Online Appendices for "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

February 26, 2024

A 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).

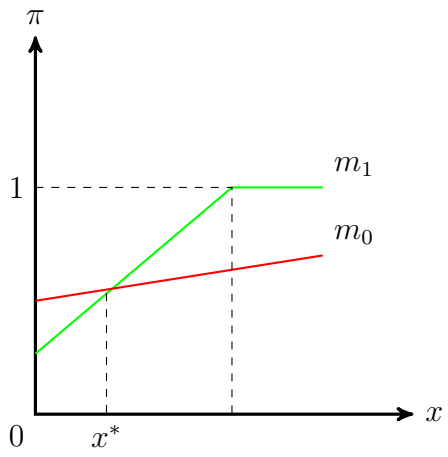
Each representative voter chooses a level of educational investment x. The voter chooses x to maximize their probability of economic success while taking into account the tax costs associated with the investment. The probability of economic success depends on how educational investments map into higher 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.

References

Autor, David H and David Dorn. 2013. "The growth of low-skill service jobs and the polarization of the US labor market." *American Economic Review* 103(5):1553–1597.

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

Autor, David H, David Dorn and Gordon H Hanson. 2015. "Untangling trade and technology: Evidence from local labour markets." *The Economic Journal* 125(584):621–646.

Autor, David H, Frank Levy and Richard J Murnane. 2003. "The skill content of recent technological change: An empirical exploration." *The Quarterly Journal of Economics* 118(4).

Autor, David H, Lawrence F Katz and Melissa S Kearney. 2008. "Trends in US wage inequality: Revising the revisionists." *The Review of Economics and Statistics* 90(2):300–323.

Berry, Donald A. 1972. "A Bernoulli two-armed bandit." *The Annals of Mathematical Statistics* pp. 871–897.

Busemeyer, Marius R and Tobias Tober. 2022. "Dealing with Technological Change: Social Policy Preferences and Institutional Context." *Comparative Political Studies* p. NA.

Callander, Steven. 2011. "Searching for good policies." *American Political Science Review* 105(4):643–662.

Callander, Steven and Bård Harstad. 2015. "Experimentation in federal systems." *The Quarterly Journal of Economics* 130(2):951–1002.

Callander, Steven and Patrick Hummel. 2014. "Preemptive policy experimentation." *Econometrica* 82(4):1509–1528.

Chamley, Christophe P. 2004. *Rational herds: Economic models of social learning*. Cambridge University Press.

Chetty, Raj, John N Friedman, Emmanuel Saez, Nicholas Turner and Danny Yagan. 2020. "Income segregation and intergenerational mobility across colleges in the United States." *The Quarterly Journal of Economics* 135(3):1567–1633.

Desrochers, D.M. and J. Sun. 2015. IPEDS Analytics: Delta Cost Project Database 1987-2012 (NCES 2015-091). Technical report U.S. Department of Education. National Center for Education Statistics.

URL: *http://nces.ed.gov/pubsearch*

Hacker, Jacob S and Paul Pierson. 2010. *Winner-take-all politics: How Washington made the rich richer–and turned its back on the middle class*. Simon and Schuster.

Knapp, L, JE Kelly-Reid and SA Ginder. 2018. "Integrated Postsecondary Education Data System (IPEDS) methodology report." *Washington, DC: US Department of Education* .

McLennan, Andrew. 1984. "Price dispersion and incomplete learning in the long run." *Journal of Economic dynamics and control* 7(3):331–347.

Mettler, Suzanne. 2010. "The unintended consequences of social policy." *American Political Science Review* 104(2):327–346.

Ortoleva, Pietro. 2012. "Modeling the change of paradigm: Non-Bayesian reactions to unexpected news." *American Economic Review* 102(6):2410–36.

Piketty, Thomas. 1995. "Social mobility and redistributive politics." *The Quarterly Journal of Economics* 110(3):551–584.

Rothschild, Michael. 1974. "A two-armed bandit theory of market pricing." *Journal of Economic Theory* 9(2):185–202.

