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

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Abstract

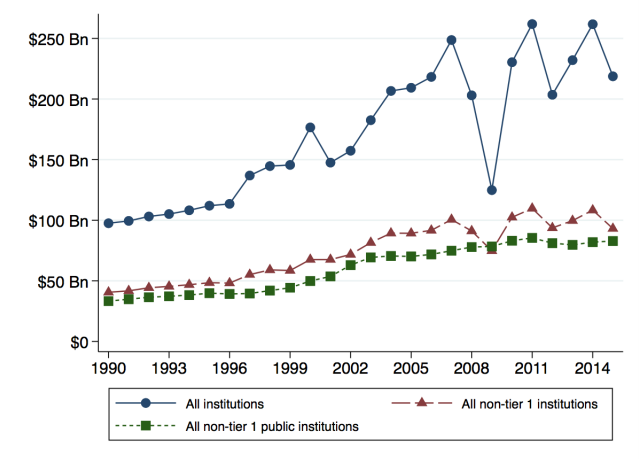
Why do voters have divergent beliefs about the role of government in solving social problems? We study this question in the context of skill-biased technological change and investment in higher education. We document that the negative income consequences of technological change are, descriptively, mitigated in US counties with greater levels of higher education investment. We show that exposure to these conditions is, in turn, correlated with greater public support for higher education spending. We conclude that higher education investments are productive. However, we also find evidence consistent with the idea that whether people in a community learn the benefits of higher education spending depends on what they believed to begin with. Learning is history dependent. In a context where higher education spending dampens the negative employment effects of technological change, a history of believing that education is productive may advantage local communities in learning the true productivity of higher education investments.

1 Introduction

Workplace automation has had well-known polarizing effects on the labor market over the last several decades in the United States. The trends in labor market outcomes by educational attainment are striking in having advantaged more educated workers and disadvantaged others. 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—with an even starker growth in differences in the college wage premium.[1]

A large literature (see e.g. Goldin and Katz, 2009; Autor, 2014; Acemoglu and Autor, 2011) has shown that skill-biased technological change is a major contributor to these trends. Since those who experience shocks may be liquidity-constrained or not choose optimally to make private investments in education, a natural policy reaction would be to invest more in higher education (HE). However, that does not seem to have happened over the last two decades. The trajectory of U.S. public and private real spending (excluding tuition) in higher education has been flat since 2005. This is shown in Figure 1. This is particularly true in non-research universities and colleges (non-tier 1), where 67% of all students enrolled in 2015.

Figure 1: Higher education investment by type of institution



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

[1] These relations are shown in Appendix Figures B.1a and B.1b.

One possibility is that even if there is a consensus that more investment is an optimal policy response, the political process may be captured by wealthy groups wanting to minimize tax costs. A different possibility is that voters do not agree that higher spending is the correct policy response. This view is consistent with the ambivalent perceptions in survey evidence. Pew (Parker, 2019) has asked since 2012 a question on whether colleges and universities "are having a positive effect on the way things are going in this country today". 50% of those surveyed (and only 33% of Republicans) in 2019 thought that colleges and universities have a positive effect on the country, compared to 60% in 2012.[2]

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

There are at least two salient answers to these questions in the literature. The first is self-interest. Individuals will support the policies they stand to benefit the most from. Groups whose jobs may be automated away will support more welfare or protectionist policies that slow down technological change, while college graduates may prefer greater investments in higher education (Busemeyer and Tober, 2022; Busemeyer et al., 2022; Gallego et al., 2022; Thewissen and Rueda, 2019).[3] The beliefs about and theories of policy that individuals adopt will ultimately justify their underlying interests. For example, a high income person may rationalize a preference for low taxes by adopting a belief that the government is inefficient in producing a given public good from taxes.

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

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

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

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

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

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

One may expect respondents from counties with lower investment levels to demand more of it, particularly if they are effective elsewhere. However, the opposite is the case, and this is independent of partisan identification. Individuals may become more supportive of higher

education investments only when they are in a place conducive to learning about its effectiveness. They do not "learn" about the effectiveness of higher education from experiences elsewhere, perhaps because they do not think it would be effective in their own context, or they have few connections in places with high investments in higher education so as to obtain such information.

