

Online Appendix to “Routine-Biased Technological Change and Endogenous Skill Investments”

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A Data

A.1 Details on ACS and Variable Definitions

We use data on the American Community Survey (ACS) for the years 2001 to 2019, a nationally representative sample of the population conducted annually by the US Census Bureau. The ACS provides rich demographic characteristics (including gender, age, race, and state of birth) as well as basic socioeconomic information (such as education and earnings). A compelling feature of these data relative to other population surveys is their enormous sample sizes, covering on average between 1.5 and 3 million individuals per year. The number of people sampled changed sharply in 2005 and onward, going from 1.1 to more than 2.8 million individuals. This discontinuity is visible in our estimation sample (see Appendix Figure A.1). We have no reason to believe it has important implications for our identification strategy. The results are essentially the same if we exclude the ACS conducted before 2005.

These data are publicly available from the Integrated Public Use Microdata Series (IPUMS). The samples are limited to native-born in the 1953-83 birth cohorts who are above age 30 at the time of the survey. This restriction excludes individuals from Hawaii and Alaska, so the resulting sample includes all individuals born in one of the remaining 48 states or the District of Columbia. In the ACS, the District of Columbia is considered a separate state. This sample restriction also excludes immigrants (about 10 percent of the observations), as it is not possible to infer whether or not they were exposed to automation technologies in the United States. In addition, we exclude individuals residing in institutional group quarters to increase consistency between the different rounds of the ACS. The basic sample consists of approximately 15.3 million records.

In terms of labor market outcomes, we consider total personal income, earned income, and income wages. Total personal income (INCTOT) refers to pre-tax personal income or losses from all sources for the previous year. Earned income (INCEARN) is the income earned from wages or a person's own business or farm for the previous year. Income wages (INCWAGE) represent the pre-tax wage received as an employee for the previous year. Income observations at the top of the distribution (typically 99 percentile) are top coded, with the top code value often defined as the state means of values above a given income cutoff. Following [Acemoglu and Autor \(2011\)](#), we replace the top code values for 1.5 times the value of the respective top code values. To render the income variables comparable across time, we convert them to constant 1999 dollars applying the CPI-U to the relevant year.

A.2 Construction of Robot Exposure

Our main analysis relies on the measure of robot exposure developed by [Acemoglu and Restrepo \(2020b\)](#):

$$\text{Robot penetration}_s = \sum_{j \in \chi} \overbrace{\ell_{sj} \left(\frac{\Delta M_j}{L_{jb}} - g_j \frac{M_{jb}}{L_{jb}} \right)}^{\text{Industry share}} \underbrace{\hspace{1.5cm}}_{\text{Robot Penetration}} \quad (\text{A.1})$$

where ℓ_{sj} is the initial employment share of industry j in state s , which we calculate using the census conducted in 1970 to capture the long-term industrial composition that was prevailing before the major advance in automation. The variable $\Delta M_j = M_{j\tau} - M_{jb}$ is the change in the number of robots in each industry between the base year b and final year τ , normalized by the number of workers L_{jb} . In the model of automation developed by [Acemoglu and Restrepo \(2020b\)](#), the labor market effects are related to the change in the number of robots per thousand workers after adjusting for the growth rate of output g_j of each industry (captured by the expression $g_j M_{jb}/L_{jb}$). For consistency with their conceptual framework and ease of comparison, we keep this adjustment term in equation (1).

Data on robots come from the International Federation of Robotics (IFR), which are available since 1993 based on yearly surveys of robot suppliers. These data cover 50 countries, including the United States, and are consistently available for 13 manufacturing and 6 non-manufacturing industry categories. The manufacturing sector is disaggregated into 13 categories (automotive, plastics and chemicals, metal products, industrial machinery, food and beverages, basic metals, electronics, miscellaneous manufacturing, minerals, wood and furniture, shipbuilding and aerospace, textiles, and paper and printing), while the remaining non-manufacturing corresponds to six broad groups (mining, education and research, agriculture, utilities, construction, and services). We use the 1993 to 2007 period to measure the adjusted penetration of robots, using data on average robot adoption in the top 5 non-US countries with greater advances in robotics (Denmark, Finland, France, Italy, and Sweden). This group excludes Germany, which is well ahead of the United States and thus is less relevant for robot adoption trends in the latter. In robustness exercises, we use measures of robot penetration expanding the top 5 to include Germany and other European countries with available data on robots. We also present results using a measure of robot penetration in the United States.

