly polarized with regards to national policies while actually being in agreement on local or state matters (Jensen et al., 2021).[3] We suggest that the formation of policy preferences is partly

[3]It can likely also contribute to our understanding of why cleavages among the highly educated may have shifted over time (Dalton, 2018; Gethin, Martínez-Toledano and Piketty, 2022), potentially by creating a demand for policy effectiveness. And to our understanding of the differences in the politics of prosperous

the result of past highly localized experiences with policies, and that when they are seen to have broad positive effects, individuals can overcome their immediate self-interest (Busemeyer and Tober, 2022), and the partisan tendencies, institutional limitations, and sectoral constraints (Ansell, 2008; Ansell and Gingrich, 2013) other authors have emphasized condition higher education spending. This implies a way in which government intervention could become more popular over time: by being effective at problem-solving for citizens on the specific issues it does handle.[4]

2 Technological Change, Higher Education Investment and Income

Consistent with skill-biased technological change, exposure to technology has been found to have negative effects at least for some subgroups of the population, such as women and older workers (Autor, Dorn and Hanson, 2015; Dauth et al., 2018), although these studies do not find evidence for sizeable overall effects. Moreover, some specific forms of technological change such as the introduction of robots have been found to have negative effects on aggregate employment and wages by Acemoglu and Restrepo (2020) (although Graetz and Michaels (2018) find less widespread displacement effects, only for low-skilled workers).

Less explored in the empirical literature is the aggregate effect of policies that may mitigate the impact of technological change. We focus on higher education investments because this policy intervention has been proposed widely as an effective way of tackling the potentially negative effects of technological change on earnings (e.g. Turner, 2017; Deming, 2019). Free access to community college and increased financial aid was proposed in April 2021 by President Biden (White House, 2021).[5]

cities and others, where voters may become less supportive of government as a result of prior ineffectiveness (McKay, 2019).

[4]It also contrasts with previous findings (Gingrich, 2019) that country-level welfare expansion and labor market regulation have not mitigated the political effects of automation.

[5]This policy was dropped in February 2022 (Rogers, 2022).

2.1 Data

In our empirical analysis, following Autor, Dorn and Hanson (2015), we use changes in per capita income in real 2000 dollars at the county level to measure labor market outcomes.

We have two main independent variables. For exposure to technological change by geographic area, the main measure we use follows Autor, Dorn and Hanson (2015) and is the share of employment in routine occupations in the 741 commuting zones (CZ). The rationale for using this as a measure of exposure to technological change is that a large part of the automation "shock" starting in the 1980s involved substituting human labor by computer-enabled data processing.[6]

The second main independent variable measures investment in higher education at the county level, collected by the federal Department of Education. We focus on institutions of higher education that are not research-focused and so, whose primary role is educational and develop a measure of investment by county.

2.2 Econometric Model

Our specifications relate automation measures, higher education investments, and per capita income changes. Similar to Autor, Dorn and Hanson (2015, p.11), we implement stacked first difference models, with decade changes in the dependent variables, while focusing on the heterogeneity by levels of pre-determined educational investments.

We use changes by decade for 1990-2000, 2000-10, 2010-2020. These decades follow the onset of rapid computerization in 1980 and matches the start of the collection of higher education institution data by IPEDS (1987). Unlike Autor, Dorn and Hanson (2015), we interact the exposure to automation shocks with higher education investment, as follows:

[6] We detail in Apppendix D how each of these measures is constructed, and their distribution across the country and in California.

$$\triangle Y_{cd} = \beta HEinvestment_{cd} \times Routine_{cd} + \gamma HEinvestment_{cd} + \\ + \delta Routine_{cd} + \eta \mathbf{X}_{cd} \times D_d + \zeta \mathbf{X}_{cd} + D_d + R_c + \epsilon_{cd} \tag{1}$$

Observations are indexed by county c, and decade d. In our main specifications we include a vector of controls $\mathbf{X}$ for counties at the beginning of the period we study (1990): share of employment in manufacturing, share of female employment, share of the population with some college, share foreign born (Autor, Dorn and Hanson (2015)'s controls), population density and controls for white and black share of the population. We interact this vector with our decade dummies. D are two decade fixed effects (2000, 2010) and R are eight census divisions fixed effects. We weight regressions by the national population share in the county and cluster standard errors by commuting zone.[7]

One concern about a OLS implementation of the equation above is that income evolution may be driven endogenously, e.g. since most jobs created are non-routine, places with lower job growth and lower income will tend to have over time comparatively greater shares of routine occupations. To assuage these concerns, we use models where we "freeze" levels of higher education investments and of the routine share of employment to their 1990 levels which could not possibly have been influenced by later developments. This does not ensure a causal link, since places with greater 1990 HE investment levels may differ in other ways, but does characterize variation across different types of high automation exposure counties.

We also present models where, like Autor, Dorn and Hanson (2015), we instrument the levels of the routine share of employment in 1990 with their corresponding values in 1950 (the earliest available), before our contemporary routine exposure distinction was relevant for the automation of jobs and so, before jobs growth (or other economic trends) since the 1990s could have been affected by the routine share of occupations. It is hard to imagine

[7]All our results are robust to the inclusion of county-by-decade covariates, instead of the interacted specifications.

1950s levels of routine employment being locally determined by subsequent developments, or indeed by the levels of investment in higher education as long after as the 1990s.[8]

2.3 Results

We estimate the effect of technology exposure by higher education investment levels on changes to real per capita income, with two specifications. The first implements OLS with the running variables set to their 1990 values, in model 1 of Appendix Table B.1. In model 2, we use 1990 levels of Higher Education investment and instrument 1990s levels of routine share of employment by their 1950 levels. In both specifications, the marginal effect of routine exposure on outcomes is attenuated at greater higher education investment levels, indicating that the effects of technological change are less negative or more positive when higher education investment is greater.[9]

We plot in Figure 3 the marginal effects of routine share on per capita income from our instrumental variable estimates in Table B.1.[10] The plots show that the higher pre-

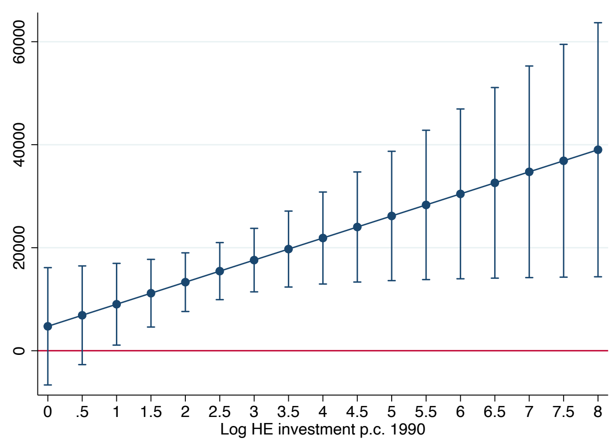
[8]We also implement a similar historic instrument for HE investments, using the number of institutions in the county in 1950 (no investment data is available). Given the high initial costs to setting up higher education institutions, contemporary levels of investment in higher education may have been determined a long time ago. In turn, early determinants of such investments may today look irrelevant for economic outcomes, as the reasons those institutions were set up had little to do with their current role in mitigating recent automation shocks. Although investment in educational goods is never randomly assigned geographically and is the result of political processes (Harjunen, Saarimaa and Tukiainen, 2023), higher education investments in the 1950s were not designed to mitigate the effects of computerization from the 1980s and in fact non-research institutions may have been set up to provide training for such routine occupations. It just so happens that having the buildings, administration, and systems of these institutions in place makes investments in higher education easier and more likely today. Other long range determinants of institutional presence are also unlikely to affect employment trajectories after the onset of computational technology. Goldin and Katz (1999), for instance, have argued that for the first half of the 20th century that agricultural productivity and religious uniformity positively affected investments in higher education. The (similar) results from these models are shown in Appendix Table B.3.

[9]In Appendix B, we run specifications using investments in all higher education institutions, tier 1 institutions alone, and public community colleges. We show OLS results in Table B.10 and IV results in Table B.11. In the IV estimates, results are similar for all subsets of institutions. We also distinguish between high- and low- manufacturing share counties in Table B.2, with similar results in the IV models, although larger in low manufacturing areas. We also show models in Table B.12 of the difference in effects from the extensive (presence of investment at all) and intensive margins of higher education investment, as well as others where we do not weight counties by population (Tables B.13, B.14, B.15). Results are very similar.

[10]We also show in Appendix Figure A.1 the corresponding marginal effect plots for the OLS estimates in model 1 of Table B.1. To get a sense of the types of counties that are driving our results, Table B.4 shows what county characteristics correlate with investments in higher education. Share of college educated, share

existing investments in education are, the more positive the income growth associated with automation is. In counties with no 1990 investments in higher education, greater exposure to automation was associated with a near-zero effect on the change in per capita income in each of the three decades 1990-2020. A one standard deviation change in the routine share of employment (.033) was associated with about 156 dollar difference in the decadal change in per capita income, or six percent of a standard deviation. At high levels of investment (8 log-HE investment, the 95th percentile), by contrast, the effects are positive and large: a one standard deviation change in routine share is associated with a $1,287 greater change in per capita income, or about fifty-two percent of a standard deviation.

Figure 3: IV estimates: Marginal effects of differences in routine employment share on economic outcomes, by level of investment in higher education.



Note: Shows marginal effects of a percent change (0-1) in routine share of employment in 1990 on labor market outcomes, as log-total HE revenue per population in the county increases, estimated from model 2 in Table B.1.

