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

Carlos Lastra-Anadón
IE University
clastra@faculty.ie.edu

Kenneth Scheve
Yale University
kenneth.scheve@yale.edu

David Stasavage
New York University
david.stasavage@nyu.edu

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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 labor market consequences of technological change are significantly 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 further present evidence that technological change induced a vote towards more centrist ideological positions and a pro-government shift in partisan voting in counties with higher initial levels of educational investment. We conclude that higher education investments are productive, but there is also evidence of history-dependent diverging support for such investments. We present a model of incomplete learning as a possible interpretation for our findings. In a context where higher education spending dampens the negative employment effects of technological change, a history of believing that education is productive advantages local communities in learning the true productivity of higher education investments, while the absence of such a history favors incomplete learning.

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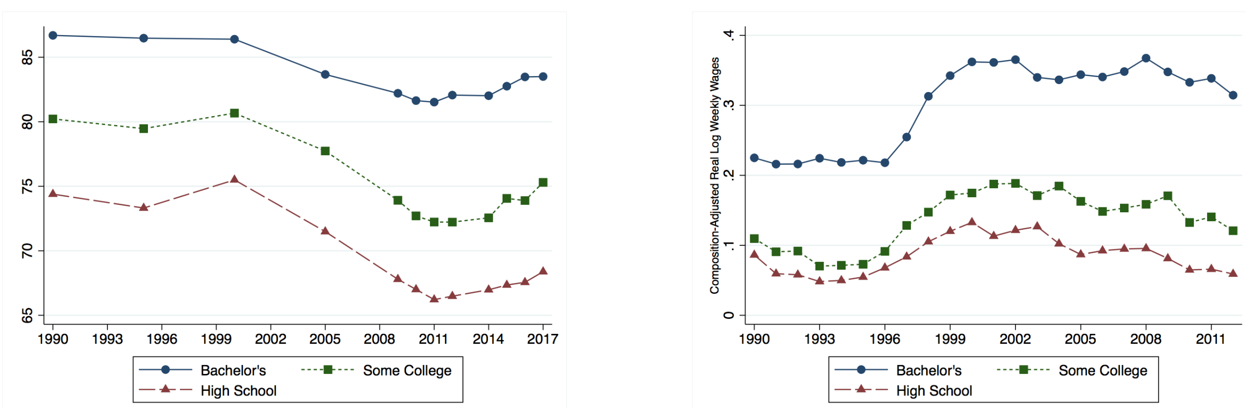
1 Introduction

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. Generally, these changes have advantaged more educated workers and disadvantaged others. For those of working age, a much larger portion of those with some college education (including an Associate's degree) or a Bachelor's degree are in employment, compared to those with only a high school education. As shown in Figure 1a, the difference between employment rates for those with some college compared to those with only High School degrees has grown since 1990 and is currently at a peak. 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. By contrast, in 1990 these numbers were closer: 74% of those with a high school diploma, 80% of those with some college and 87% of those with a Bachelor's degree were employed. Figure 1b documents even starker increases in differences in earnings for the wage premium of workers with different levels of education.

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

(a) Employment rate (percent) (b) Earnings



Note: Outcome is share of the working age population (25-64 years old) in employment. Some college includes those receiving an Associate's diploma. Source: CPS.

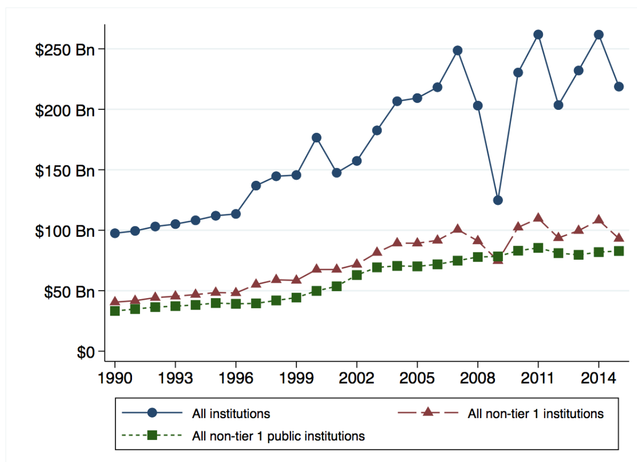
Note: Outcome is Log-weekly real wages for full-time full-year male workers. Source: March CPS.

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 non-optimizing, a natural policy reaction would be to invest more in higher education, as for example Bound and Turner (2007); Bound, Lovenheim and Turner (2010); Deming and Walters (2017) have suggested.

However, that does not seem to have happened over the last two decades. The trajectory of spending in higher education in real terms has been flat since about 2005, as shown in Figure 2. This is particularly true in non-tier 1 institutions (non-research universities and colleges), which educated 67% of total enrolled students in all institutions in 2015.

Figure 2: Higher education investment for different types of institution



Note: Higher education investment defined as revenues from federal, state and private investment sources. Source: IPEDS.

In order to explain this flat investment, one possibility is that there may be a consensus that more investment is an optimal policy response, but the political process does not deliver it. These include the possibility of interest group capture by relatively 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 (who are not currently attending college due to financial constraints) that the United State's political system fosters. They also highlight the lack of college-preparedness stemming from the inequalities in funding and provision from a decentralized school system. A different possibility is that voters do not share a consensus that higher spending is the correct policy response.

This latter view is consistent with survey evidence which suggests ambivalent perceptions about higher education. Although national public opinion data is limited, Pew (Parker, 2019) has asked since 2012 a general question on whether a series of institutions, including colleges and universities, "are having a positive effect on the way things are going in this country today". Despite the positive association between outcomes and college participation that we documented above, the perceived positive effect of higher education institutions is trending downwards. Currently, 50% of those surveyed (and only 33% of Republicans) think that colleges and universities have a positive effect on the country, compared to 60% in 2012.[1] A more direct question on the public's perceived value of higher education comes from a multi-year survey of the California public. Between 2007 and 2018, the share of those polled that said that "a college education is necessary for a person to be successful in today's work world" in fact went down from 68% to 49% (Baldassare et al., 2018). Nationally, in a 2016 survey, only 43% of those surveyed think that cuts in state government funding of public colleges are a "serious problem" (Public Agenda, 2016).

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

There are at least two salient answers to these questions emphasized in the literature. The first emphasizes the possibility that the theories of policy that individuals adapt 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 highlights the importance of early socialization into

[1]Some of this effect could be attributable to an increasing divide between the perceptions of universities across the political spectrum that is related with the perception of the ideology prevalent in universities. Still, in the same 2018 survey 65% of those polled 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.

partisan identities associated with beliefs about the effectiveness of government. Partisans have a standing positive or negative view of the proper role of government in solving social problems and altering that view will take a great deal of contradictory evidence.

In this paper, we suggest a third type of answer is found in the idea that divergent beliefs about higher education spending, and more broadly about the size of government are in part due to diverging experiences.