To compute the measure of adjusted penetration of robots by industry, we use industry-level data on employment from the European Union–level analysis of capital, labor, energy, materials, and service inputs (EUKLEMS) Growth and Productivity Accounts ([Jäger, 2016](#)). We use a “crosswalk” between the US industry codes in the census and IFR industry codes to match the robot penetration variable to the baseline employment shares in each state. We collapse the 199 detailed industry categories in the census into the 19 IFR industries, as detailed in Table A.1.

To sum up, we construct the overall measure of robot exposure in each state using the following

step-by-step procedure in which we:

- Step 0: collapse the 199 detailed industry codes in the census to the 19 IFR industries.
- Step 1: construct the initial employment share of each industry in state s using the 1970 census.
- Step 2: compute the adjusted penetration of robots for each industry using data from the IFR and EUKLEMS database.
- Step 3: combine the results in steps 1 and 2 using equation (A.1) to generate the measure of robot exposure.

Table A.2 provides descriptive statistics for the main measure of exposure to robots, displaying the substantial variation in the adjusted penetration of robots across industries.

Cross-sectional Variation in Robot Exposure Intensity. Figure A.4 shows that there is substantial variation in the data, with a standard deviation of about 1.35 robots per thousand workers (relative to the mean of 2 robots per thousand workers). This variation stems not only from differences in robot adoption rates across industries but from substantial differences in the baseline industrial composition of employment across states. Figure A.5 shows this substantial variation in initial employment share across states.

The labor market analysis of Acemoglu and Restrepo (2020b) relies on data at the commuting-zone level. Because we have no information on an individual’s birthplace detailed at the commuting zone level, our analysis focuses on state-level data. While this comes at a cost in terms of loss of variation, much of the variation in the commuting-zone level data in fact stems from differences between (rather than within) states. Figure A.7 illustrates this visually. Remarkably, state fixed effects account for about 75 percent of the overall cross-commuting zone variation in robot exposure intensity. This suggests that our state-level analysis captures a substantial portion of the relevant identifying variation.