3 Public Preferences for Higher Education Spending

The analysis in the previous section provided new evidence about the value of higher education investments in a political economy setting marked by substantial technological change. In this section, we seek to ascertain whether technological change influenced the policy opin-

manufacturing, or population foreign born are correlates of investment in higher education (we control for those variables in our main models).

ions of voters about higher education spending, and whether this effect varied across counties by differences in initial levels of higher education investments. We turn to a survey on policy opinions about higher education spending in California, the Public Policy Institute of California (PPIC) "Statewide Surveys." We use this survey as we do not know of a national survey with questions on attitudes towards higher education and sufficient coverage to study variation by levels of technological shock and investments in education.[11]

PPIC has been conducting monthly surveys for over a decade on California's citizens. Most of their November issues include a series of questions on higher education in the state. Each of them has between 1,700 and 2,500 adult respondents resident drawn at random using random-digit-dialing by telephone. We use raw observations, representative of the California public overall.[12]

We focus on a question that gets directly at the willingness to invest in higher education: "Do you think that the current level of state funding for California's public colleges and universities is more than enough, just enough or not enough?" We dichotomize responses and construct the dependent variable *HE Spending Support* equal to 1 if individuals gave the "just enough" or "not enough" response and 0 otherwise.[13]

We have responses across seven surveys in the period 2007-18 that contained the question for a total of 13,390 observations.[14] Since all the surveys are concentrated towards the end of the multi-decade period over which technological change has taken place, we cannot study changes in opinion but rather pool the observations and study the partial correlation between exposure to technological change and support for higher education spending and whether this correlation varies by initial levels of higher education investment. We estimate using OLS linear probability models regressing *HE Spending Support* on routine share, higher education

[11]We include in Appendix E three additional empirical tests in alternative settings, all with more limited data: exploiting Colorado referenda, a survey in Wisconsin, and a survey in cities around the United States. In all of them our results are consistent.

[12]For survey details see (PPIC, 2023).

[13]Appendix Figure A.2 plots the average levels of HE Spending Support by county in the pooled PPIC data.

[14]The question is not asked in 2008, 2009, 2012, 2013, 2015, 2019, or 2020.

investment in 1990 and their interaction. We cluster standard errors on commuting zones, the assignment level of our routine share variable. We do not include survey weights as we opt to explicitly include and show individual covariates in our models.

Figure 4a shows descriptively how the level of support varies by county subgroups of routine exposure and investment. We see that counties that have both high exposure to automation and the highest levels of investment in HE are more supportive of HE funding than other places.[15] Figure 4b reports our key quantity of interest which is how the marginal effect of routine share on the support for HE spending varies with the levels of prior investment on HE. The effects are such that a one standard deviation (SD) change in prior HE investment shifts by about 1 percentage point the marginal effect of a 1 SD difference in routine share.[16] This effect on the probability of support for more investment in HE is relatively small, but of a similar magnitude to other variables that we may think are explanatory of support for HE, such as being a parent, or being a college graduate –albeit smaller than others such as self-identifying as Republican.[17] Appendix Table B.5 reports coefficient estimates with different sets of conditioning variables at the individual and county level (we report in the figure the most conservative one, with full individual, and county controls, including partisanship). Table B.7 shows results are similar for the unemployed, those who have not attended college themselves, those earning modest salaries, and self-identified Republicans. Since these groups are the least likely to support investment in higher education (Busemeyer and Tober, 2022),

[15]Note that our theoretical argument does not make specific predictions across each subgroup presented in Figure 4a or about the functional form of the conditional relationship. The key expectation is that the starkest contrast is between places with large automation shocks and the highest, more visible investment levels and the rest.

[16]To check the representativeness of our findings for the whole nation, we use SDs of these measures in our California data, which are smaller than national SDs (see Appendix Table B.8), implying these are likely a lower bound of potential national effects. We also restrict in Appendix Table B.6 our analyses to the subsets of counties in California that are not outside the bottom or top decile of automation exposure levels in the country and our results are similar or even stronger.

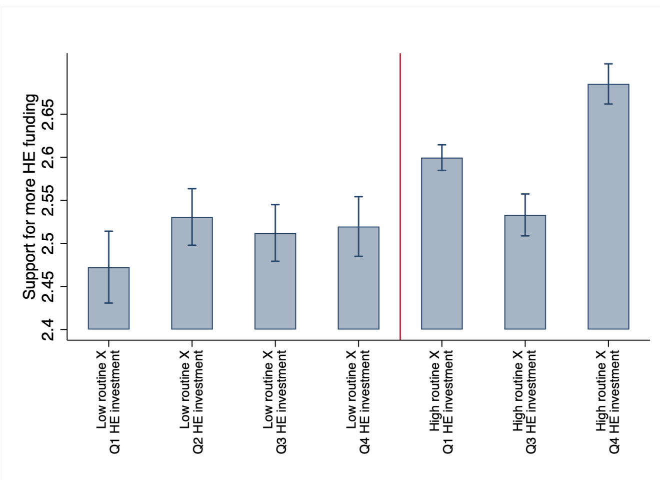
[17]Clearly, support for further investment in HE has a partisanship component and there is a strong case that partisanship has, in turn, a strong early socialization component (Green, Palmquist and Schickler, 2004; Rodden, 2019). We take our mechanism of learning to be an additional source of support for greater investment, beyond partisanship. Our main results control for partisanship and column 4 of Table B.6 suggest very similarly sized-effects for Republicans, although in heavily Democratic California there are too few for these to be statistically significant.

this suggests a mechanism different from self-interest is at play in places with high routine share and high investment.[18] [19]

Taken together, the evidence from California surveys is consistent with a view that those who live in places with greater past levels of investments in higher education, who have had first-hand experience of how higher education can contribute to economic growth, may be more supportive of greater such investments in the future. They have had a chance to learn about the effectiveness of government.

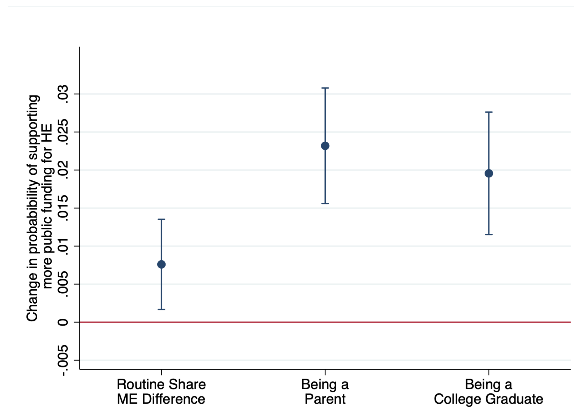
Figure 4: Support for HE spending in California in PPIC surveys.

(a) Average support for HE spending in, by county subgroup



Note: Simple county averages from pooled PPIC surveys. Counties divided by median levels of automation exposure, and quartiles of HE investment (in California). There is no county in the second quartile by investment share and with high exposure to automation.

(b) Correlates of support for HE spending in California's public universities and colleges.



Note: The column labeled Routine Share ME Difference compares the difference in the ME of routine exposure (1 sd) on support, as the level of HE investment shifts by 1 standard deviation. The other two columns are coefficient estimates for indicator variables used to benchmark routine share ME Diff. estimate. Estimates are obtained from Model 4 in Table B.5.

[18] Appendix Table B.16 reports results where we do not rebase routine exposure and investment in 1990 to its SDs. We also obtain similar results with the same binary variable when using probit models and ordered probit models (Appendix Tables B.17 and B.18).

[19] We may be concerned that these results overstate the true relation between past local HE investment and support for investment given ideological clustering due to geographic mobility. However, when we restrict our analyses to those who have lived in the same address for over twenty years, the results are very similar, as shown in Table B.19.

4 Conclusion

The public is divided in its view of many public policies, even when faced with similar external circumstances. Our contribution is to first document that places that experienced a greater degree of technological change did better in terms of per capita income when they had predetermined higher levels of higher education investment. This is consistent with the common claim that human capital investments are valuable in the current era of technological change. We then show that individuals in places with greater initial educational investment react to exposure to technological change with greater support for higher educational spending than individuals living in places similarly effected by technological change but having lower initial levels of educational investment. One may have expected to see the opposite: places with little investment demanding more and those that experienced high investment demanding the same or less, as the contribution of additional marginal spending may be lower. We present this as a puzzle to be further investigated and suggest that the data is consistent with differential learning paths for those exposed to higher levels of effective higher education spending vs others. To establish clearly the learning that results from the observation of successful policies and how it may affect policymaking at a later date via mass preferences, partisanship and elite attitudes, we would need additional survey studies. This would benefit from complementary research across policy domains, as well as the use of experimental lab-based evidence.

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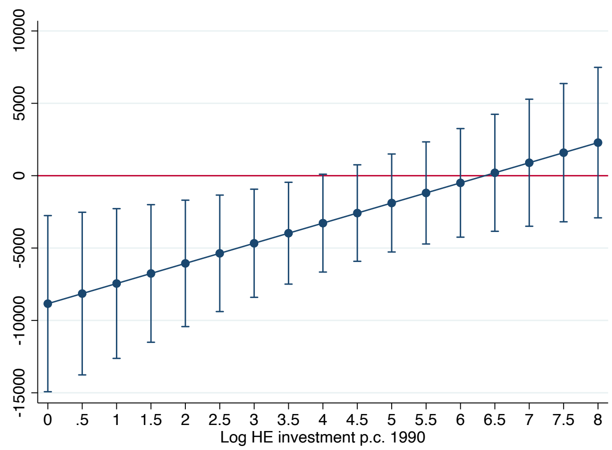
Online Appendices for: Learning to Love Government? Technological Change and the Political Economy of Higher Education

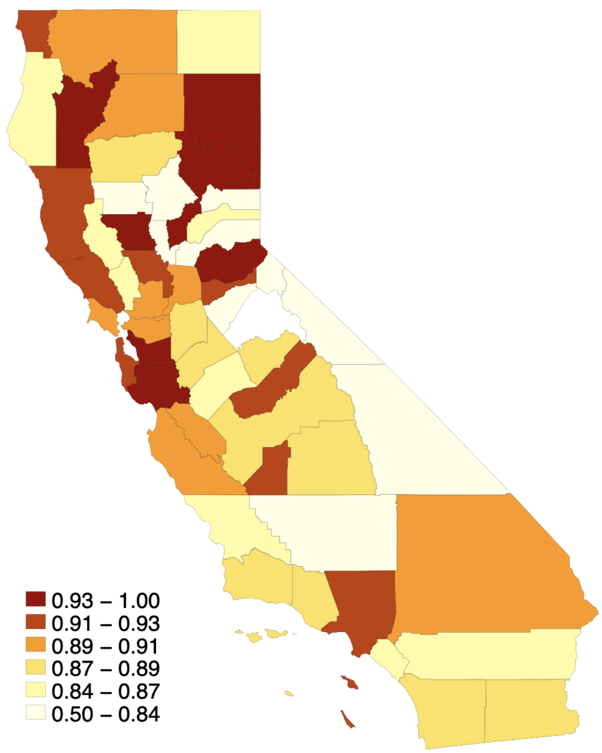
A Appendix Figures

Figure A.1: OLS estimates: Marginal effects of a change (percent 0-1) in routine share of employment by level of investment in higher education on income.