We approach this question empirically and first investigate what voters may have learned about the effectiveness of higher education investment over the last three decades. We construct new measures of county-level higher education investments for every county in the United States in 1990, 2000, and 2010. We estimate the effect of technological change, as measured by routine share of employment, on county labor market outcomes including share employed, unemployment rate, and real per capita income and whether these estimates vary by pre-period levels of county higher education investment. We show that investments in higher education mitigate the negative economic effects of technological change. Our estimates suggest that individuals in US counties with high levels of technological change and higher education investments were more likely to have had the opportunity to learn that higher education investments are productive.

We next investigate whether individuals who were exposed to environments where the negative effects of technological change were mitigated by higher education investments, preferred more future higher education spending. To do this 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 higher education spending. In other words, it appears that people in counties with high levels of higher education investment became more convinced of its usefulness while people in counties with low levels of investment do not seem to have updated their views in a similar fashion.

Finally, we investigate whether environments in which the productivity of public higher education investment is evident because they experience greater shocks and higher education investments are also associated with more general ideological movements about the role and size of government. We show that the effects of exposure to technological change on changes in ideology and partisan voting between the early 1990s and the late 2010s is conditional on initial levels of investment in higher education. Once again it appears that people in counties with high initial levels levels of education investment learned differently when compared to people in counties with low initial levels of investment.

As one way of interpreting these different learning trajectories, we introduce a model of passive learning similar to McLennan (1984) and Chamley (2004, ch. 8), whereby individuals become more supportive of higher education investments when they happen to be in a place conducive to learning about its effectiveness. The word "passive" here refers to a situation where individuals take actions maximizing only their expected payoff in in the next period, as opposed to possibly experimenting so as to learn what strategy would be best for all future periods. Generalizations of McLennan (1984) have shown, as one might expect, that whether individuals are passive or experiment depends on how heavily they discount the future (N.d.). In our case of higher education there is an analogous reason that points in the direction of passive learning. 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 we lay out shows that individuals are more likely to learn that higher educational investments are productive when their historically determined priors are relatively favorable toward education spending to begin with. Voters also learn from failure and those with less favorable priors who observe failure update their beliefs toward thinking that educational investments are productive. But learning is incomplete and those in places with low priors—and the model predicts that actual spending will reflect these beliefs—are less likely to learn the true—high—productivity of higher educational investments. This helps to explain the divergence in beliefs that we observe in the data. It suggests that there are limits to the learning about policy effectiveness that can take place whenever people start with different beliefs and have different experiences. This also provides a strong policy rationale for large scale public investments in education to shift the beliefs of even those who start out thinking that education investment is not worth the cost.

Our results have important implications, starting with the case we study of mitigation of the negative effects of technology through government policies. Our findings suggest that those who posit an unstoppable negative effect of technological change on the economic prosperity of large fractions of the population that will be out of jobs (Brynjolfsson and McAfee, 2014; Ford, 2015; Kurzweil, 2005) 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. An argument advanced by Boix (2019) is that the highly educated and wealthy electorate (by historical standards) in contemporary advanced societies will eventually be successful at making the political choices that will mitigate such negative effects. We suggest that divergent paths are more likely where geographical areas where government intervention has been successful to date acknowledge its importance and continue to support it at the ballot box. At the same time, areas that due to historical circumstances or other reasons have not benefited from successful intervention will tend to support parties that reduce government interventions and efforts to mitigate negative outcomes, since they do not believe those interventions can be successful.

2 Technological Change, Higher Education Investment and Labor Market Participation

The economic displacement effects of the automation of the production system have been studied extensively. The question is of empirical interest given the possibility of complementarities of technological advances to enhancing the productivity of labor, which is perhaps the most important change in United States economy for the second part of the twentieth century (Goldin and Katz, 2009). 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).

Moreover, some specific forms of technological change such as the introduction of robots have been found to have negative effects on aggregate commuting zone employment levels and wages by Acemoglu and Restrepo (2020) (although Graetz and Michaels (2018) find a less widespread displacement effect, only for low-skilled workers). Alternative measures of the transformation of economic activity by country, such as levels of investment in IT, show an effect that leads to polarization through increases in high- and low- skill employment (Michaels, Natraj and Van Reenen, 2014; Goos, Manning and Salomons, 2014) and to lower levels of labor's value added (Autor and Salomons, 2018).

Less explored in the empirical literature is the aggregate effect of policies that may mitigate the impact of technological change. In particular, the null average effects of automation shocks in employment may mask significant heterogeneity that depends on policy conditions.

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 the employment rate (e.g. Turner, 2017). Theoretically, much technological change creates demand for new jobs that require higher order skills of the sort higher education provides that complement technological developments. This is the case even within occupations.

For example, while secretaries where described in 1976 as "relieving their employers of routine duties so they can work on more important matters. Although most secretaries type, take short-hand, and deal with callers, the time spent on these duties varies in different types of organizations" (US DOL 1976). In 2000, the occupation description read as follows: 'Office automation and organizational restructuring have led secretaries to assume a wide range of new responsibilities once reserved for managerial and professional staff. Many secretaries now provide training and orientation to new staff, conduct research on the Internet, and learn to operate new office technologies." Today's secretaries need more years of higher education compared to those in the 1980s.

2.1 Data

In our empirical analysis, following Autor, Dorn and Hanson (2015) (ADH), we use changes in the employed share of the working age population, in the unemployment rate, and in per capita income in real 2000 dollars, all for the decades 1990-2000 and 2000-2010, and 2010-2019, to measure labor market outcomes.

2.1.1 Independent variables: Per Capita Higher Education Investment and Routine Share of Occupation

We have two main independent variables. For exposure to technological change by geographic area, the main measure we use follows ADH and is the share of employment in routine occupations in the commuting zone. Routine occupations are defined as those in the top third of the distribution of occupations by degree of routine-ness of the tasks involved. These occupation-level measures get aggregated to commuting zone measures through the share of employment in high-routine occupations in the commuting zone.[2] The rationale for using this as a measure of exposure to technological change is that a large part of the automation

[2] In the methodology introduced by Autor, Levy and Murnane (2003) census occupations are merged with job task requirements from the US Department of Labor's Dictionary of Occupational Titles (US Department of Labor, 1977). The classification was simplified into three types of tasks (routine, abstract and manual) by Autor, Katz and Kearney (2008).

"shock" starting in the 1980s took the form of a decline in the cost of performing tasks by substituting human labor by computer-enabled data processing. To measure the degree of exposure to those shocks, we use the degree of local employment that is in principle subject to substitution by being "routine". Figure 3a shows the distribution of the high-routine share of employment for the counties in the United States (with commuting zone data attributed to each county). Figure 3c displays its distribution in the country 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 relatively low-skilled routine occupations (e.g. typists and many clerical occupations).

The second main independent variable measures investment in higher education (from government and private and philanthropic sources) at the county level. 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. It includes data on finances, admissions and enrollment, tuition, graduation rates and human resources.

We focus on institutions of higher education that according to the Carnegie classifications are not research-focused and so, whose primary role is educational.[3] We use as the basis of our measure of investment in counties the total non-tuition revenue data for the 2,051 non-research institutions (excludes the 263 research institutions), which include federal, state, local government, private and endowment return and investment revenues.