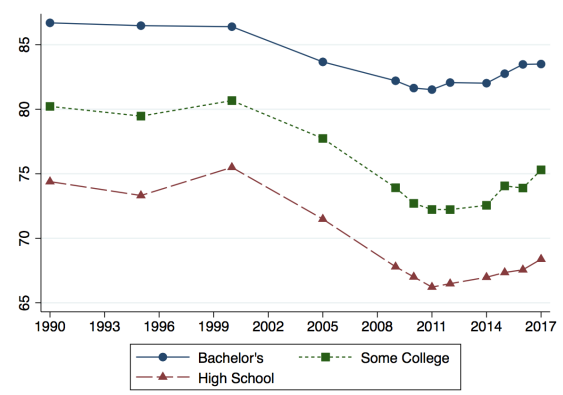
US Department of Labor. 1977. *Dictionary Of Occupational Titles*. US Federal Government.

Volden, Craig, Michael M Ting and Daniel P Carpenter. 2008. "A formal model of learning and policy diffusion." *American Political Science Review* 102(3):319–332.

B Appendix Figures

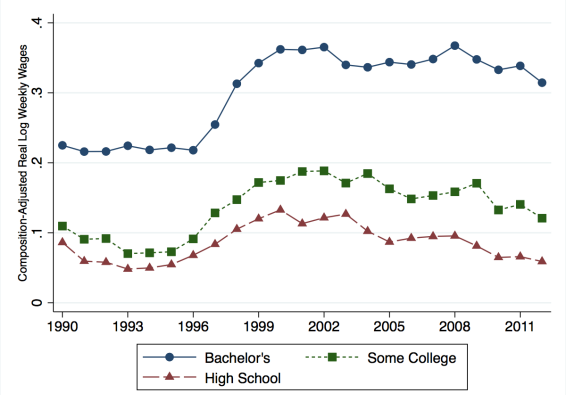
Figure B.1: Evolution since 1990 in employment and earnings by education level

(a) Employment rate (percent)



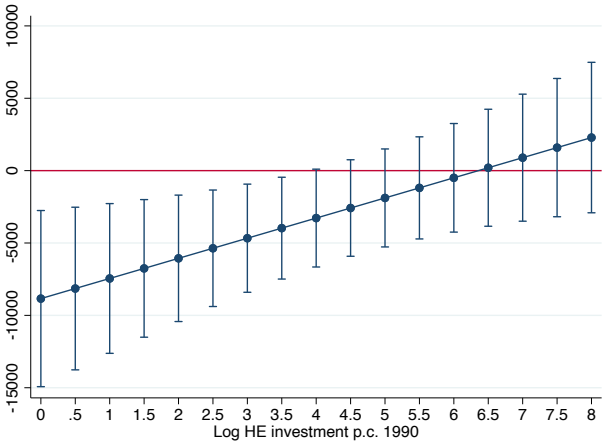
Note: Outcome is share of 25-64 years old in employment. Source: US Census' Current Population Survey (CPS).

(b) Earnings



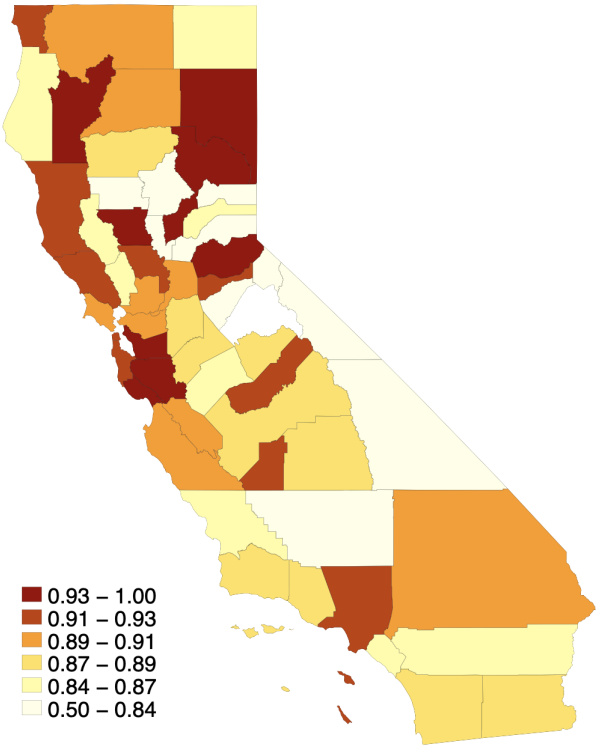
Note: Outcome is Log-weekly real wages for full-time full-year male workers. Source: March CPS.