Note: Shows marginal effects of percent (0-1) differences in routine share of employment in 1990 on real per capita income, as log-total HE revenue per county increases, estimated from model 1 in Table B.1.

Figure A.2: Average levels of support for more investment in higher education, by California county



Note: Shows county averages in the nine pooled cross sections (1997-2008) of the PPIC surveys, with no further adjustments.

B Appendix Tables

Table B.1: Technological change, higher education investments, and decadal change in per capita income

	(1)	(2)
	OLS	IV routine share
Routine exposure 1990 × HE Investment 1990	1390.8**	4285.6*
	(526.0)	(1913.0)
HE Investment 1990	-366.6*	-1278.6*
	(150.4)	(576.3)
Routine exposure 1990	-8841.7**	4739.4
	(3297.6)	(9278.1)
Observations	9313	9313

Estimates with HE investment levels for each of 3,054 counties and routine exposure in 1990 (for 742 CZs). In model 2, county routine shares in 1990 is instrumented by county routine share in 1950. Models include county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.2: Technological change, higher education investments, and decadal change in per capita income: low and high manufacturing share counties

	(1) Low manufacturing sh. counties	(2) High manufacturing sh. counties
Panel A: OLS Models		
Routine exposure 1990 × HE investment 1990	1924.2**	-340.4
	(724.6)	(342.7)
Routine exposure 1990	-9315.8**	-2892.9
	(3040.9)	(2576.7)
HE investment 1990	-513.4*	123.0
	(221.0)	(100.5)
Observations	4648	4665
Panel B: IV routine share		
Routine exposure 1990 × HE investment 1990	5012.3*	1636.2+
	(2195.0)	(922.6)
Routine exposure 1990	12219.4	-9908.4
	(8530.4)	(7229.3)
HE investment 1990	-1482.8*	-472.2+
	(674.9)	(268.5)
Observations	4648	4665

Specifications are as in Appendix Table B.1, with HE investment levels for each of 3,054 counties and routine exposure in 1990 (for 742 CZs). Models are subsetted for counties with a low manufacturing employment shares in 1990, defined as below median for the country (column 1), and above median for the country (column 2). Median manufacturing employment share for the country is 21.67 percent. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.3: Technological change, higher education investments, and decadal change in per capita income, exploiting the number of HE institutions per county in 1950

	IV share HE routine + IV investment
Routine exposure 1990 × HE Investment 1990	3169.3***
	(867.7)
HE Investment 1990	-832.8***
	(236.2)
Routine exposure 1990	-17030.8***
	(3434.0)
Observations	9313

Estimates with HE investment levels for each of 3,054 counties and routine exposure in 1990 (for 742 CZs), in 1990. Both are instrumented: county routine share in 1990 is instrumented by county routine share in 1950, and HE investment is instrumented by the number of non-tier 1 HE institutions within 50 km of the county centroid in 1950. Models include county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: Technological change, higher education investments, and county characteristics

	(1) Share College Educated	(2) Share Manufacturing Empl.	(3) Share Pop. foreign Born	(4) Share White	(5) Population Density	(6) Presidential Dem. share
Routine exposure 1990 × HE Investment 1990	2.880	1.072	-8.371	-0.0937^{+}	10993.7*	0.2384***
	(3.906)	(2.674)	(9.943)	(0.0552)	(656114.9)	(0.0631)
HE Investment 1990	-0.752	-0.0946	1.760	0.0191	-3096.7*	-0.0633
	(1.102)	(0.788)	(2.732)	(0.0153)	(1418.1)	(0.018)
Routine exposure 1990	117.7***	72.18***	111.6^{+}	0.742*	-33565.7^{+}	-0.3276
	(17.52)	(9.926)	(60.69)	(0.303)	(17602.0)	(0.04382)
Observations	3105	3105	3105	3105	3105	3105

Estimates with HE investment levels and routine exposure in 1990. Each model includes the other county covariates in 1990 (except Democratic share in 1990). Standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.5: Models of supporting state funding for California's public colleges and universities –OLS Models with standard deviations

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990 × HE investment 1990	0.010***	0.010**	0.008**	0.008*
	(0.002)	(0.003)	(0.002)	(0.003)
Routine exposure 1990	0.012***	0.010*	0.008*	-0.002
	(0.003)	(0.004)	(0.004)	(0.008)
HE investment 1990	0.017***	0.016***	0.013***	0.013*
	(0.003)	(0.004)	(0.003)	(0.005)
Parent		0.024***	0.023***	0.023***
		(0.003)	(0.004)	(0.004)
Homeowner		-0.063***	-0.051***	-0.052***
		(0.008)	(0.007)	(0.006)
College graduate		0.024***	0.020***	0.020***
		(0.004)	(0.004)	(0.004)
White		-0.036*	-0.024+	-0.024+
		(0.013)	(0.012)	(0.013)
Male		-0.064***	-0.060***	-0.061***
		(0.004)	(0.004)	(0.004)
Republican			-0.128***	-0.128***
			(0.007)	(0.007)
Share manufacturing				0.001
				(0.001)
Share foreign born				0.000
				(0.001)
Female employment rate				0.003*
				(0.001)
Population density				-0.000
				(0.000)
Observations	13390	13252	13252	13252

OLS coefficients on answering "just enough" or "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Estimates with HE investment levels for each of 58 counties and routine exposure in 1990 for 19 CZs. 9 pooled cross-sections within 2007-2018. Routine exposure and HE investment rebased to have mean 0 and a standard deviation of 1. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.6: Models of supporting state funding for California's public colleges and universities, restricted to California counties more representative of the country as a whole –OLS Models

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990 × HE investment 1990	0.015**	0.012**	0.010**	0.013***
	(0.004)	(0.003)	(0.003)	(0.002)
Routine exposure 1990	0.007	0.009	0.009	0.013
	(0.006)	(0.007)	(0.007)	(0.008)
HE investment 1990	0.026**	0.020***	0.016**	0.024***
	(0.007)	(0.005)	(0.004)	(0.003)
Parent		0.032**	0.031**	0.032**
		(0.009)	(0.009)	(0.010)
Homeowner		-0.088***	-0.073***	-0.073***
		(0.007)	(0.006)	(0.006)
College graduate		0.011	0.006	0.006
		(0.007)	(0.007)	(0.006)
White		-0.011	0.005	0.006
		(0.013)	(0.012)	(0.012)
Male		-0.064***	-0.061***	-0.061***
		(0.010)	(0.009)	(0.009)
Republican			-0.141***	-0.140***
			(0.016)	(0.017)
Share Manufacturing Empl.				0.003*
				(0.001)
Share Pop. foreign Born				0.000
				(0.001)
Female Employment Rate				-0.001
				(0.002)
Population Density				-0.000
				(0.000)
Observations	4217	4182	4182	4182

Excludes the 19 counties (out of 58) that are above in the top or bottom decile nationally by routine exposure. These are Alameda, Contra Costa, Los Angeles, Marin, Napa, Orange County, Riverside, San Bernardino, San Francisco, San Mateo, Santa Clara, Santa Cruz, Solano, Sonoma, Ventura, Yolo (top national decile), and Lassen, Modoc, Siskiyou (bottom decile). OLS coefficients on answering "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Pooled cross-sections 2007-2018. Routine exposure and HE investment rebased to have mean 0 and a standard deviation of 1. Includes survey-year fixed effects and individual level controls, as shown. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.7: Models of supporting state funding for California's public colleges and universities, for least likely subgroups –OLS Models

	(1) Less than BA	(2) Unemployed	(3) Earning less than 60K	(4) Republican
Routine exposure 1990 × HE investment 1990	0.009**	0.008+	0.008**	0.012
	(0.003)	(0.004)	(0.003)	(0.007)
Routine exposure 1990	0.008*	0.008+	0.007+	0.008
	(0.003)	(0.004)	(0.003)	(0.007)
HE investment 1990	0.013***	0.005	0.011*	0.014
	(0.003)	(0.005)	(0.004)	(0.009)
Parent	0.031***	0.026**	0.024***	0.031+
	(0.005)	(0.007)	(0.004)	(0.016)
Homeowner	-0.065***	-0.033***	-0.056***	-0.077**
	(0.010)	(0.005)	(0.006)	(0.020)
College graduate	NA	0.007	0.020*	-0.011
		(0.007)	(0.008)	(0.016)
White	-0.033*	-0.046***	-0.034*	-0.068***
	(0.015)	(0.007)	(0.012)	(0.012)
Male	-0.063***	-0.066***	-0.063***	-0.111***
	(0.008)	(0.004)	(0.003)	(0.016)
Observations	8833	4614	8869	2272

Analogous to column 2 of Table B.5. OLS coefficients on answering "just enough" or "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Estimates with HE investment levels for eachof 58 counties and routine exposure in 1990 for 19 CZs, 9 pooled cross-sections 2007-2018. Includes survey-year fixed effects and individual level controls, as shown. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.8: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Ch. in real per capita income (decadal)	1332	2463	-31174	17559	9486
Routine share of employment 1990	0.295	0.032	0.2	0.377	9321
Routine sh. empl. 1990 (Cal. sample)	0.331	0.023	0.248	0.345	17712
Routine share of employment 1950	0.200	0.049	0.095	0.387	9321
HE investment 1990	3.647	2.913	0	8.952	9500
HE inv. 1990 (Cal. sample)	4.172	1.891	0	7.120	17712
Share college educated	0.431	0.087	0.199	0.696	9321
Share manufacturing empl.	0.187	0.095	0.001	0.546	9321
Share pop. foreign born	0.039	0.047	0.004	0.399	9321
Female employment rate	0.628	0.068	0.332	0.796	9321
White share	0.833	0.163	0.096	0.992	9319
Black share	0.09	0.146	0	0.857	9319
Population Density	228	1406	0.05	52419	9660

Shows variables in Table B.1. Higher Education investment is logged and computed as explained in the text. Statistics are computed over three cross-sections (1990, 2000, 2010) of data for US counties, except routine exposure in 1990, calculated for 742 commuting zones. For California statistics they are computed over all individual observations in the PPIC surveys in years 2007-2020.