[3]These are institutions not belonging to Carnegie classification 15-17: very high research activity (R1), high research activity (R2) and doctorate-granting universities. Community Colleges belong in this category, as do many institutions cited promoting higher mobility in Chetty et al. (2017), such as Cal State LA, UT-Rio Grande or most of CUNY's colleges (not the Graduate Center), but not others such as UT-Rio Grande. Adding the research institutions to our measure does not have a substantial impact on our results. All of our main estimates are robust to this alternative. Focusing on these institutions alone, however, generally yields smaller and insignificant coefficients.

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.

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

c indexes the county, i the institution and d the decade (1990, 2000 or 2010). $\mathbf{1}_{<50kmic}$ takes the value 1 if the distance between the institution i and the centroid of county c is less than 50km, and 0 otherwise. In our specifications below we take the ration of this measure over the population in the county and take its logarithm.

Figure 3b shows the distribution of this 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 and we impute a zero-level value of investment in higher education for the rest. Figure 3d shows the distribution of investments in higher education.[4]

2.2 Econometric Model

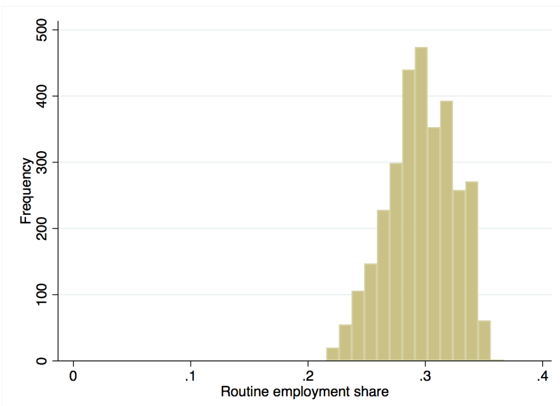
Our specifications relate automation measures, higher education investments, and labor market outcomes (and below we use similar models for political variables). Our goal is to employ methods similar to those used in previous work estimating the effect of technological change on labor market outcomes but investigate whether our estimates of this effect vary by levels of pre-determined educational investments. Similar to Autor, Dorn and Hanson (2015, p.11), we implement first difference models, with decadal changes to the dependent variables, with regions but not county fixed effects.

We use changes by decade for 1990-2000, 2000-10, 2010-2020. These decades follow the onset of rapid computerization in 1980 (ADH's rationale for starting their analyses in 1990)

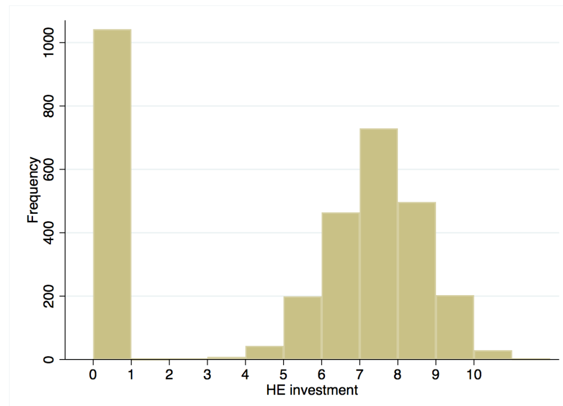
[4] Appendix Table B.1 summarizes the independent and dependent variables we use.

Figure 3: The distribution of technology exposure and higher education investment by county

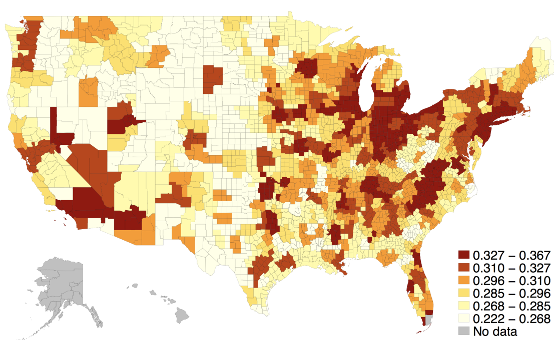
(a) Distribution Routine share of employment by county



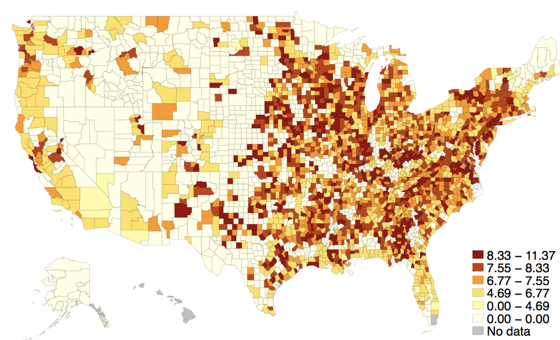
(b) Logged HE investment levels by county



(c) Geographic distribution of routine share of employment



(d) Geographic distribution of logged HE investment levels



and matches the start of the collection of higher education institution data by IPEDS (1987).[5] Unlike ADH, we interact the effects of the exposure to automation shocks with the levels of investment in higher education to understand if there is a significant gradient in the economic effects of a shock by prior levels of higher education investment. We implement specifications of the following form:

$$\begin{aligned}\triangle Y_{czrd} = \beta HEinvestment_{cd} \times Routine_{zd} + \gamma HEinvestment_{cd} + \\ + \delta Routine_{zd} + \eta \mathbf{X}_{cd} \times D_d + \zeta \mathbf{X}_{cd} + D_d + R_r + \epsilon_{czrd}\end{aligned} \tag{2}$$

Observations are indexed by county c, commuting zone z, region r 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): the share of employment in manufacturing, share of female employment, share of the population with some college, share foreign born (ADH'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 regional fixed effects for the nine census divisions. We weigh regressions by the share of the national population in the county and cluster standard errors by county. [6]

Models employing first differences across decades in the dependent variables would eliminate concerns for differences in levels of the economic (and political) variables associated with county characteristics that are stable over time, analogously to estimates with county fixed effects. However, a concern about a direct OLS implementation of the equation above is that the share of contemporaneous routine jobs in the economy may be driven endogenously, e.g. since most jobs created are non-routine, places with lower job growth will tend to have over time comparatively greater shares of routine occupations. To assuage concerns over the endogeneity of our measure of exposure to automation, we use models where we freeze levels of higher education investments and of the routine share of employment in their 1990 levels

[5] Economic data is available to 2019.

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

which could not possibly have been influenced by later developments.

Additionally, we present models where, like ADH, we instrument the levels of the routine share of employment in 1990 with their corresponding values in 1950 (the earliest available). The rationale for this strategy is that it is hard to imagine 1950s levels of routine share being locally determined by subsequent economic and political developments, or indeed by the levels of investment in higher education as long after as the 1990s.