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

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

We also complement the view that Republicans and Democrats may be increasingly polarized with regards to national policies while actually being in agreement on local or state matters (Jensen et al., 2021).[4] We suggest that the formation of policy preferences is partly the result of past highly localized experiences with policies, and that when they are seen to

[4]It can likely also contribute to our understanding of why cleavages among the highly educated may have shifted over time (Dalton, 2018; Gethin, Martínez-Toledano and Piketty, 2022), potentially by creating a demand for policy effectiveness. And to our understanding of the differences in the politics of prosperous cities and others, where voters may become less supportive of government as a result of prior ineffectiveness (McKay, 2019).

have broad positive effects, individuals can overcome their immediate self-interest (Busemeyer and Tober, 2022), and partisan tendencies, institutional limitations, and sectoral constraints (Ansell, 2008; Ansell and Gingrich, 2013). This implies a way in which government intervention could become more popular over time: by being effective at problem-solving for citizens on the specific issues it does handle.

2 Technological Change, Higher Education Investment and Income

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

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

2.1 Data

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

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

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

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

2.2 Econometric Model

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

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

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

Observations are indexed by county c, and decade d. In our main specifications we include a vector of controls $\mathbf{X}$ for counties at the beginning of the period we study (1990): share of employment in manufacturing, share of female employment, share of the population with

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

some college, share foreign born (Autor, Dorn and Hanson (2015)'s controls), population density and controls for white and black share of the population. We interact this vector with our decade dummies. D are two decade fixed effects (2000, 2010) and R are eight census divisions fixed effects. We weight regressions by the national population share in the county and cluster standard errors by commuting zone.[7]

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

We also present models where, like Autor, Dorn and Hanson (2015), we instrument the levels of the routine share of employment in 1990 with their corresponding values in 1950 (the earliest available), before our contemporary routine exposure distinction was relevant for the automation of jobs and so, before jobs growth (or other economic trends) since the 1990s could have been affected by the routine share of occupations. It is hard to imagine 1950s levels of routine employment being locally determined by subsequent developments, or indeed by the levels of investment in higher education as long after as the 1990s.[8]

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

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

2.3 Results

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

We plot in Figure 2 the marginal effects of routine share on per capita income from our instrumental variable estimates in Table C.1.[10] The plots show that the higher pre-existing investments in education are, the more positive the income growth associated with automation is. In counties with no 1990 investments in higher education, greater exposure to automation was associated with a near-zero effect on the change in per capita income in each of the three decades 1990-2020. A one standard deviation change in the routine share of employment (.033) was associated with a 156 dollar difference in the decadal change in per capita income, or six percent of a standard deviation. At high levels of investment (8 log-HE investment, the 95th percentile), by contrast, the effects are positive and large: a one

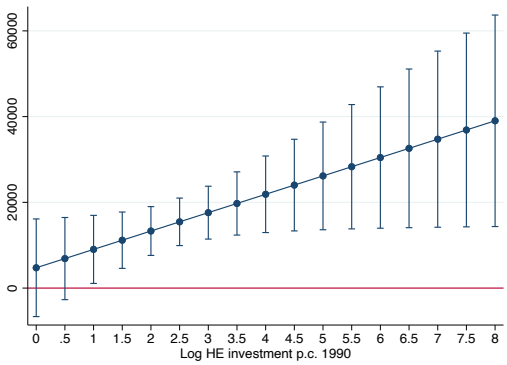
(1999), for instance, have argued that for the first half of the 20th century that agricultural productivity and religious uniformity positively affected investments in higher education. The (similar) results from these models are shown in Appendix Table C.2.