Figure A.1: Birth Cohorts in the ACS

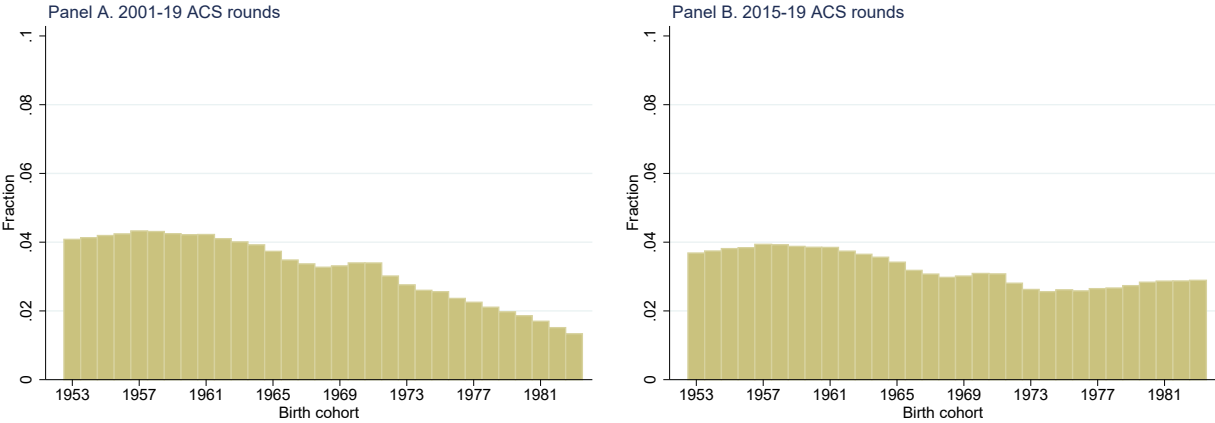


Figure A.2: Observations by Survey Year

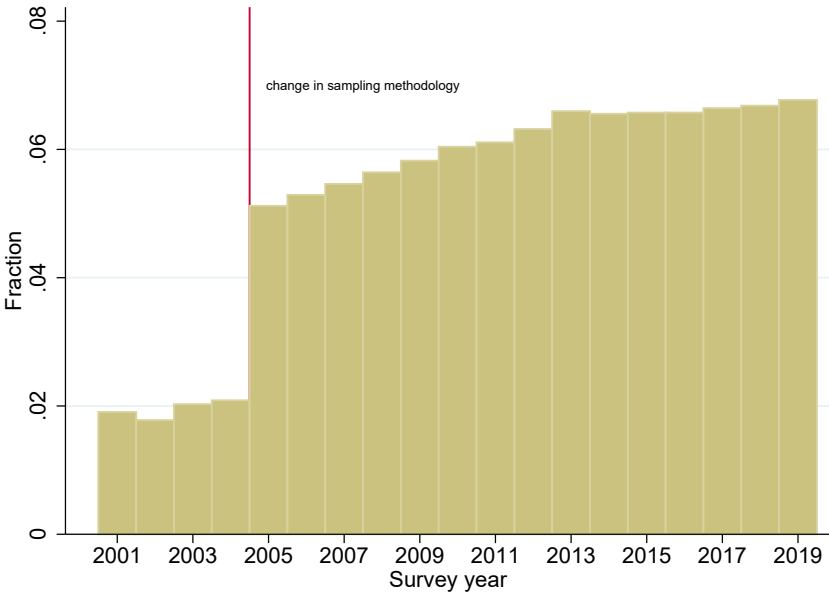
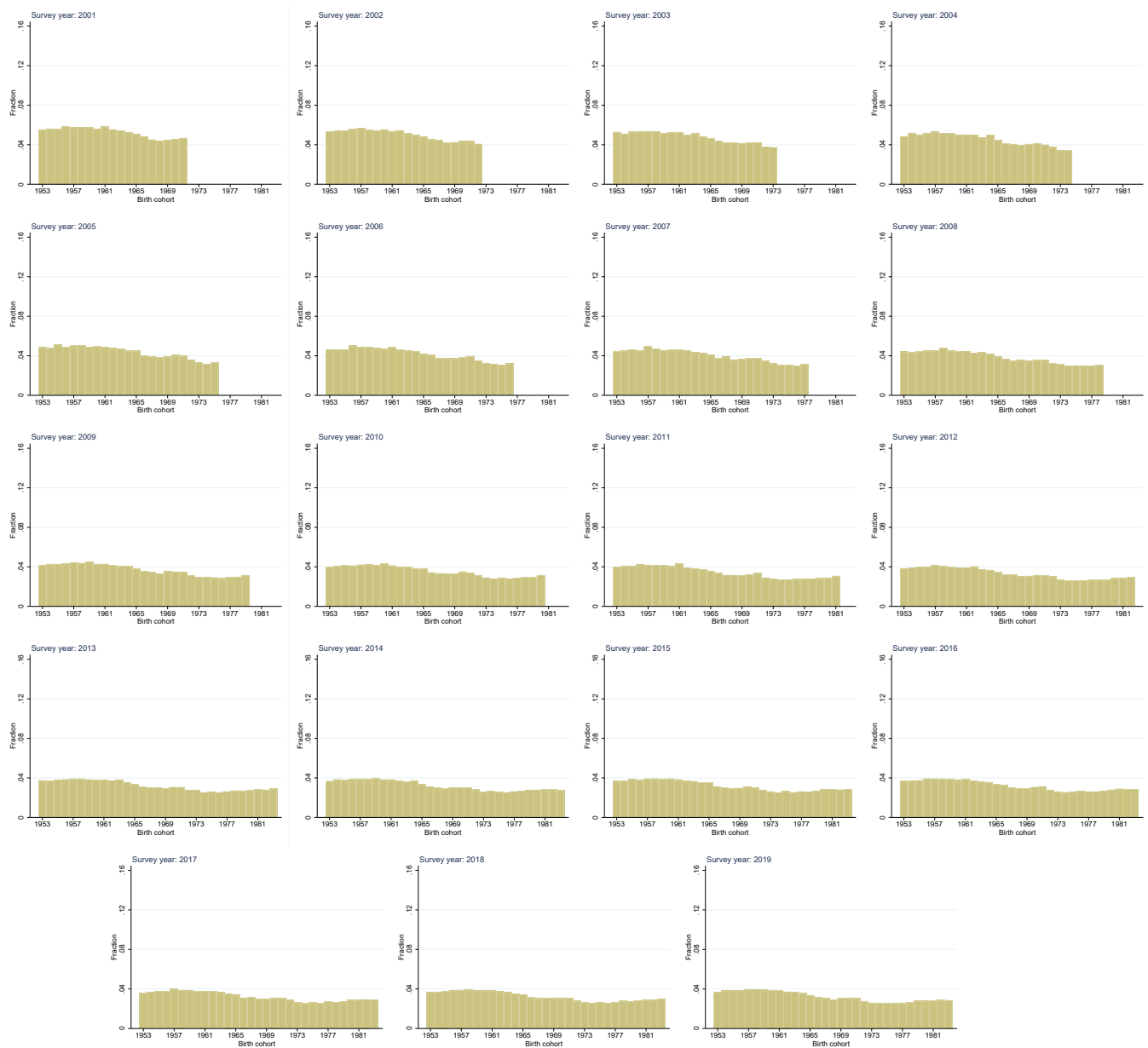
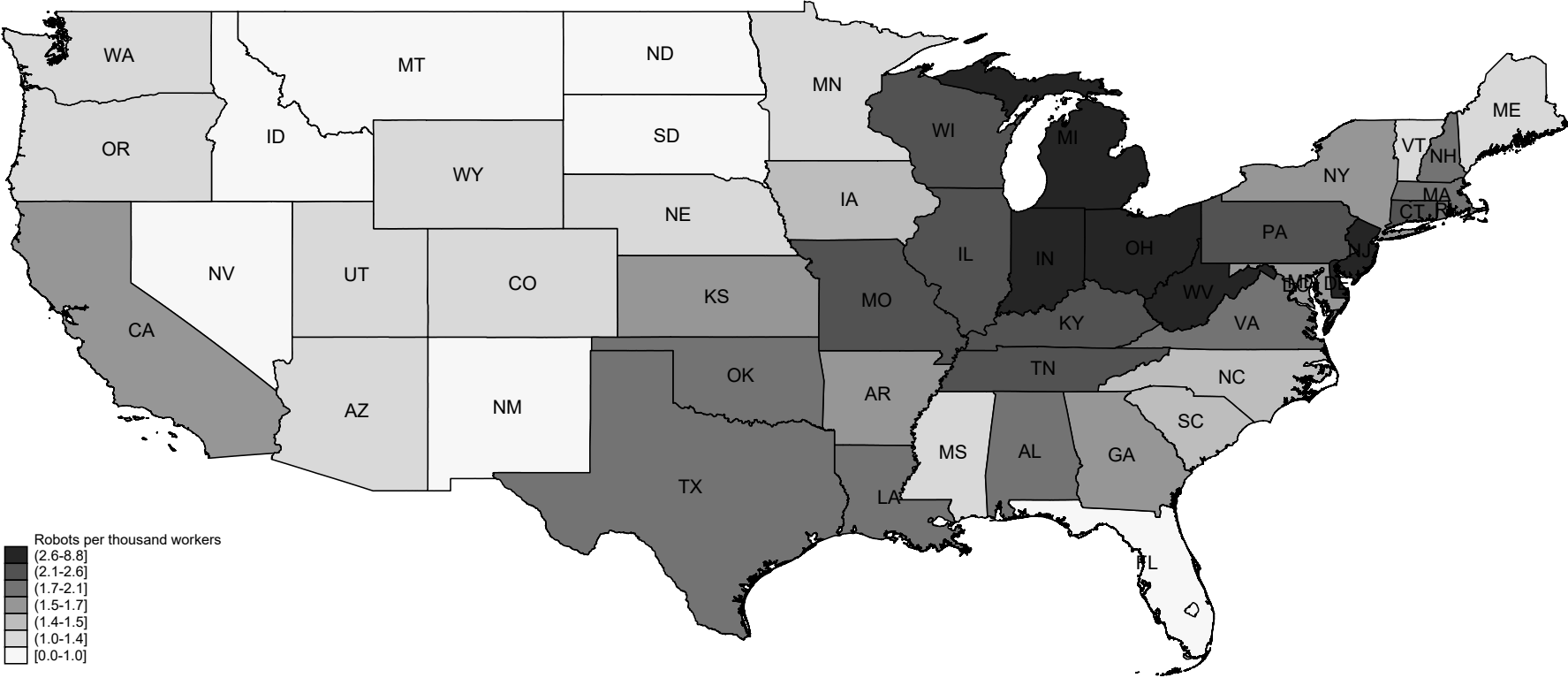