2.3 Results

We present our first set of estimates for the effect of technology exposure and higher education investment levels on changes to employment levels, unemployment rates and real per capita income with counties weighed by their share of the national population. We present two specifications. The first implements OLS and with the running variables set to their 1990 values in Table 1. In the second specification, we use 1990 levels of Higher Education investment and instrument 1990s levels of routine share of employment by their 1950 in Table 2. In all specification the marginal effect of routine share on outcomes is more positive for the local economy at greater higher education investment levels.[7]

We plot in Figure 4 the marginal effects of routine share on labor market outcomes from our instrumental variable estimates in Table 2.[8] The plots show that the higher pre-existing investments in education are, the more positive the labor market outcomes associated with automation are. To take the first outcome, in counties with no 1990 investments in higher education, greater exposure to automation was associated with an average decline in the employment of the working age population in each of the three decades 1990-2020. A one standard deviation change in the routine share of employment (.033) was associated with about .2 percentage point decadal decrease in the share of those in employment, or about ten percent of a standard deviation. At high levels of investment (8 log-HE investment, the 95th

[7]In Appendix Table 1, we show OLS models with county covariates that vary by year. The results are substantially the same.

[8]We also show in Appendix Figure A.1 the corresponding marginal effect plots for the OLS estimates in Table 1.

Table 1: Technological Change, Higher Education Investments, and Labor Market Outcomes–OLS Estimates

	(1) △ Share employed	(2) △ Unemp. rate	(3) △ Real PC Income
Routine exposure 1990 × HE Investment 1990	0.335*	-0.00612*	1390.8**
	(0.169)	(0.00304)	(508.2)
HE Investment 1990	-0.110	0.00164	-366.6*
	(0.125)	(0.00110)	(145.5)
Routine exposure	-12.39***	0.0851***	-8841.7**
	(2.305)	(0.0198)	(2989.4)
Observations	9313	9313	9313

OLS estimates with HE investment levels and routine exposure in 1990, as well county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by county in parentheses.

Table 2: Technological Change, Higher Education Investments, and Labor Market Outcomes–IV Estimates

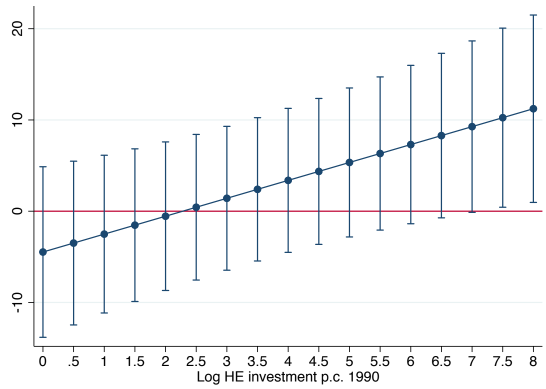
	(1) △ Share employed	(2) △ Unemp. rate	(3) △ Real PC Income
Routine exposure × HE Investment 1990	1.963**	-0.0111*	4285.6***
	(0.745)	(0.00520)	(1223.9)
HE Investment 1990	-0.623**	0.00324*	-1278.6***
	(0.228)	(0.00157)	(366.5)
Routine exposure	-4.473	0.0420	4739.4
	(4.769)	(0.0309)	(6778.9)
Observations	9313	9313	9313

IV estimates with actual HE investment levels in 1990 and routine share of occupations in 1990 predicted by 1950s levels of the same variable, as well county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by county in parentheses.

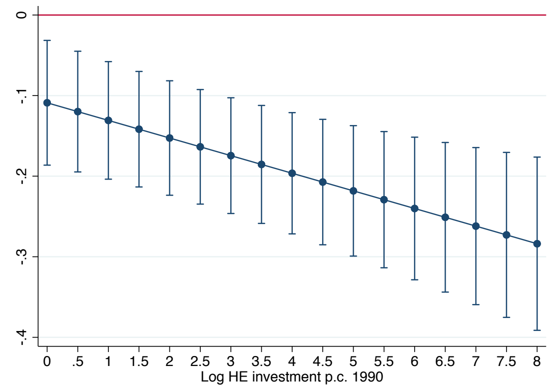
percentile), by contrast, the effects are positive and large: a one standard deviation change in routine share is associated with a .3 percent increase in the share of employed population, or about fifteen percent of a standard deviation. The effects follow a similar pattern for the other two variables.

Figure 4: IV estimates: Marginal effects of a change (percent 0-1) in routine share of employment by level of investment in higher education on economic outcomes.

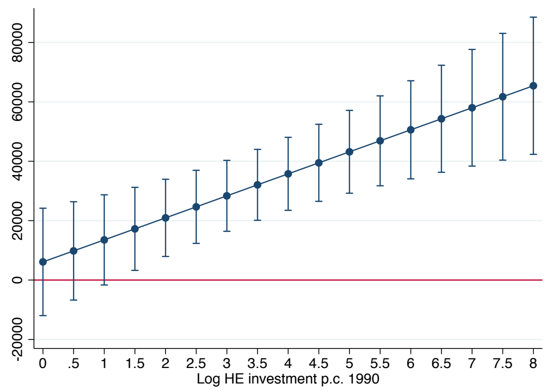
(a) △ Employment Share



(b) △ Unemployment Rate



(c) △ Real Per Capita Income



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

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 opinions of voters about higher education spending and whether this effect varied across counties by differences in initial levels of higher education investments. It is, of course, possible that we observe little learning because mapping the productivity of higher education investments is simply too difficult for voters. Alternatively, it may be that everyone learns in this environment that higher education investments are relatively productive and increase their demand for such policies independent of the conditions in their geographic region. This section investigates these alternatives empirically by turning to a survey on policy opinions about higher education spending in California, the Public Policy Institute of California (PPIC) "Statewide Surveys".

California is one of the most populous and one of the most prosperous (9th) states in the country. It also has significant variation in its economic mix across its 116 counties. Its level of technological change as measured by routine share of employment in 1990 is somewhat higher than national levels (median is 0.6 percentage points higher than the national median using simple means and 1.4 percentage points higher when weighing counties by population). The levels of investment in higher education in 1990 are slightly lower than the national ones (its median is 0.5 log-points lower than the national using simple means and 0.85 log-points lower when weighing counties by population). The Public Policy Institute of California (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 the yearly November surveys has between 1,700 and 2,500 adult respondents resident in California drawn at random to be representative and contacted using random-digit-dialing by telephone.[9]

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 a dependent variable *HE Spending Support* equal to 1 if individuals gave the "not enough" response and 0 otherwise.

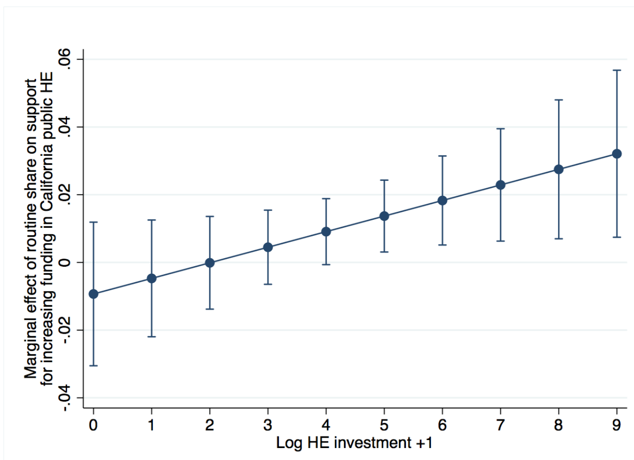
We have responses across six surveys in the period 2007-17 that contained the question for a total of 12,631 observations. Since all the surveys occur towards the end of the periods we consider in other models, we do not focus on changes in the dependent variable over time but

[9]For survey details see https://www.ppic.org/wp-content/uploads/SurveyMethodology.pdf. We use raw observations (representative of the California public overall), as the survey is not representative at the county level or at indeed for any geographic area below five regions: Central Valley, San Francisco Bay Area, Los Angeles County, Orange/San Diego Counties, and the Inland Empire.

pool the observations. We estimate by OLS linear probability models regressing *HE Spending Support* on routine share, higher education investment in 1990 and their interaction.[10] We cluster standard errors on counties.