Figure B.2: 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 C.1.

Figure B.3: 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.

C Appendix Tables

C.1 Models of economic effect of higher education investment

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

	(1) OLS	(2) 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 C.2: 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 ment	routine + IV invest-
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 C.3: 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 C.4: 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 C.5: 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 C.6: 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 C.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 C.7: Technological change, higher education investments, and decadal change in per capita income, extensive and intensive margins

	(1) OLS	(2) 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 C.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. $+\ p < 0.10$, $*\ p < 0.05$, $**\ p < 0.01$, $***\ p < 0.001$

Table C.8: Technological change, higher education investments, and decadal change in per capita income

	(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 C.1. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.9: Technological Change, Higher Education Investments in different subsets of higher education, 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	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 C.4. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.10: Technological change, higher education investments in different subsets of higher education, 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	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 C.5. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table C.11: 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 ×	2.880	1.072	-8.371	-0.0937^{+}	10993.7*	0.2384***
HE Investment 1990	(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. $+ p < 0.10$, $* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

C.2 Models of support for more higher education investment in California

Table C.12: 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 C.13: 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 C.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.

Table C.14: 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

Table C.15: 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	0.009**	0.008+	0.008**	0.012
× HE investment 1990	(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 C.12. 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 C.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 C.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 C.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 C.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. + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

D Data Appendix for economic effect analysis

D.1 Routine exposure

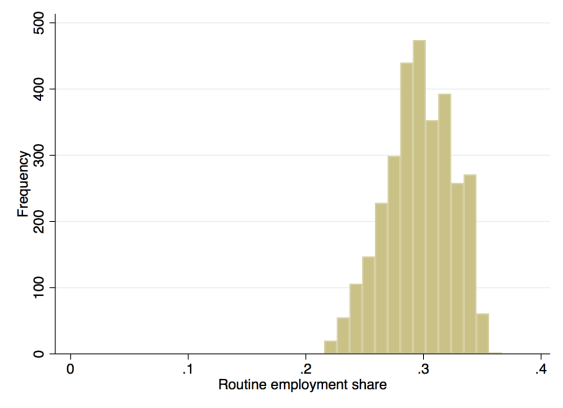
We use exposure to routine occupations as our measure of exposure of technological change. Routine occupations are defined as those in the top third of the distribution of occupations by degree of "routine intensity" of the tasks involved in the occupation (job). To measure the degree of exposure to 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).

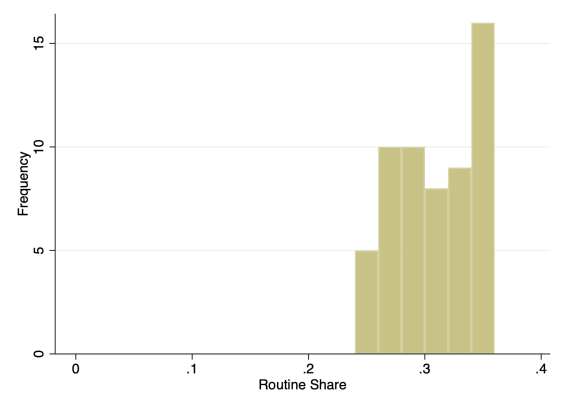
[3] This classification methodology was first introduced by Autor, Levy and Murnane (2003), and simplified into three types of tasks (routine, abstract and manual) by Autor, Katz and Kearney (2008).