B.1 Models using alternative measures of investment in higher education

Table B.9: Summary statistics of different measures of county higher education investment per in 1990, by type of institution

Variable	Mean	S.D.	Min.	Max.	N
Investments in all inst.	2676.76	6132.97	0	100673.73	2356
Investments in Tier 1 inst.	5325.08	9016.20	0	95518.45	727
Investments in non-Tier 1 inst.	520.55	772.14	0	7733.74	2300
Investments in public community colleges	205.83	489.28	0	8054.43	1554

Investments in 1990 by county, computed as described in the text (but here shown not logged). All measures are 1990 dollars per capita. Shows all counties with non-zero values. In regression models zero values are included.

Table B.10: Technological change, higher education investments in different subsets of higher education institutions, and real per capita income–OLS Estimates

	(1) All institutions	(2) Tier 1 institutions	(3) Public Community Colleges
Routine exposure 1990 × All inst. Investment 1990	1351.7**		
	(502.6)		
All inst. Investment 1990	-349.1*		
	(145.8)		
Routine exposure 1990 × Tier 1 Investment 1990		578.7+	
		(326.5)	
Tier 1 Investment 1990		-129.7	
		(104.6)	
Routine exposure 1990 × Public CC Investment 1990			-190.9
			(959.3)
Public CC Investment 1990			80.91
			(290.8)
Routine exposure 1990	-9761.8***	-4988.5**	-2731.1
	(2925.4)	(1765.5)	(2049.7)
Observations	9313	9313	9313

OLS estimates with HE investment levels for alternative subsets of institutions (for each of 3,054 counties), and routine exposure in 1990 (for 742 CZs) for three stacked cross-sections, as well county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. and routine exposure in 1990 Standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.11: Technological change, higher education investments in different subsets of higher education institutions, and real per capita income–IV Estimates

	(1) All institutions	(2) Tier 1 institutions	(3) Public community colleges
Routine exposure 1990 × All inst. Investment 1990	4092.7*		
	(1944.7)		
All inst. Investment 1990	-1224.7*		
	(600.7)		
Routine exposure 1990 × Tier 1 Investment 1990		4688.6*	
		(1853.2)	
Tier 1 Investment 1990		-1472.0*	
		(599.1)	
Routine exposure 1990 × Public CC Investment 1990			3166.4+
			(1847.6)
Public CC Investment 1990			-994.0+
			(575.5)
Routine exposure 1990	2731.2	11989.3***	19577.1***
	(6024.1)	(2564.8)	(4818.7)
Observations	9313	9313	9313

IV estimates with routine exposure in 1990 (for 742 CZs) instrumented by its 1950 levels. HE investment levels (for each of 3,054 counties) for alternative subsets of institutions, with three stacked cross sections. Includes county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.12: Technological change, higher education investments, and decadal change in per capita income, extensive and intensive margins

	(1)	(2)
	OLS	IV routine share
Panel A: Districts with some investment vs none in 1990 (extensive margin)		
Routine exposure 1990 ×	4705.7^{+}	28065.5^{***}
Some HE Investment 1990	(2503.6)	(8044.6)
Some HE Investment 1990	-1231.4^{+}	-8592.7^{***}
	(742.8)	(2475.4)
Routine Exposure 1990	-7650.1^{*}	-622.6
	(3030.2)	(5527.8)
Observations	9313	9313
Panel B: Only districts with some investment in 1990 (intensive margin)		
Routine exposure 1990 ×	1278.3	-473.2
HE Investment 1990	-308.1	329.9
	(422.7)	(1448.4)
HE Investment 1990	-308.1	329.9
	(422.7)	(1448.4)
Routine Exposure 1990	-8733.9	33637.6
	(7320.1)	(27930.1)
Observations	6057	6057

In panel A, "Some HE Investment 1990" is a binary variable with value 1 if investment in the county is non-zero and 0 otherwise. Panel B estimates models as in Table B.1, restricted to counties where investment is non-zero. Estimates with HE investment levels and routine exposure in 1990. In model 2, county routine share in 1990 is instrumented by county routine share in 1950. Models include county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. HE investment levels computed for each of 3,054 counties, and routine exposure in 1990 for 742 CZs. Standard errors, clustered by commuting zone in parentheses. Models are weighted by county population. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.2 Models that do not weight by county population share

Table B.13: Technological change, higher education investments, and decadal change in per capita income, without county weights

	(1) OLS	(2) IV routine share
Routine exposure 1990 × HE Investment 1990	334.3	2638.1***
	(264.3)	(720.9)
HE Investment 1990	-81.15	-749.7***
	(77.14)	(207.1)
Routine Exposure 1990	-6331.3***	-12679.1**
	(1558.2)	(4512.6)
Observations	9313	9313

Estimates with HE investment levels and routine exposure in 1990. In model 2, county routine share in 1990 is instrumented by county routine share in 1950. Models include county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. HE investment levels computed for each of 3,054 counties, and routine exposure in 1990 for 742 CZs. Standard errors, clustered by commuting zone in parentheses. Models are not weighted by county population. Compare to weighted results in Table B.1. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.14: Technological Change, Higher Education Investments in different subsets of higher education, and real per capita Income–OLS Estimates, without county weights

	(1) All institutions	(2) Tier 1 institutions	(3) Public Community Colleges
Routine exposure 1990 × All inst. Investment 1990	482.4*		
	(222.9)		
All inst. Investment 1990	-118.1+		
	(65.69)		
Routine exposure 1990 × Tier 1 Investment 1990		432.7*	
		(204.5)	
Tier 1 Investment 1990		-95.09	
		(63.21)	
Routine exposure 1990 × Public CC Investment 1990			958.0**
			(308.4)
Public CC Investment 1990			-262.9**
			(92.66)
Routine exposure 1990	-7296.1***	-6084.2***	-5912.5***
	(1299.7)	(891.2)	(887.0)
Observations	9313	9313	9313

OLS estimates with HE investment levels for alternative subsets of institutions, and routine exposure in 1990, as well county covariates in 1990 interacted with decade dummies. HE investment levels computed for each of 3,054 counties, and routine exposure in 1990 for 742 CZs. Specifications also include decade, region fixed effects. Standard errors, clustered by commuting zone in parentheses. Models are not weighted by county population. Compare to weighted results in Table B.10. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.15: Technological change, higher education investments in different subsets of higher education, and real per capita income–IV Estimates, without county weights

	(1) All institutions	(2) Tier 1 institutions	(3) Public community colleges
Routine exposure 1990 × All inst. Investment 1990	2877.0***		
	(733.8)		
All inst. Investment 1990	-819.6***		
	(212.9)		
Routine exposure 1990 × Tier 1 Investment 1990		2881.4**	
		(952.5)	
Tier 1 Investment 1990		-860.5**	
		(296.2)	
Routine exposure 1990 × Public CC Investment 1990			3925.2***
			(1085.5)
Public CC Investment 1990			-1148.4***
			(322.8)
Routine Exposure 1990	-15494.4**	-7348.9*	-4535.1
	(4919.4)	(3242.5)	(3102.9)
Observations	9313	9313	9313

IV estimates with HE investment levels for alternative subsets of institutions, and routine exposure in 1990, as well county covariates in 1990 interacted with decade dummies. HE investment levels computed for each of 3,054 counties, and routine exposure in 1990 for 742 CZs. Specifications also include decade, region fixed effects. Standard errors, clustered by commuting zone in parentheses. Models are not weighted by county population. Compare to weighted results in Table B.11. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.3 Additional models of support for more higher education investment in California

Table B.16: Models of supporting state funding for California's public colleges and universities –OLS Models, raw data rather than SDs

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990 × HE investment 1990	0.230***	0.215**	0.187**	0.172*
	(0.049)	(0.061)	(0.054)	(0.064)
Routine exposure 1990	-0.439+	-0.460*	-0.429*	-0.786*
	(0.227)	(0.210)	(0.192)	(0.344)
HE investment 1990	-0.067***	-0.063**	-0.055**	-0.050*
	(0.016)	(0.019)	(0.017)	(0.019)
Parent		0.024***	0.023***	0.023***
		(0.003)	(0.004)	(0.004)
Homeowner		-0.063***	-0.051***	-0.052***
		(0.008)	(0.007)	(0.006)
College graduate		0.024***	0.020***	0.020***
		(0.004)	(0.004)	(0.004)
White		-0.036*	-0.024+	-0.024+
		(0.013)	(0.012)	(0.013)
Male		-0.064***	-0.060***	-0.061***
		(0.004)	(0.004)	(0.004)
Republican			-0.128***	-0.128***
			(0.007)	(0.007)
Share manufacturing				0.001
				(0.001)
Share foreign born				0.000
				(0.001)
Female employment rate				0.003*
				(0.001)
Population density				-0.000
				(0.000)
Observations	13390	13252	13252	13252

OLS coefficients on answering "just enough" or "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Pooled cross-sections 2007-2018. Includes survey-year fixed effects. Estimates with HE investment levels for each of 58 counties and routine exposure in 1990 for 19 CZs. 9 pooled cross-sections within 2007-2018. Includes survey-year fixed effects. Uses raw measures of routine exposure and HE investment. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.17: Models of supporting funding for California's public colleges and universities –Probit Models