Table 3 reports our coefficient estimates with a number of alternative sets of conditioning variables at the individual and county level.[11] Figure 5 reports our key quantity of interest which is the marginal effect of changes to routine share on support for higher education by level of prior investment in higher education. These marginal effects are increasing on the level of 1990s higher education investment.

Figure 5: California: ME of a one standard deviation change in routine exposure by level of HE investments in higher education on attitudes towards funding levels of California's public universities and colleges.



Note: Marginal Effects obtained from Model 4 in Table 3.

4 Public Preferences about the Role of Government

The next question we turn to is whether the variation in the learning environment—as defined by the heterogeneity in the effects of technological change by educational investment—had a more general impact on views about the role and size of government.

[10]There is too little variation in the routine share variable to implement instrumental variables, since there are only 18 commuting zones in California, the level at which we have routine share of employment.

[11]We obtain similar results using a probit model. See Appendix Table B.3.

Table 3: Linear probability models of supporting increased state funding for California's public colleges and universities

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine share 1990 × HE investment 1990	0.230***	0.207***	0.183**	0.172*
	(0.0607)	(0.0600)	(0.0601)	(0.0694)
Routine share 1990	-0.565*	-0.569*	-0.527+	-0.924*
	(0.271)	(0.269)	(0.270)	(0.379)
HE investment 1990	-0.0687***	-0.0621**	-0.0553**	-0.0512*
	(0.0198)	(0.0196)	(0.0196)	(0.0220)
Parent		-0.0311***	-0.0302***	-0.0300***
		(0.00592)	(0.00588)	(0.00588)
Homeowner		-0.0577***	-0.0495***	-0.0501***
		(0.00583)	(0.00579)	(0.00581)
College graduate		0.0360***	0.0341***	0.0339***
		(0.00632)	(0.00628)	(0.00629)
White		-0.0288***	-0.0227***	-0.0231***
		(0.00617)	(0.00616)	(0.00623)
Male		-0.0679***	-0.0652***	-0.0653***
		(0.00591)	(0.00586)	(0.00586)
Republican			-0.0963***	-0.0964***
			(0.0101)	(0.0101)
Share manufacturing				0.000471
				(0.00101)
Share foreign born				0.000754
				(0.000860)
Female employment rate				0.00253+
				(0.00141)
Population density				-0.00000185
				(0.00000124)
Observations	10227	10135	10135	10135

Coefficients from lpm from of answering "not enough" 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 2007-2017. Includes survey-year fixed effects. Robust standard errors, clustered by county in parentheses.

Recent work suggests that workers susceptible to automation may demand more redistribution (Thewissen and Rueda, 2019). Aggregate data suggests they are more likely to vote for far-right parties (Anelli, Colantone and Stanig, 2019; Frey, Berger and Chen, 2018; Dal Bó et al., 2018). By contrast, the "winners" of the technological revolution seem to be individually more likely to support more conservative parties (Gallego, Kurer and Schöll, forthcoming).

There is a small literature with inconclusive results that relates the effect of *policies* upon the recent economic disruption caused by technological change or trade to shifting perceptions of the role of government. Margalit (2011) finds that mitigation policies in the form of federal worker compensation (Trade Adjustment and Assistance) have the effect of diminishing the anti-incumbency advantage of trade shocks in presidential elections. Vlandas and Halikiopoulou (2018) use cross-country evidence in Europe and find that more generous unemployment benefits and employment protection laws mitigate the effect of unemployment on far-right support. Gingrich (2019) using survey evidence from developed countries finds that a broader set of compensation policies such as early retirement benefits, greater public spending and more regulated labor markets has limited effects on voting preferences, and may heighten far-right voting (conditional on individual technological exposure).

Our argument is distinct from these studies in that we focus on learning about the productivity of a public good investment, higher education spending, that has specific complementarities with an environment characterized by high levels of technological change. Our data also allows for a more credible research design for studying the consequences of these complementarities on political outcomes.

4.1 Ideology and Partisanship

We assess two types of measures. First, we study changes in support to Democratic party candidates in Governor and Presidential races. Second, we examine changes in counties' ideological liberalism as measured by the liberalism of and support for winning candidates for the United States Senate.

4.1.1 Data and Econometric Model

We examine decadal changes in the partisanship of the vote since 1980s/early 1990s and late 2010s (the last year in our election data is 2018), using Leip's election Atlas (Leip, 2017). For the presidential vote, we look at the shift between presidential elections in 1988 and 2016. For gubernatorial elections, the starting period is either 1990 or 1992 depending on whether a state had a governor's election in 1990 and the ending period is 2016 or 2018 based on the same consideration.

We use DW-NOMINATE (Lewis et al., 2020) and the DIME dataset (Bonica, 2015) to measure the ideology of the electorate in each county, through the ideology of winning candidates.[12]. Given changes in districts for other types of elections and the availability of rich data, we use Senate elections. Our focus is on the shift of the ideologies of winning candidates in these elections with increasing values indicating more liberal ideological positions.

We use an analogous econometric model to the one we estimated for studying economic outcomes. We again estimate the model using OLS and an instrumental variable estimation that employs 1950s routine exposure as an instrument for beginning of period routine exposure. We weigh regressions by the share of the national population in the county and cluster standard errors by county.

4.1.2 Results

Table 4 reports our coefficient estimates for all the dependent variables relating to political outcomes, based on 1990s levels of Higher Education investment and of routine exposure. Additionally, Table 5 displays models with 1990 HE investment and 1990 levels of routine

[12]DW-NOMINATE has been used in countless studies since its predecessor NOMINATE was introduced in (Poole and Rosenthal, 1985). The DIME score has been validated as powerful predictor of positions in a vast range of policy domains, and in particular, of fiscal policy preferences (Bonica, 2019)

exposure, instrumented by their 1950 levels.[13]

Figure 6 plots marginal effect using 1950 levels as an instrument for routine exposure in 1990, and 1990 levels of higher education investment.[14] We find that the higher pre-existing investments in education are, the greater the shift towards more Democratic partisanship and towards more liberal election winners that is associated with automation are. In counties where there were no investments in higher education in 1990, greater exposure to automation was associated with a shift towards Democratic voting in gubernatorial elections in the three decades 1990-2020. A one standard deviation change in the routine share of employment (.033) was associated with a 1.2 percentage point decadal decrease in Democratic vote share (or about eight percent of a standard deviation in changes to Democratic vote in these elections). At the 95th percentile of investment the effects are instead positive: the Democratic vote share is greater the bigger the automation levels: a one standard deviation change in routine share of employment is associated with a 1.5 percentage point increase in the Democratic vote share (or 9.7% of a standard deviation). In Presidential elections, the effects of automation at low and high levels of higher education investment similarly increase, although they are positive for all levels of higher education investment. We also find that using their DW-NOMINATE scores, the winning candidates in Senate elections associated with more exposure to automation tend to be more liberal as investments in higher education increase (estimates using DIME are too noisy). The magnitudes are larger for ideology: at places with no investment in higher education, a one standard deviation change in routine exposure is associated with half a standard deviation *decrease* in the liberalism of winners, while it is associated with a quarter deviation *increase* at high levels of education investments.