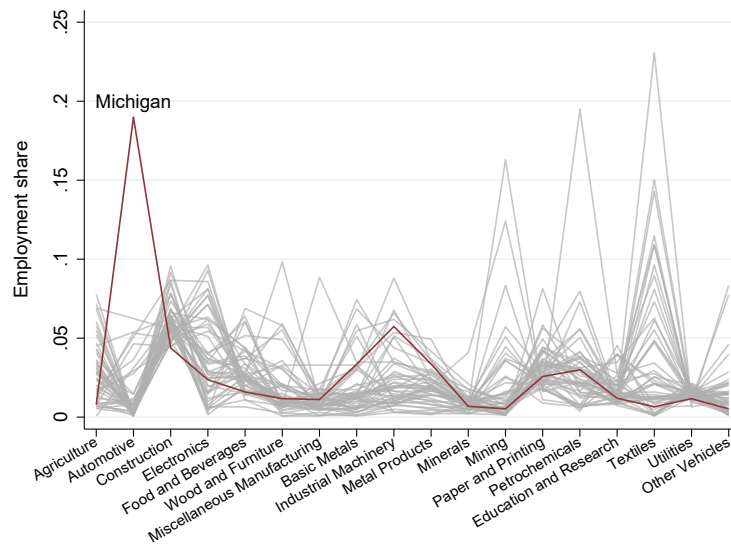
Figure A.3: Composition of Birth Cohorts by Survey Year