	(1) Probit (no controls)	(2) Probit with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990× HE investment 1990	1.207***	1.123**	1.011**	0.874**
	(0.285)	(0.365)	(0.333)	(0.334)
Routine exposure 1990	-2.352+	-2.309+	-2.261*	-3.967*
	(1.228)	(1.206)	(1.144)	(1.811)
HE investment 1990	-0.352***	-0.329**	-0.298**	-0.256*
	(0.090)	(0.112)	(0.103)	(0.102)
Parent		0.142***	0.143***	0.144***
		(0.018)	(0.020)	(0.020)
Homeowner		-0.372***	-0.313***	-0.316***
		(0.038)	(0.038)	(0.034)
College graduate		0.129***	0.113***	0.112***
		(0.031)	(0.031)	(0.030)
White		-0.216**	-0.148*	-0.152*
		(0.070)	(0.074)	(0.076)
Male		-0.368***	-0.359***	-0.360***
		(0.018)	(0.017)	(0.018)
Republican			-0.572***	-0.571***
			(0.025)	(0.025)
Share manufacturing				0.004
				(0.005)
Share foreign born				0.001
				(0.005)
Female employment rate				0.017*
				(0.007)
Population density				-0.000
				(0.000)
Observations	13390	13252	13252	13252

Coefficients from probit models on answering "just enough" or "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Pooled cross-sections 2007-2018. Estimates with HE investment levels for each of 58 counties and routine exposure in 1990 for 19 CZs. 9 pooled cross-sections within 2007-2018. Includes survey-year fixed effects. Uses raw measures of routine exposure and HE investment. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.18: Models of supporting state funding for California's public colleges and universities –Ordered Probit Models

	(1) O.Probit (no controls)	(2) O.Probit with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990 × HE investment 1990	0.751*	0.712*	0.589+	0.286
	(0.297)	(0.340)	(0.311)	(0.275)
Routine exposure 1990	-0.398	-0.392	-0.265	-2.527
	(1.204)	(1.069)	(0.993)	(1.545)
HE investment 1990	-0.216*	-0.204*	-0.170+	-0.080
	(0.092)	(0.102)	(0.093)	(0.084)
Parent		0.127***	0.127***	0.127***
		(0.009)	(0.008)	(0.008)
Homeowner		-0.240***	-0.180***	-0.179***
		(0.035)	(0.034)	(0.031)
College graduate		0.050**	0.030	0.027
		(0.019)	(0.018)	(0.018)
White		-0.173**	-0.112+	-0.112+
		(0.055)	(0.057)	(0.061)
Male		-0.291***	-0.278***	-0.279***
		(0.012)	(0.011)	(0.011)
Republican			-0.603***	-0.603***
			(0.027)	(0.028)
Share manufacturing				-0.002
				(0.004)
Share foreign born				0.006+
				(0.004)
Female employment rate				0.018**
				(0.006)
Population density				0.000
				(0.000)
Observations	13390	13252	13252	13252

Ordered probit model coefficients on answering "more than enough" (1) "just enough" (2) or "not enough" (3) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Estimates with HE investment levels for each of 58 counties and routine exposure in 1990 for 19 CZs. 9 pooled cross-sections within 2007-2018. Includes survey-year fixed effects. Uses raw measures of routine exposure and HE investment. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.19: Models of supporting state funding for California's public colleges and universities, restricted to those who have resided in their current address for over 15 years –OLS Models

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine exposure 1990 × HE investment 1990	0.293**	0.262*	0.244*	0.207+
	(0.079)	(0.091)	(0.092)	(0.099)
Routine exposure 1990	-0.726*	-0.732*	-0.735*	-1.222**
	(0.266)	(0.278)	(0.305)	(0.370)
HE investment 1990	-0.086**	-0.076*	-0.072*	-0.060+
	(0.026)	(0.029)	(0.030)	(0.031)
Parent		0.026**	0.027**	0.028**
		(0.007)	(0.007)	(0.007)
Homeowner		-0.061***	-0.057***	-0.057***
		(0.009)	(0.009)	(0.009)
College graduate		0.033**	0.029**	0.028**
		(0.009)	(0.009)	(0.009)
White		-0.038+	-0.030	-0.031
		(0.021)	(0.021)	(0.021)
Male		-0.072***	-0.068***	-0.068***
		(0.007)	(0.008)	(0.008)
Republican			-0.118***	-0.118***
			(0.010)	(0.010)
Share manufacturing				0.001
				(0.001)
Share foreign born				0.001
				(0.001)
Female employment rate				0.004*
				(0.002)
Population density				-0.000
				(0.000)
Observations	5350	5235	5235	5235

OLS coefficients on answering "just enough" or "not enough" (1-0) to "Do you think the current level of state funding for California's public colleges and universities is more than enough, just enough, or not enough?" in PPIC statewide survey. Restricted to those answering "15 years or more" to the question "Could you please tell me if you have lived at your current address for fewer than five years, five years to under 10 years, 10 years to under 20 years, or 20 years or more?". Pooled cross-sections 2007-2018. Includes survey-year fixed effects. Robust standard errors, clustered by commuting zone in parentheses. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Learning to Love Government? A Model of Complete and Incomplete Learning about Public Policy

The empirical results in the main text suggest that higher education investments are productive in mitigating the negative labor market consequences of skill-biased technological change. Economic theory and prior empirical work are also consistent with the view that technological change has made human capital investments more productive than ever. We introduce a simple formal model consistent with these empirical findings.

Higher education spending trends do not show a substantial public policy response. This can have different explanations. One of them is that voters have divergent policy opinions about whether investing more is productive, and therefore whether it ought to be supported by additional public spending. This in turn determines how willing voters are to tax themselves to make such investments. Voters are modeled as passive learners who choose their preferred educational investments based on what they believe will maximize their well being in the given period, but they do not take into account the potential benefits for the future in learning about how productive such investments are. The alternative would be for individuals to experiment—say by making a particularly high investment in higher education—so that future generations of a family dynasty would have better information in making their decisions. This seems implausible. If we think of families as dynasties in which one generation makes its education decision in each period, then the time between periods is very long. Said otherwise, it is hard to imagine parents making what might be a suboptimal education choice for their children based on the logic that this experiment could be useful in guiding what choices are best for their grandchildren.

The model predicts incomplete learning for voters whose beliefs about the productivity of educational investments start off far from the true values. In an environment in which educational investments have become more productive over time, we show why voters whose initial beliefs are such that investments are productive are more likely to learn the true values.

More generally, the model provides an answer to a common question about the geographic divergence of public policy preferences. One might expect that successful and unsuccessful places both learn what works and what doesn't work and therefore discover good policy. To some extent, our model predicts that learning pushes policy in this direction. But learning is imperfect and some voters and places are advantaged while others are disadvantaged in discovering the true mapping between policy and outcomes.

A large literature has focused on how policymakers and voters learn about the mapping from policies to outcomes (McLennan, 1984; Piketty, 1995; Callander, 2011; Callander and Hummel, 2014; Callander and Harstad, 2015; Volden, Ting and Carpenter, 2008) and even more broadly on how individuals act when the relationship between their actions and consequences is uncertain (Rothschild, 1974; Berry, 1972; Ortoleva, 2012).[1] Our model is based on McLennan (1984) and Chamley (2004, ch.8) in the social learning process it follows but differs in the object of learning and political economy setting.

Consider a series of representative voters in a particular community who decide the level of higher educational investment that they believe will maximize their expected utility in a single period. A single period involves both a choice of tax-funded educational investment and a realization of economic success, or the lack of it. A single representative voter makes the policy choice in each period and then a new representative voter makes the policy choice in the next period. We assume that the voter only learns about the mapping from policy to outcomes by what happens in their own community. This assumption could be justified if it is the case that for a whole set of idiosyncratic reasons education investment is seen to "work" in some places but not others, so individuals in Kansas might not be able to draw much inference from what takes place in Massachusetts. For example, they may be unaware of the effectiveness of investments elsewhere due to informational frictions. Or, perhaps,

[1] A separate literature in political science has emphasized the concept of "policy feedback", which theorizes how policies become entrenched through the creation of coalitions that benefit from existing policies (Mettler, 2010), and the many veto points that make it hard for any policy changes to be introduced (Hacker and Pierson, 2010). We differ in that the fundamental mechanism we theorize is one where observing the success of past policies can lead broad groups to support them, and not solely those who benefit from it.

they are aware of it, but believe that effectiveness elsewhere is conditional on the particular circumstances of the other place but "would not work here" since those circumstances differ.

Each representative voter is aware of the history of higher education investments and economic outcomes in their community. To keep things simple, economic outcomes are dichotomized to be either successful or unsuccessful. This is most easily interpreted as whether or not an individual has lifetime earnings, y, that allow them to live an economically secure and enriched life. We normalize the values of these outcomes to $y = 1$ (successful) and $y = 0$ (unsuccessful).

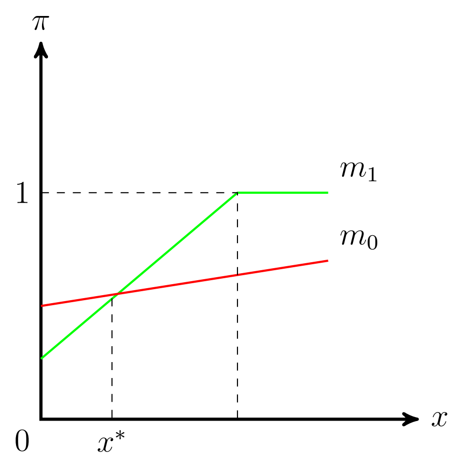
Each representative voter chooses a level of educational investment x. The voter chooses x to maximize their probability of economic success while taking into account the tax costs associated with the investment. The probability of economic success depends on how educational investments map into higher chances of economic success. This mapping is determined by nature and not known precisely by the voter. It is known that the probability of success ($y = 1$) has the following form:

$$\pi_\theta(x) = max\{0, min\{1, a_\theta + m_\theta x\}\}$$

Figure A.1 provides a visual representation of the relationship between educational investment and the probability of economic success under the two alternative states of the world. In this formulation, the voter knows that educational investments increase the probability of economic success but not by how much. For our purposes $\theta = 1$ is the state of the world in which educational investments have a big impact on the probability of success while $\theta = 0$ is the state of the world in which such investments are less productive. The key idea is that voters don't know the right policy mapping because they don't know the environment. We assume only two possible states of the world and we assume the two different mappings as a function of investment intersect.