[13]In Appendix Table B.4, we show OLS models with county covariates that vary by year, with very similar results.

[14]Analogously, Appendix Figure A.2 displays the marginal effect from models in Table 4 with very similar patterns.

Table 4: Technological change, higher education investments and political outcomes–OLS Estimates

	(1) △ Governor Dem. share	(2) △ President Dem. share	(3) △ Senate winner liberalism (DIME)	(4) △ Senate winner liberalism (DW-NOMINATE)
Routine exposure 1990 × HE Investment 1990	0.0648** (0.0236)	0.0570** (0.0184)	0.208 (0.227)	0.107+ (0.0640)
HE Investment 1990	-0.0174* (0.00693)	-0.0159** (0.00537)	-0.0602 (0.0644)	0.0311+ (0.0183)
Routine Exposure 1990	-0.0634 (0.119)	-0.132 (0.0944)	-1.292 (1.411)	-0.220 (0.398)
Observations	8850	9315	9220	9220

OLS Models with HE investment levels and routine exposure in 1990, as well county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by county in parentheses.

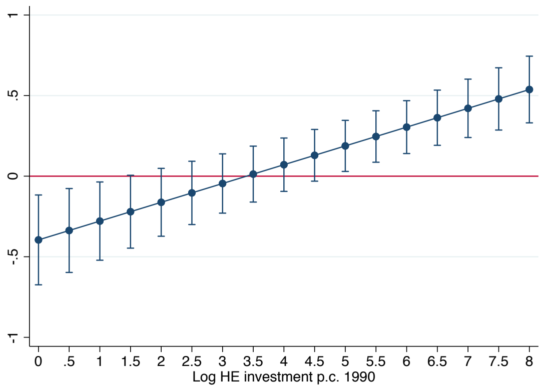
Table 5: Technological Change, Higher Education Investments, and Political Outcomes–IV Estimates.

	(1) △ Governor Dem. share	(2) △ President Dem. share	(3) △ Senate winner liberalism (DIME)	(4) △ Senate winner liberalism (DW-NOMINATE)
Routine exposure × HE Investment 1990	0.00493+ (0.00304)	0.0616* (0.0302)	-0.117 (0.272)	0.315** (0.130)
HE Investment 1990	0.00117 (0.0108)	-0.0175+ (0.00970)	0.0915 (0.140)	0.104** (0.0388)
Routine Exposure	0.0484 (0.205)	0.242 (2.778)	-0.481 (0.634)	2.114**
Observations	8850	9315	9220	9220

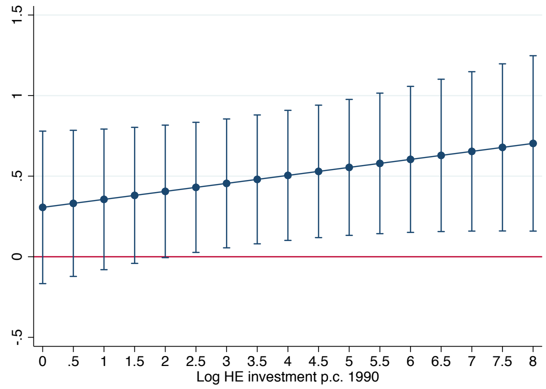
IV estimates with actual HE investment levels in 1990 and routine share of occupations in 1990 predicted by 1950s levels of the same variable, as well county covariates in 1990 interacted with decade dummies. Specifications also include decade, region fixed effects. Standard errors, clustered by county in parentheses.

Figure 6: IV: Marginal effect of the change (percent) in routine share of employment by level of investment in higher education on political variables.

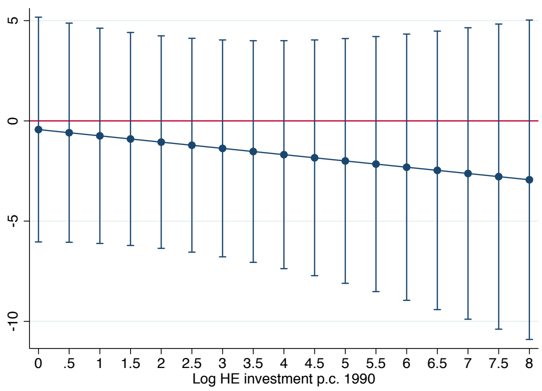
(a) △ Governor Democratic share



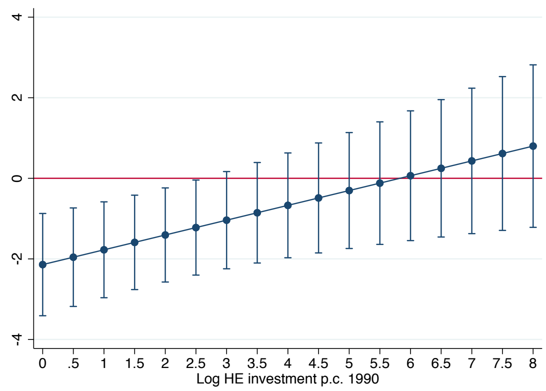
(b) △ Presidential Democratic share



(c) △ Liberalism of winning Senate candidate (DIME)



(d) △ Liberalism of winning Senate candidate (DW-NOMINATE)



Note: Shows marginal effects of percent (0-1) differences in routine share of employment in 1990 on political outcomes, as log-total HE revenue per capita in the county increases, estimated from IV models in Table 5.

5 Learning to Love Government? Complete and Incomplete Learning about Public Policy

Our empirical results 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.

Nonetheless, higher education spending trends do not suggest a substantial public policy response. Our empirical results suggest that one possible reason why is that voters have divergent policy opinions about whether investing more individuals–realistically–are uncertain about the productivity of educational investments. This in turn determine 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. For the reasons we described in the introduction, this seems implausible.

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). 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 "works" in some places but not others, so individuals in Kansas might not be able to draw much inference from what takes place in Massachusetts.

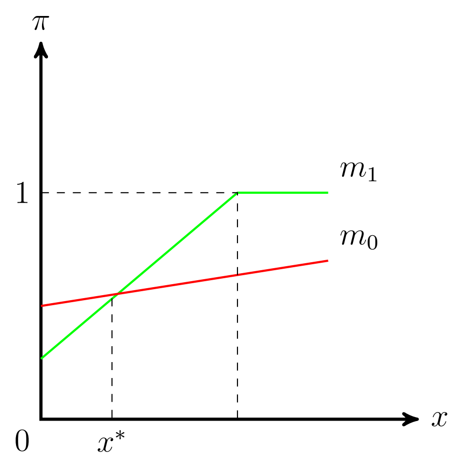
Each representative voter is aware of the history of higher education investments and economic outcomes in their community. To keep things simple, economic outcomes are dichotomized to be either successful or unsuccessful. This is most easily interpreted as whether or not an individual has lifetime earnings, 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 7 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

Figure 7: 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.