[9]In Appendix B, we run specifications distinguishing investments in all higher education institutions, tier 1 institutions alone, and public community colleges (summary statistics of investments by type of institution are shown in Table C.3). We show OLS results in Table C.4 and IV results in Table C.5. In the IV estimates, results are similar for all subsets of institutions. We also distinguish between high- and low- manufacturing share counties in Table C.6, with similar results in the IV models, although larger in low manufacturing areas. We also show models in Table C.7 of the difference in effects from the extensive (presence of investment at all) and intensive margins of higher education investment, as well as others where we do not weight counties by population (Tables C.8, C.9, C.10). Results are very similar.

[10]We also show in Appendix Figure B.2 the corresponding marginal effect plots for the OLS estimates in model 1 of Table C.1. To get a sense of the types of counties that are driving our results, Table C.11 shows what county characteristics correlate with investments in higher education. Share of college educated, share manufacturing, or population foreign born are correlates of investment in higher education (we control for those variables in our main models).

standard deviation change in routine share is associated with a $1,287 greater change in per capita income, or about fifty-two percent of a standard deviation.

Figure 2: IV estimates: Marginal effects of differences in routine employment share on economic outcomes, by level of investment in higher education.



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

3 Public Preferences for Higher Education Spending

The analysis in the previous section provided new evidence about the value of higher education investments in a political economy setting marked by substantial technological change. In this section, we seek to ascertain whether technological change influenced the policy opinions of voters about higher education spending, and whether this effect varied across counties by differences in initial levels of higher education investments. We turn to a survey on policy opinions about higher education spending in California, the Public Policy Institute of California (PPIC) "Statewide Surveys." We use this survey as we do not know of a national survey with questions on attitudes towards higher education and sufficient coverage to study variation by levels of technological shock and investments in education.[11]

PPIC has been conducting monthly surveys for over a decade on California's citizens. Most of their November issues include a series of questions on higher education in the state.

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

Each of them has between 1,700 and 2,500 adult respondents drawn at random using random-digit-dialing by telephone. We use raw observations, representative of the California public overall.[12]

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

We have responses across seven surveys in the period 2007-18 that contained the question for a total of 13,390 observations.[14] Since all the surveys are concentrated towards the end of the multi-decade period over which technological change has taken place, we cannot study changes in opinion but rather pool the observations and study the partial correlation between exposure to technological change and support for higher education spending and whether this correlation varies by initial levels of higher education investment. We estimate using OLS linear probability models regressing *HE Spending Support* on routine share, higher education investment in 1990 and their interaction. We cluster standard errors on commuting zones, the assignment level of our routine share variable. We do not include survey weights as we opt to explicitly include and show individual covariates in our models.

Figure 3a shows descriptively how the level of support varies by county subgroups of routine exposure and investment. We see that counties that have both high exposure to automation and the highest levels of investment in HE are more supportive of HE funding than other places.[15] Figure 3b reports our key quantity of interest which is how the marginal effect of routine share on the support for HE spending varies with the levels of prior investment

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

[13]Appendix Figure B.3 plots the average levels of HE Spending Support by county in the pooled PPIC data.

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

[15]Note that our theoretical argument does not make specific predictions across each subgroup presented in Figure 3a or about the functional form of the conditional relationship. The key expectation is that the starkest contrast is between places with large automation shocks and the highest, more visible investment levels and the rest.

on HE. The effects are such that a one standard deviation (SD) change in prior HE investment shifts by about 1 percentage point the marginal effect of a 1 SD difference in routine share.[16] This effect on the probability of support for more investment in HE is relatively small, but of a similar magnitude to other variables that we may think are explanatory of support for HE, such as being a parent, or being a college graduate –albeit smaller than others such as self-identifying as Republican.[17] Appendix Table C.12 reports coefficient estimates with different sets of conditioning variables at the individual and county level (we report in the figure the most conservative one, with full individual, and county controls, including partisanship). Table C.15 shows results are similar for the unemployed, those who have not attended college themselves, those earning modest salaries, and self-identified Republicans. Since these groups are the least likely to support investment in higher education (Busemeyer and Tober, 2022), this suggests a mechanism different from self-interest is at play in places with high routine share and high investment.[18] [19]

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

[16] To check the representativeness of our findings for the whole nation, we use SDs of these measures in our California data, which are smaller than national SDs (see Appendix Table C.13), implying these are likely a lower bound of potential national effects. We also restrict in Appendix Table C.14 our analyses to the subsets of counties in California that are not outside the bottom or top decile of automation exposure levels in the country and our results are similar or even stronger.