We leave taxes and a balanced budget constraint in the background and make the expected pay off of the representative voter:

Figure A.1: Probability of economic success as a function of investment in higher education; $\theta = 1$ (m_1) indicates a state in which higher educational investments are highly productive and, alternatively, $\theta = 0$ (m_0) indicates low productivity.



$$E[\pi_\theta(x)] - \frac{\gamma x^2}{2}$$

where π, θ, and x are defined above and γ measures losses from taxation to fund educational investments.

The representative voter chooses x to maximize their payoffs. Once we substitute our expression for $\pi_\theta(x)$ and maximize with respect to x, we get

$$x = \frac{E[m_\theta]}{\gamma}$$

This simply says that voters will prefer higher education investments, the more productive they are (the higher their expectations about m, the slope parameter determined by state θ) in raising the probability of economic success and the less inefficiency created by taxation. If learning m was easy, voters would have the same expectations and in this model the same preferred level of higher education spending x.

Given that there are only two states of the world $\theta \in \{0, 1\}$, the $E[m_\theta] = m_0 + \mu(m_1 - m_0)$, where μ is the representative voter's subjective probability that $\theta = 1$, or that we are in the state of the world in which educational investments are really productive. The key question for understanding divergent beliefs about the policy mapping and therefore preferences over higher education is understanding how the voter learns about μ. Again, we assume fully rational Bayesian learners who know the history of investments and outcomes in their community but that they are passive in that they do not take into account the benefits for future periods from learning in making their educational investment choices.

We assume that the investment, x^* at which m_1 and m_0 intersect is between the optimal investments in states $\theta = 1$ and $\theta = 0$. If $\mu = 1$, the optimal educational investment is greater than x^* and if $\mu = 0$, the optimal investment is less than x^*. Therefore, there is some intermediate belief μ^* for which the optimal investment is x^* and at which the representative voter does not learn from economic success about the relative probability of m_1 versus m_0 or $\theta = 1$ and $\theta = 0$—the point is on both lines. It is also the case at this point that not only does success or failure not change the voter's belief, but they also have no reason to change the level of investment.

We now need to specify precisely how learning takes place. Let $\mu^+(\mu)$ and $\mu^-(\mu)$ be the end of period beliefs following observing economic success or failure with beginning of period belief being μ and educational investment is optimal given beliefs.

$$\mu^+ = \frac{\pi_1(x(\mu))\mu}{\pi_1(x(\mu))\mu + \pi_0(x(\mu))(1-\mu)}$$

and

$$\mu^- = \frac{(1-\pi_1(x(\mu)))\mu}{(1-\pi_1(x(\mu)))\mu + (1-\pi_0(x(\mu)))(1-\mu)}$$

These expressions highlight the ambiguity of observing a success or failure for posterior beliefs μ in the next period about the probability of being in state 1. For the representative voter with $\mu > \mu^*$, observing a success increases μ^+ while for a voter with $\mu < \mu*$, observing a success decreases μ^+. Because both functions μ^+ and μ^- have a fixed point at the invariant belief $\mu*$, the value $\mu*$ partitions beliefs so that over periods t if $\mu_t < \mu^*$, then for any $k \geq 1$, $\mu_{t+k} < \mu^*$. Further, if $\mu_t > \mu^*$, then for any $k \geq 1$, $\mu_{t+k} > \mu^*$.

If we think not just of the next period but of a succession of future periods, then we obtain a stark result regarding the possibility of incomplete learning. There will be incomplete learning if the state is 1 and a representative voter at any given t has a belief below μ^*—that educational investments are not productive. Optimal decisions by future representative voters will lead to a sequence of beliefs that converge to μ^* that is a martingale.[2]

In a starkly different outcome, if a representative voter in any given t has a belief above μ^*—that educational investments are productive, then optimal actions taken by subsequent representative voters can lead to convergence on $\mu = 1$ with positive probability.

Stepping back, the model we tentatively propose suggests that voters learn from the economic environment but their learning is imperfect and history dependent. Why does technological change lead voters in places with already relatively high educational investments to demand even more education spending? Higher spending in the model is a function of higher historical beliefs about the probability of the state of the world in which higher education spending is productive. People in places with initial higher spending are more likely to have the "right" priors and therefore more likely to learn the true—high—productivity of educational investments. People in places with low initial higher education spending are more likely to have the "wrong" priors and their learning is more likely to be incomplete, settling on a lower μ and therefore lower preferred level of higher education investment. There is not enough information in observed success and failure for passive learners to make up for their original differences in beliefs.

[2] See Chamley (2004, Proposition 8.2).

D Data Appendix for economic effect analysis

D.1 Routine exposure

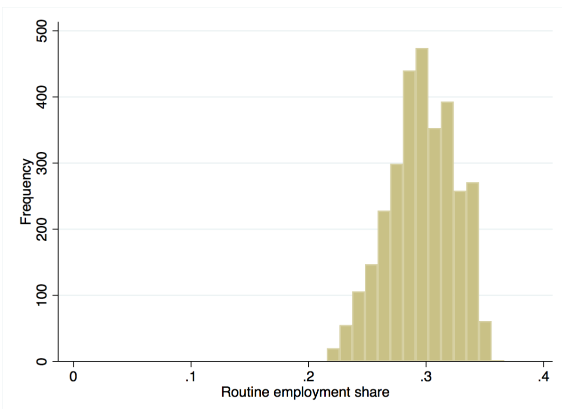
We use exposure to routine occupations as our measure of exposure of technological change. Routine occupations are defined as those in the top third of the distribution of occupations by degree of "routine intensity" of the tasks involved in the occupation (job). To measure the degree of exposure to those shocks, we use the amount of local employment that is in principle more subject to substitution by being in the top third of Autor and Dorn (2013); Autor, Dorn and Hanson (2015)'s summary measure of routine intensity (mimicking Autor, Levy and Murnane (2003)'s own approach). This measure is constructed from the US Department of Labor (1977) assignment of tasks to occupations, which in turn are classified by Autor, Levy and Murnane (2003) into their "routine", "manual" and "abstract" contents by the textual task requirements provided by US Department of Labor (1977).[3] The summary routine task intensity measure is directly proportional to the routine and inversely proportional to the manual and abstract task inputs. Occupation routine intensity will be a composite of the tasks The result is that manual tasks (at the bottom of the income distribution) are low-routine, and more abstract tasks (at the top of the distribution) are also low routine. Occupation-level measures of routine intensity get aggregated to commuting zone measures through the share of those employed in each occupation who are in high-routine occupations.

Figures D.1a and D.1b show the distribution of the high-routine share of employment for the counties in the United States and California (with commuting zone data attributed to each county). Figures D.1c and D.1d display its geographic distribution and shows that the CZs with the highest employment shares in routine task-intensive occupations are a mix of manufacturing-intensive locations (e.g., in the Midwest and in the Southeast) and large cities with an abundance of relatively low-skilled routine office-based occupations (e.g. typists and many clerical occupations).

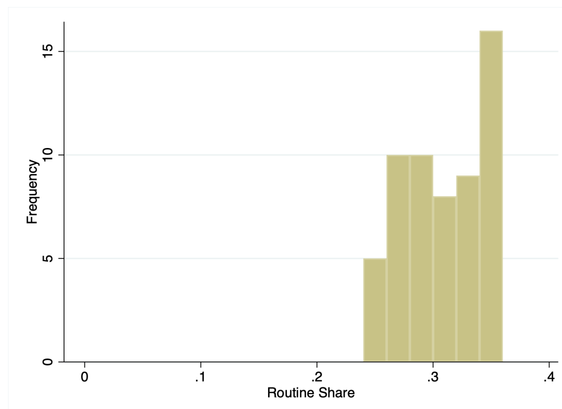
[3]This classification methodology was first introduced by Autor, Levy and Murnane (2003), and simplified into three types of tasks (routine, abstract and manual) by Autor, Katz and Kearney (2008).

Figure D.1: The distribution of automation exposure by county

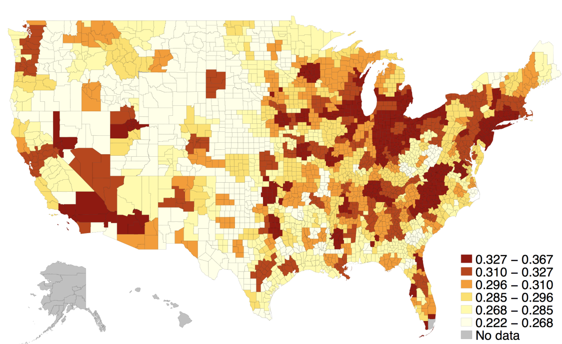
(a) Countrywide routine share of employment by county



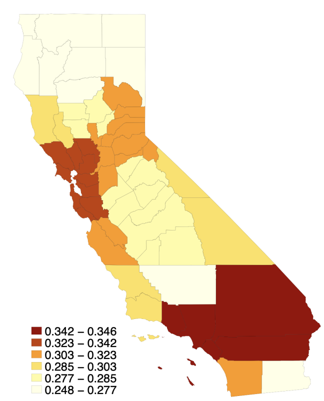
(b) California routine share of employment by county



(c) National geographic distribution of routine share of employment



(d) California geographic distribution of routine share of employment



D.2 Investment in higher education

For our measure of investment in higher education, we aggregate institutional data from the Integrated Postsecondary Education Data System (IPEDS) (Knapp, Kelly-Reid and Ginder, 2018), a survey-based dataset released annually by the National Center for Education Statistics that is submitted to all accredited postsecondary institutions in the United States and that is of mandatory completion for institutions receiving any form of federal assistance, which includes data on finances, admissions and enrollment. When possible we use the standardized taxonomy of fields in this dataset from Desrochers and Sun (2015).[4]

We use as the basis of our measure of investment in counties the revenue data for the 2,051 non-research institutions (excluding 263 research institutions). These are institutions not belonging to Carnegie classification 15-17 (so excluding very high research activity (R1), high research activity (R2) and doctorate-granting universities). Community Colleges belong in this category, as do institutions granting only bachelor's or bachelor's and master's programs.[5]

Our measure of revenues includes those coming from federal, state, local government sources, as well as private and endowment return and investment revenues. This includes financial aid from government sources but excludes tuition paid by students.[6]

We geo-locate all institutions using their zipcode and derive as our main measure of investment in higher education for each county the logged sum of all the investments in higher education that were made in a given year within 50 km of the geographical centroid of the county (a long commute), divided by population in the county.