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

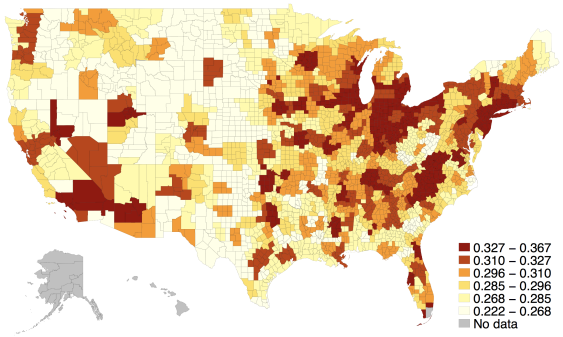
(a) Countrywide routine share of employment by county



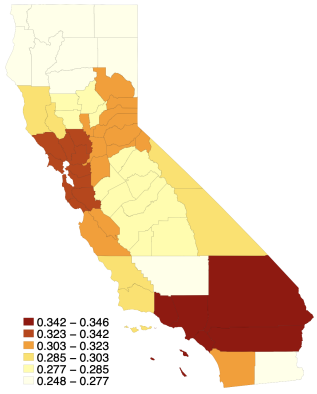
(b) California routine share of employment by county



(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 C.2.

[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).

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

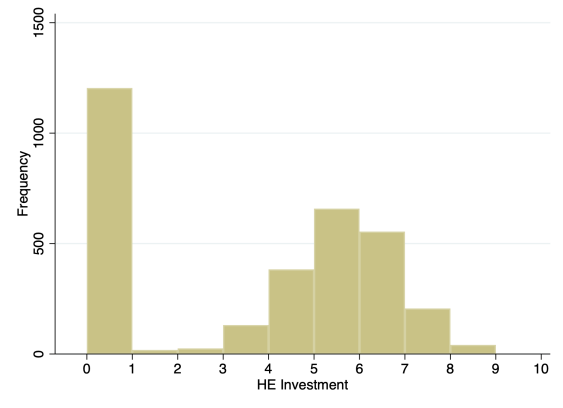
c indexes the county, i the institution and d the decade (1990, 2000 or 2010). The variable $\mathbf{1}_{<50kmic}$ takes the value 1 if the distance between the institution i and the centroid of county c is less than 50km, and 0 otherwise. We divide this sum of investments over the population in the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

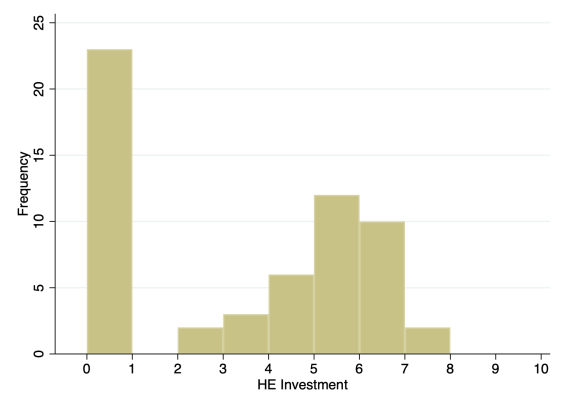
[7] Appendix Table C.13 summarizes the independent and dependent variables we use and, and Appendix Table C.3 shows the distribution of revenue for the different tiers of institutions.

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

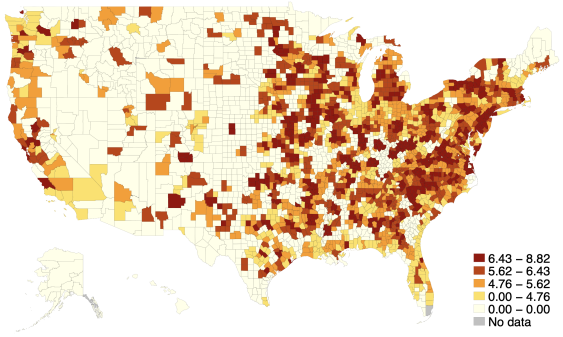
(a) National logged HE investment levels by county