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:

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

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

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

which simply says that voters will prefer more higher education investments, the more productive they are (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.[15]

In a starkly different outcome, if a representative voter in any given t has a belief above μ^*—that educational investments are not productive, then optimal actions taken by subsequent representative voters can lead to convergence on $\mu = 1$ with positive probability.

Stepping back, the model 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

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

success and failure for passive learners to make up for their original differences in beliefs.

6 Conclusion

The public is divided in its view of many public policies, even when faced with similar external circumstances. Our main contribution is to document that for higher education investments, places that experienced large economic shocks due to technological change while having greater higher education investments did better in terms of employment, unemployment rate and per capita income than those that did not have high levels of education investment. Yet, places with little investment did not seem to demand more spending or at least not as much as in places experiencing similar shocks but starting with higher levels of education investment. One may have expected to see the opposite: places with little investment demanding more and those that experience high investment demanding the same or less, as the contribution of marginal spending should be lower.

To explain these puzzling findings, we develop a model of passive learning about policy where learning is incomplete. In the model, individuals only learn from their own geographical area's experience. Whether or not they observe a particular policy as being effective depends crucially on whether they both have the policy in place and happen to experience the exogenous shock under which the policy is most effective. If they do not, given the costliness of the policy they will tend to disfavor it.

We think that this simple model fits well with our observations in the prominent case of incomplete learning in the demand for higher education investment that we study, but further research is needed to establish how widely applicable it is. Would learning about policies to mitigate less salient or more complex policies work in the same way? At what level of policy demand does learning stop? What are the role of individual, rather than collective (such as county) experiences and how much can be learned from others' experiences?

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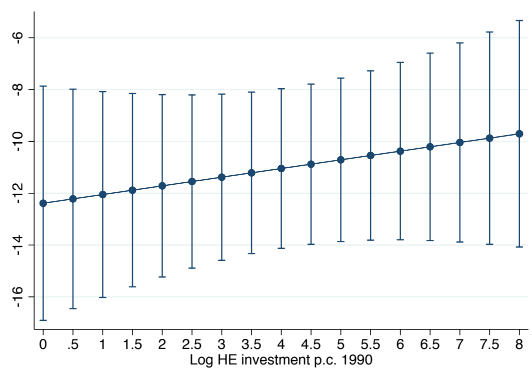
Appendix

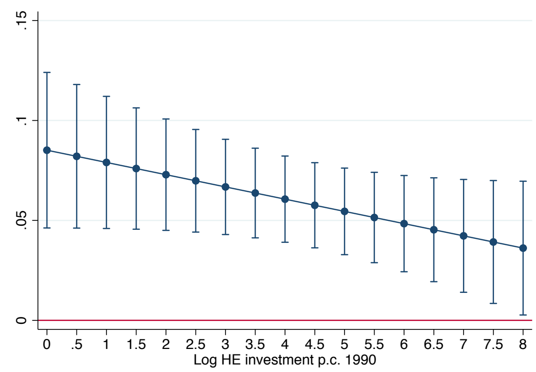
A Appendix Figures

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 economic outcomes.

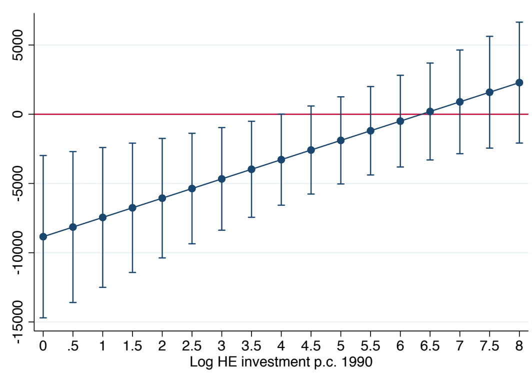
(a) △ Employment Share



(b) △ Unemployment Rate



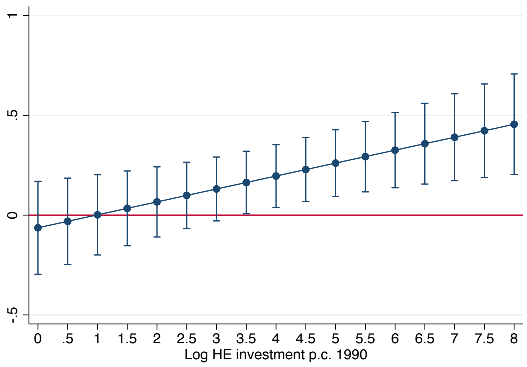
(c) △ Real Per Capita Income



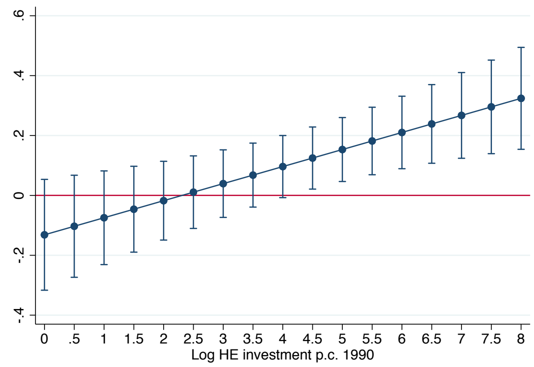
Note: Shows marginal effects of percent (0-1) differences in routine share of employment in 1990 on labor market outcomes, as log-total HE revenue per county increases, estimated from models in Table 1.

Figure A.2: OLS Models: Marginal effect of percent differences (0-1) in routine share of employment by level of investment in higher education on political variables.

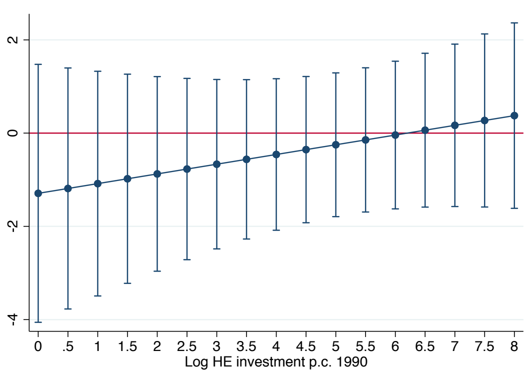
(a) △ Governor Democratic share



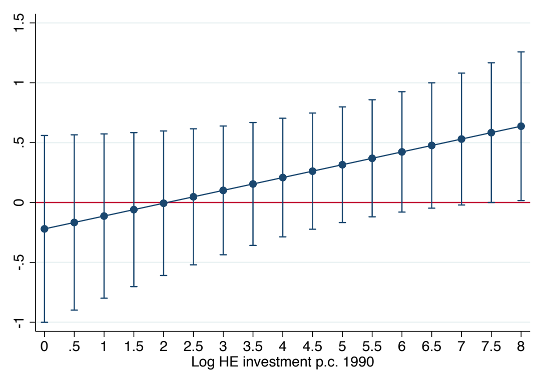
(b) △ Presidential Democratic share



(c) △ Liberalism of winning Senate candidate (DIME)



(d) △ Liberalism of winning Senate candidate (DW-NOMINATE)



Note: Shows marginal effects of percent (0-1) differences in routine share of employment in 1990 on labor market outcomes, as log-total HE revenue per capita in the county increases, estimated from models in Table 4.