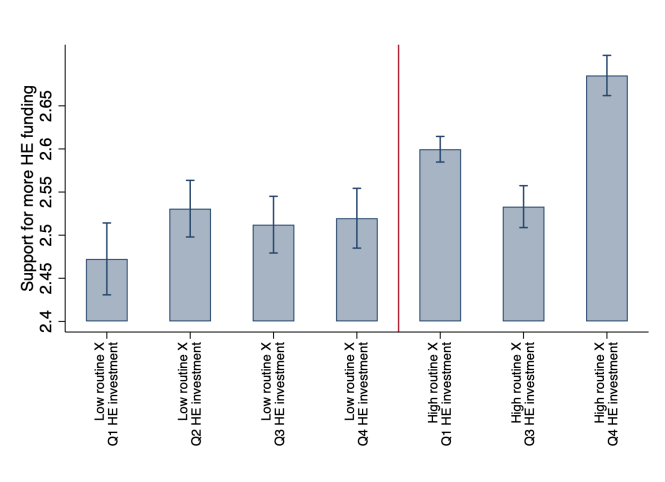
[17] Clearly, support for further investment in HE has a partisanship component and there is a strong case that partisanship has, in turn, a strong early socialization component (Green, Palmquist and Schickler, 2004; Rodden, 2019). We take our mechanism of learning to be an additional source of support for greater investment, beyond partisanship. Our main results control for partisanship and column 4 of Table C.14 suggest very similarly sized-effects for Republicans, although in heavily Democratic California there are too few for these to be statistically significant.

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

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

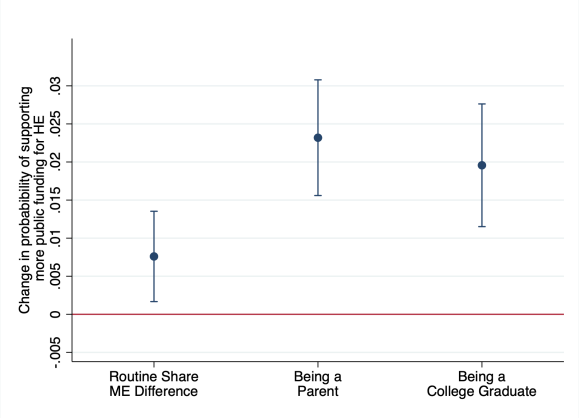
Figure 3: Support for HE spending in California in PPIC surveys.

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



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

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



Note: The column labeled Routine Share ME Difference compares the difference in the ME of routine exposure (1 sd) on support, as the level of HE investment shifts by 1 sd. The other two columns are coefficient estimates for indicator variables used to benchmark routine share ME Diff. estimate. Estimates are obtained from Model 4 in Table C.12.

4 Conclusion

The public is divided in its view of many public policies, even when faced with similar external circumstances. Our contribution is to first document that places that experienced a greater degree of technological change did better in terms of per capita income when they had pre-determined higher levels of higher education investment. This is consistent with the common claim that human capital investments are valuable in the current era of technological change. We then show that individuals in places with greater initial educational investment react to exposure to technological change with greater support for higher educational spending than individuals living in places similarly effected by technological change but having lower initial levels of educational investment. One may have expected to see the opposite: places with little investment demanding more and those that experienced high investment demanding the same or less, as the contribution of additional marginal spending may be lower. We

present this as a puzzle to be further investigated and suggest that the data is consistent with differential learning paths for those exposed to higher levels of effective higher education spending vs others. To establish clearly the learning that results from the observation of successful policies and how it may affect policymaking at a later date via mass preferences, partisanship and elite attitudes, we would need additional survey studies. This would benefit from complementary research across policy domains, as well as the use of experimental lab-based evidence.

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