[4]This dataset also contain the year of founding of institutions from which we compute which ones existed in 1950, which we use in the supplementary specification in Table B.3.

[5]Many of the institutions cited as promoting higher income mobility in Chetty et al. (2020), such as Cal State LA, UT-Rio Grande or most of CUNY's colleges (not its Graduate Center) are in this category.

[6]Specifically, it includes revenue from federal appropriations (including Pell grants, which provide need-based grants to low-income undergraduates), federal grants and contracts, revenues from state appropriations (include state financial aid), and from state grants and contracts; revenue from local appropriations (such as education district taxes), as well as revenues from local government agencies that are for training programs and similar activities. Lastly, it includes revenue coming from affiliated entities, private gifts, grants and contracts, investment returns and endowment earnings. We thus exclude other sources of revenue that would not be a reflection of a local government or institution's effort to provide education as a public good, such as student tuition, sales of goods or services, research, auxiliary enterprises (such as residence halls or dining services), or other revenues. More details on what is included under each of these fields are available in the taxonomy from Desrochers and Sun (2015).

$$HEInvestment_{cd} = log[(\sum_i \mathbf{1}_{<50kmic} \times Revenue_{id}) \times \frac{1}{Population_{cd}} + 1] \quad (2)$$

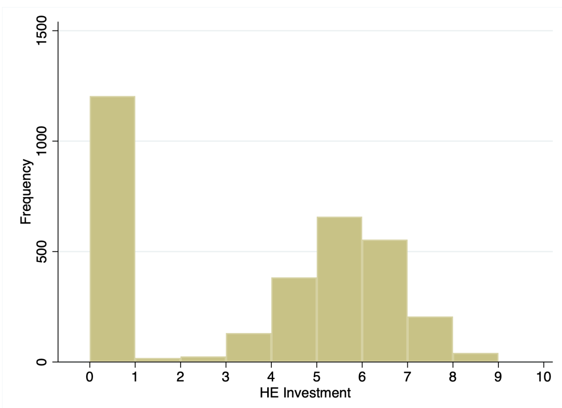
c indexes the county, i the institution and d the decade (1990, 2000 or 2010). The variable $\mathbf{1}_{<50kmic}$ takes the value 1 if the distance between the institution i and the centroid of county c is less than 50km, and 0 otherwise. We divide this sum of investments over the population in the county and take its logarithm.

Figures D.2a and D.2b show the distribution of the measure of investment by county in 2000, with the median value being $868 per person. About 2,300 counties out of 3,106 have non-zero investment levels in higher education. Figures D.2c and D.2d show the distribution of investments in higher education.[7]

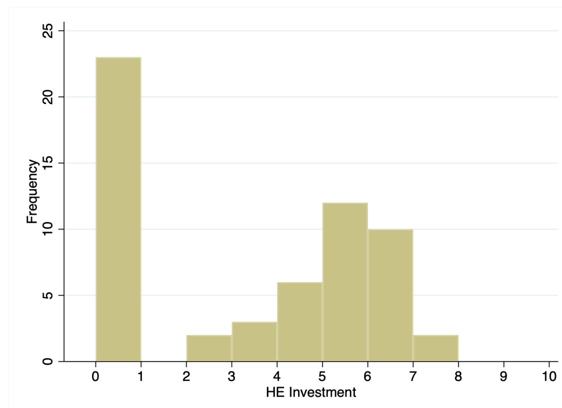
[7] Appendix Table B.8 summarizes the independent and dependent variables we use and, and Appendix Table B.9 shows the distribution of revenue for the different tiers of institutions.

Figure D.2: The distribution of higher education investment by county

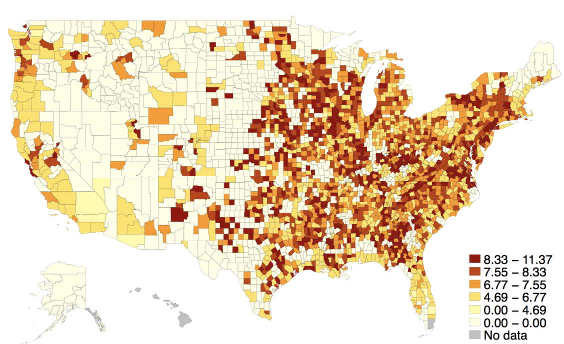
(a) National logged HE investment levels by county



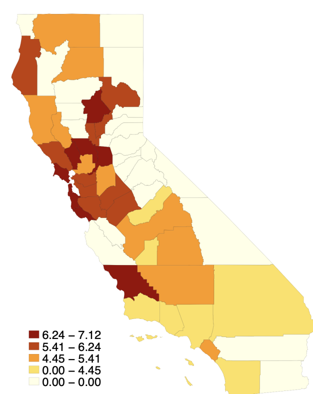
(b) California logged HE investment levels by county



(c) National geographic distribution of logged HE investment levels



(d) California geographic distribution of logged HE investment levels



E Additional empirical evidence

In this section, we seek to ascertain whether the evidence of learning to become anti-government is reflected in attitudes towards the role of government beyond the case of California we study on the main body of the article.

We exploit one state's referenda data (Colorado) and two additional surveys (Wisconsin and a survey of eight US cities) to ascertain the effects of higher levels of investment in education for counties with different shocks. Because of the specificity of the questions on the California surveys and their size, that is our preferred source of evidence.

E.1 Colorado Referenda

Rarely do voters directly faced questions on investments levels in higher education. One instance that comes close to it was on the levels of support for a "Taxpayer Bill of Rights" (TABOR) amendment in Colorado. In the first instance, in 1992, the amendment was proposed to restrict spending growth on public services, such as education. In a booming economy, there was concern for equally booming public spending. TABOR in essence was a Constitutional amendment to the effect that any tax rate increases would have to be subject to a ballot and (an even stronger constraint) budgetary spending (adjusted for inflation) could not grow more that population growth. In good economic times, where the economy grew faster than the population, citizens would receive a rebate to the tune of the difference between revenue collected above the spending cap. The amendment was passed in a 1992 referendum and effectively curtailed growth in spending in higher education.[8] Additionally, in 2005 there was another referendum on effectively loosening the restrictions imposed by TABOR: the state could retain any revenues collected and spend the money on health care,

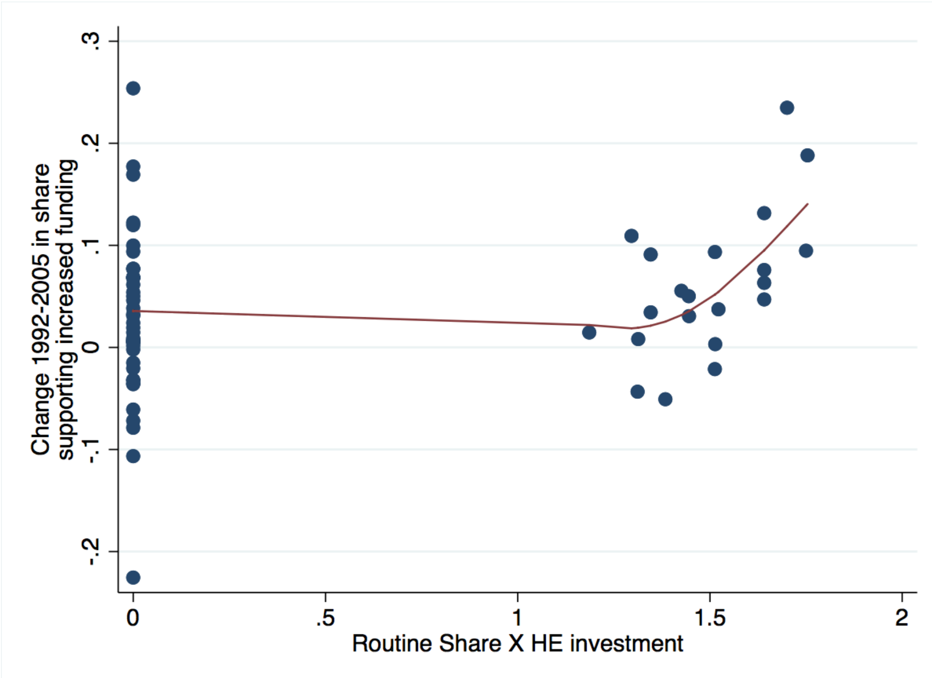
[8]Amendment 1 in the November 3, 1992 ballot (passed in the state by 53.7% of votes: "Shall there be an amendment to the Colorado constitution to require voter approval for certain state and local government tax revenue increases and debt; to restrict property, income, and other taxes; to limit the rate of increase in state and local government spending; to allow additional initiative and referendum elections; and to provide for the mailing of information to registered voters?"

education, transportation and retirement plans of certain public employees.[9] This was in effect a partial removal of the spending restrictions –and one that passed. Conveniently for our purposes, it overlaps with the period that we are studying and allows us to contrast how counties evolved over time in their position against public spending (anti-government) and how it relates to automation. Unfortunately, we can only do so in aggregate for the 64 counties in Colorado. Consistently with our theory, we find that places with higher levels of investment in higher education in 1990 reacted to a technology shock by becoming more pro-spending in the Colorado referenda, when we compare their 1992 and 2005 positions.