B Appendix Tables

Table B.1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Outcome variables					
Ch. in share employed	0.656	2.955	-8.683	15.186	9486
Ch. in unemployment rate	0.006	0.032	-0.392	0.4	9486
Ch. in real per capita income	1332	2463	-31174.473	17559	9486
Ch. in Governor elec. Dem. share	-0.048	0.144	-0.570	0.555	8869
Ch. in Presidential elec. Dem. share	-0.038	0.082	-0.424	0.242	9332
Ch. in Senate winner liberalism (DIME)	-0.05	0.37	-2.355	1.212	9220
Ch. in Senate winner liberalism (DW-NOMINATE)	-0.019	0.129	-0.521	0.35	9220
Independent variables					
Share College Educated	45.167	9.1	19.944	70.555	9321
Share Manufacturing Empl.	21.467	10.895	0.108	61.82	9321
Share Pop. foreign Born	4.705	5.396	0.385	48.908	9321
Female Employment Rate	62.763	6.812	33.243	79.606	9321
White share	0.833	0.163	0.096	0.992	9319
Black share	0.09	0.146	0	0.857	9319
Population Density	236.06	1516.38	0.05	66940.07	9497

Table B.2: Technological Change, Higher Education Investments, and Labor Market Outcomes–OLS models with contemporaneous county covariates.

	(1) △ Share employed	(2) △ Unemp. rate	(3) △ Real PC Income
Routine exposure × HE investment 1990	1.897*	-0.00766+	1409.1*
	(0.751)	(0.00396)	(566.1)
HE investment 1990	-0.521*	0.00214+	-377.7*
	(0.221)	(0.00116)	(161.9)
Routine Share	-18.49***	0.0922***	-11710.3***
	(3.821)	(0.0206)	(3373.6)
Share College Educated	0.000706	-0.00000458	19.92**
	(0.00964)	(0.0000494)	(7.521)
Share Manufacturing Empl.	-0.0571***	0.0000662+	-13.74**
	(0.00656)	(0.0000341)	(4.355)
Share Pop. foreign Born	0.0424***	0.000184***	23.19*
	(0.00807)	(0.0000402)	(10.37)
Female Employment Rate	-0.289***	-0.000104	76.63***
	(0.0375)	(0.0000744)	(14.77)
White share	4.556***	-0.0238***	2063.3*
	(0.713)	(0.00365)	(811.2)
Black share	3.228***	-0.00378	256.3
	(0.760)	(0.00436)	(875.1)
Population Density	0.0196+	-0.000210***	0.0468+
	(0.0115)	(0.00505)	(0.0270)
Observations	9313	9313	9313

OLS models with HE investment levels and routine exposure in 1990, as well as contemporaneous county covariates. Specifications also include decade, region fixed effects. Standard errors, clustered by county in parentheses.

Table B.3: Probit models of supporting state funding for California's public colleges and universities

	(1) OLS (no controls)	(2) OLS with socio-demographic controls	(3) (2) and partisanship controls	(4) (3) and county controls
Routine share X HE investment	1.254***	1.151***	1.018**	0.913*
	(0.329)	(0.335)	(0.345)	(0.379)
Routine share	-3.070*	-3.119*	-2.856+	-5.014*
	(1.506)	(1.544)	(1.599)	(2.222)
HE investment	-0.374***	-0.345**	-0.306**	-0.273*
	(0.107)	(0.109)	(0.113)	(0.121)
Parent		-0.192***	-0.189***	-0.188***
		(0.0381)	(0.0384)	(0.0384)
Homeowner		-0.361***	-0.319***	-0.323***
		(0.0397)	(0.0401)	(0.0402)
College graduate		0.213***	0.209***	0.208***
		(0.0382)	(0.0385)	(0.0386)
White		-0.170***	-0.141***	-0.143***
		(0.0364)	(0.0368)	(0.0371)
Male		-0.405***	-0.396***	-0.397***
		(0.0356)	(0.0360)	(0.0360)
Republican			-0.454***	-0.455***
			(0.0415)	(0.0416)
Share manufacturing				0.00132
				(0.00603)
Share foreign born				0.00418
				(0.00479)
Female employment rate				0.0157+
				(0.00863)
Population density				-0.0000108
				(0.00000860)
Observations	10227	10135	10135	10135

Coefficients from probit from of answering "not enough" in answering 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 2007-2017. Includes survey-year fixed effects. Robust standard errors, clustered by county in parentheses.

Table B.4: Technological Change, Higher Education Investments, and Political Outcomes– OLS models with contemporaneous county covariates.

	(1)	(2)	(3)	(4)
	△ Governor Dem. share	△ President Dem. share	△ Senate winner liberalism (DIME)	△ Senate winner liberalism (DW-NOMINATE)
Routine exposure × HE Investment 1990	0.0510^{+}	0.0476*	0.210	0.115^{+}
	(0.0274)	(0.0187)	(0.227)	(0.0644)
HE Investment 1990	-0.0137^{+}	-0.0131*	-0.0602	0.0331^{+}
	(0.00799)	(0.00547)	(0.0644)	(0.0184)
Routine Exposure	0.0182	-0.160^{+}	-1.198	0.325
	(0.131)	(0.0944)	(1.401)	(0.397)
Share College Educated	0.000719*	0.000588**	-0.00509	-0.000261
	(0.000327)	(0.000210)	(0.00345)	(0.00122)
Share Manufacturing Empl.	-0.000125	-0.000484***	-0.000662	0.000214
	(0.000219)	(0.000139)	(0.00201)	(0.000636)
Share Pop. foreign Born	0.000897**	0.00132***	0.000814	0.00626***
	(0.000345)	(0.000287)	(0.00263)	(0.00139)
Female Employment Rate	0.0000855	0.00189***	0.0140***	0.00373**
	(0.000891)	(0.000297)	(0.00390)	(0.00122)
White share	-0.114***	-0.162***	-0.574	-0.259*
	(0.0232)	(0.0206)	(0.358)	(0.107)
Black share	0.0311	-0.0225	-0.276	-0.303**
	(0.0313)	(0.0256)	(0.381)	(0.110)
Population Density	-0.000672^{+}	-0.00141***	-0.000605	-0.0200*
	(0.000347)	(0.000339)	(0.0163)	(0.00982)
Observations	8850	9315	9220	9220

OLS models with HE investment levels and routine exposure in 1990, as well as contemporaneous county covariates. Specifications also includes decade, region fixed effects. Standard errors, clustered by county in parentheses.