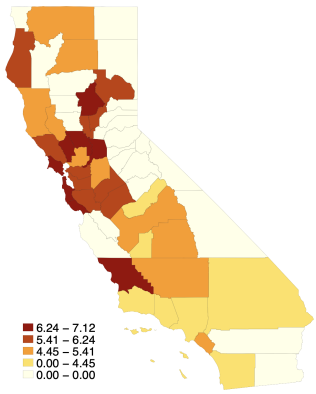
(b) California logged HE investment levels by county



(c) National geographic distribution of logged HE investment levels



(d) California geographic distribution of logged HE investment levels



E Additional empirical evidence on support for higher education investment

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

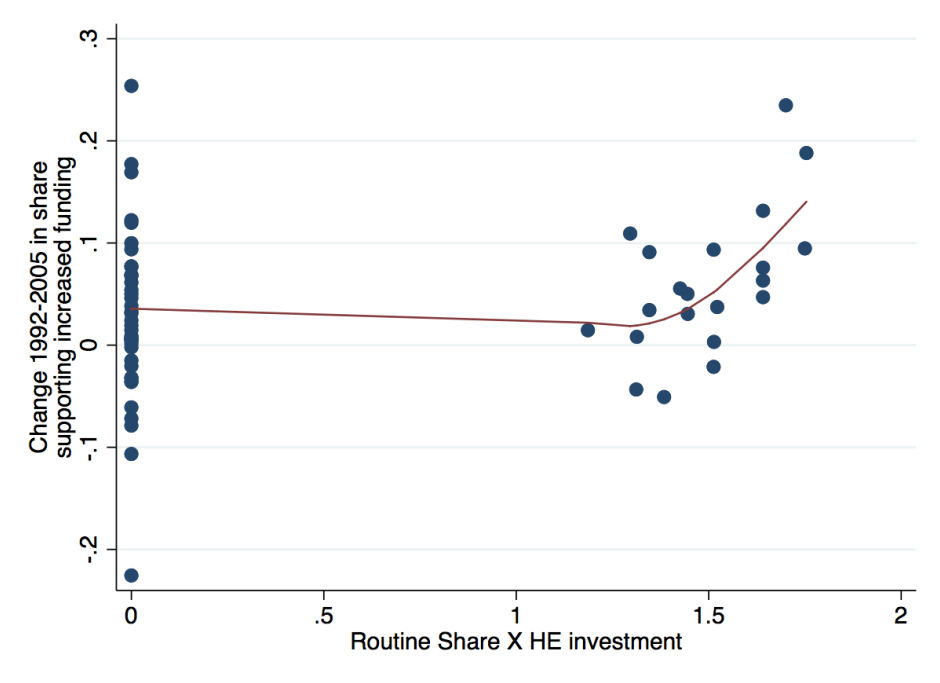
[8] Amendment 1 in the November 3, 1992 ballot (passed in the state by 53.7% of votes: "Shall there be an amendment to the Colorado constitution to require voter approval for certain state and local government tax revenue increases and debt; to restrict property, income, and other taxes; to limit the 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?"

TABOR: the state could retain any revenues collected and spend the money on health care, 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.