We show these suggestive results in the Figure E.1, where we fit a LOWESS curve. Due to the smalll sample these results are not statistically significant, but suggest that at least for counties with non-zero investment levels, automation shocks led to more pro-government stances between 1992 and 2005.

[9] Amendment C in the November 1, 2005 election, passed by 52.1% in elections: "Without raising taxes and in order to pay for education; health care; roads, bridges, and other strategic transportation projects; and retirement plans for firefighters and police officers, shall the state be authorized to retain and spend all state revenues in excess of the constitutional limitation on state fiscal year spending for the next five fiscal years beginning with the 2005-06 fiscal year, and to retain and spend an amount of state revenues in excess of such limitation for the 2010-11 fiscal year and for each succeeding fiscal year up to the excess state revenues cap, as defined by this measure?"

Figure E.1: Change in support for HE funding, investment in HE and routine share in Colorado



E.2 Wisconsin survey data

A second survey source with granular data on individuals' support for investments in higher education comes from Wisconsin, which has featured prominently in debates about higher education spending and were notorious spending freezes were proposed by Governor Scott Walker in 2013 and 2015, and cuts were introduced in the 2017, while tuition increased (CITES). Before that, and in the middle of the period under consideration, we have access to the "Badger poll", a survey conducted with a 500 person panel of adults in Wisconsin by the University of Wisconsin-Madison on a range of current affairs issues. In the March 2005 edition, the question "The state will have to choose how it spends money on various programs. Please tell me – compared to other areas – whether each of the following should be a higher priority than it is now, a lower priority, or have about the same priority?" was included. Among the options, roads, transit, local aid, public higher education, prisons, local schools, fighting crime, illegal drugs and environment were asked.

We code whether respondents answer that public higher education should be a "Higher priority", rather than "lower" or "same" priority. Of all respondents, 54.5% answered that it should be a higher priority, the second highest of all options, after local schools (54.9%). We are interested in whether automation shocks have different effects for parts of the state with different levels of investment in higher education. Indeed, although our sample is small and our results are only suggestive, we show in Figure E.2 patterns that support the view that, after controlling for county and individual characteristics, the effect of being in an area with greater exposure to automation on prioritizing higher education flips from being negative to positive as prior levels of investment in higher education are higher. These effects are noisily estimated, however, as the sample size is rather small.

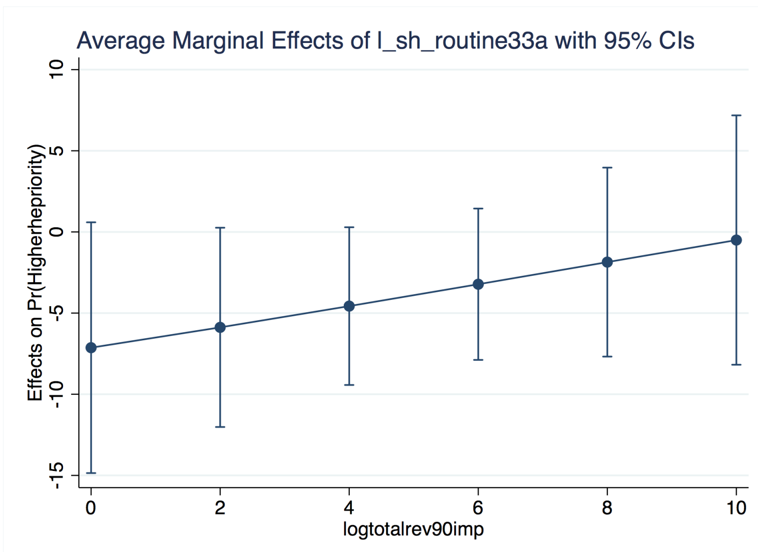


Figure E.2: Wisconsin: ME of routine exposure by level of HE investments on individual probability of responding that public higher education should be higher priority

E.3 Survey on cities

Lastly, we exploit a proprietary data on eight metropolitan locations with higher levels of exposure to automation than the United States as a whole: while the median routine share at the start of the period for the US as a whole is 29.6% (with 25th percentile is 27.4% and 75th percentile is 31.9%), it is 32.6% (with 25th percentile is 31.1% and 75th percentile is

34.0%) for the eight metropolitan areas included in our survey. The range of county level investments per capita are also larger, with median levels about 49% higher than those in the whole sample (where about 800 counties have zero levels of higher education investment in our measure).

Both automation and investment in higher education are more intense in our sample, but we nonetheless still have a range of values for both. At the same time, we may imagine that quite separately from these measures, the fact that we are studying cities help us to focus on populations that are more comparable with each other (which would bias us against finding large differences due purely to differential characteristics).

We use questions that try to get a perceptions about the role of government. The main question we consider is the following:

[...] Consider three different policy approaches to dealing with technological change like robots and automation. Which approach is closest to your own view?

- **(Build walls)** The federal government should implement policies that limit technological change that hurts workers; for example, by taxing businesses that replace workers with machines and robots. Even if new technologies are good for the economy overall, they hurt regular people too much and should be limited.

- **(Build safety nets)** The federal government should encourage technological change to increase economic growth. But it should also adopt new policies that substantially tax those firms and individuals that benefit from technological change and then spend the new revenue on government income programs for everyone else.

- **(Build ladders)** The federal government should encourage technological change to increase economic growth. But it should also adopt new policies that substantially tax those firms and individuals that benefit from technological change and then spend the new revenue on programs—for example, training and education—that provide more people with greater opportunity to benefit from technology.

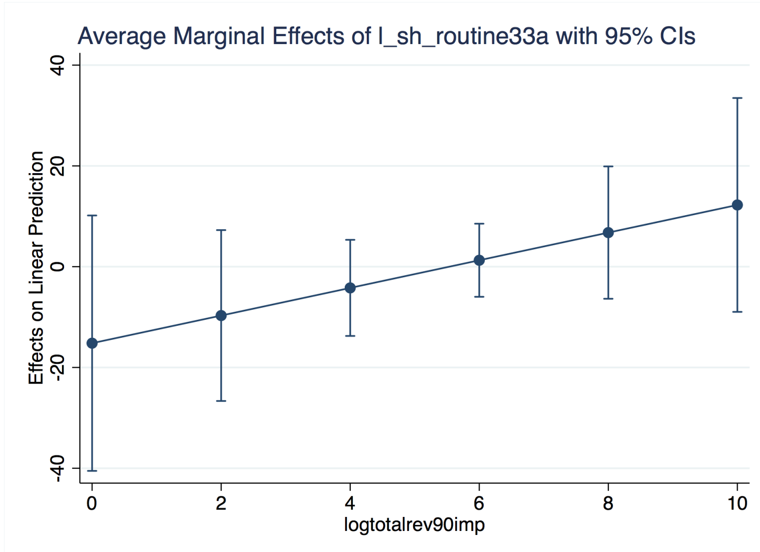


Figure E.3: Support for "building ladders" as a policy strategy to deal with technological changes (IV LP models with number of institutions in 1950s as instrument for HE investments)

We fit multinomial logit models to assess how the probability of responding that "Building ladders" in the form of new revenue programs (with training and education given as examples), relates to the levels of exposure to automation. As predicted, this relation is conditional on the levels of higher education investment in the area. While at the lowest levels of investment in higher education, the effect of 1 percentage point higher exposure to automation is of reducing support for ladder-building policies by 6.5% , it is a positive 2% for those at the highest levels of investment. We see this pattern in Figure E.3.

We also look at other survey items regarding higher education institutions, which have effects in a similar direction but not as strong, such as differences in the expressed levels of trust in state universities as institutions; the importance afforded to local colleges. For instance, the marginal effects of being exposed to automation is increasing on the levels of investment in higher education (Figure E.4). The gradient is also positive although much smaller for trust in state governments (Figure E.5).

In summary, from the city survey data we find that the relation between higher education investments and policy views extends beyond narrowingly circumscribed to higher education

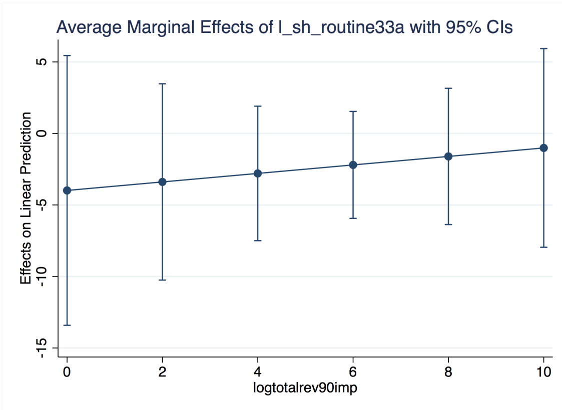


Figure E.4: ME of log routine exposure on trust in State Universities (linear model, 1-4)

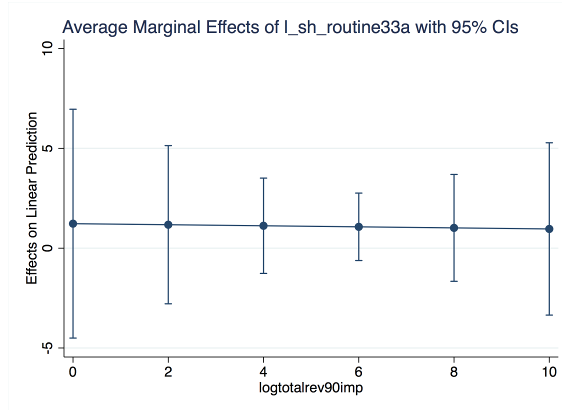


Figure E.5: ME of log routine exposure on trust in State Governments (linear model, 1-4)

investment) to a broad range of policies of the type that higher education investment belongs to: we find that the marginal effects of technological shock increase the probability of supporting policies for "building ladders" the greater the levels of investment in higher education in the county. Similarly, prior investment also seems to have some positive effect on the trust afforded to universities themselves and to state government more broadly.

This suggests that the learning from higher education investment extends to a broader set of policy domains but not to support simply for bigger government or a protectionist government, as the support for "safety nets" or "walls" actually diminishes as levels of higher education investment are higher, consistent with some of the findings from Busemeyer and Tober (2022).