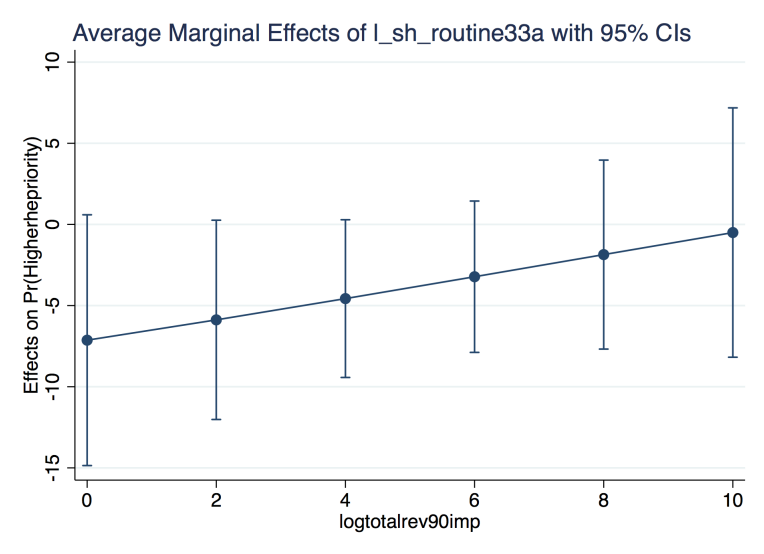


Figure E.2: Wisconsin: ME of routine exposure by level of HE investments on individual probability of responding that public higher education should be higher priority

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.

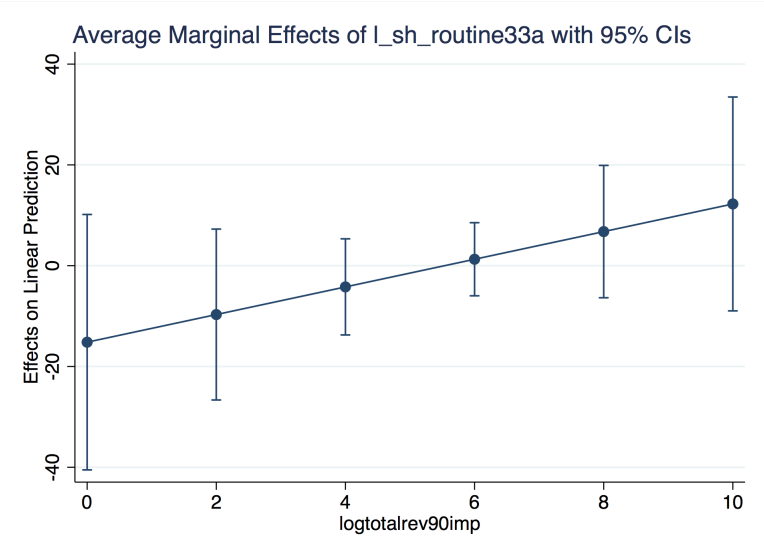


Figure E.3: Support for "building ladders" as a policy strategy to deal with technological changes (IV LP models with number of institutions in 1950s as instrument for HE investments)

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

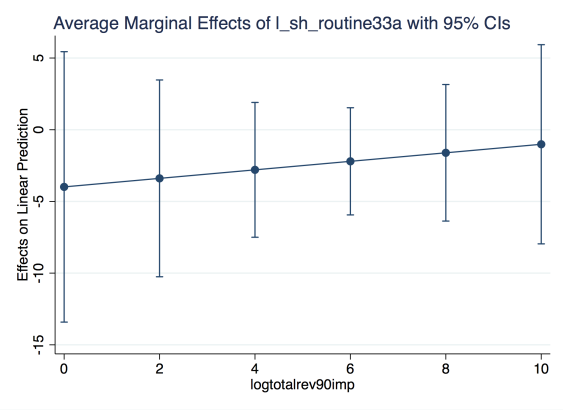


Figure E.4: ME of log routine exposure on trust in State Universities (linear model, 1-4)

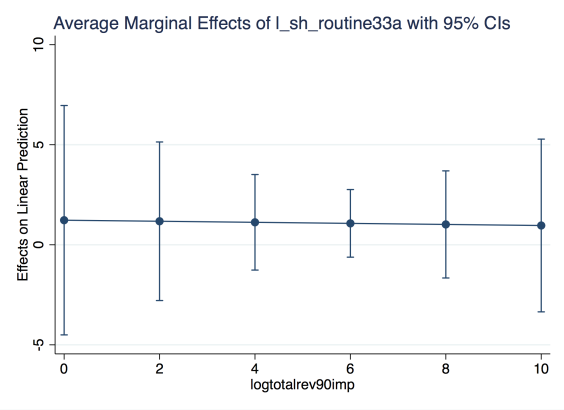


Figure E.5: ME of log routine exposure on trust in State Governments (linear model, 1-4)

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).