Notes. This figure shows the birth cohorts by survey year.

Figure A.4: Robot Exposure Intensity by State

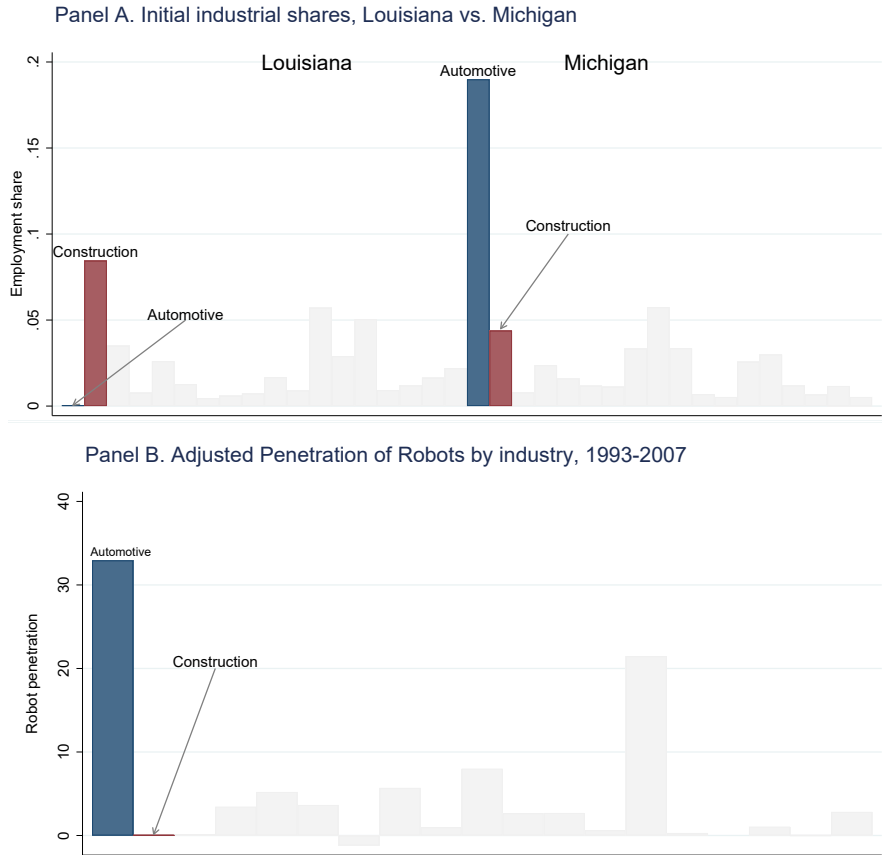


Notes. This map displays the intensity of robot exposure across states.

Figure A.5: Baseline Industrial Shares across States

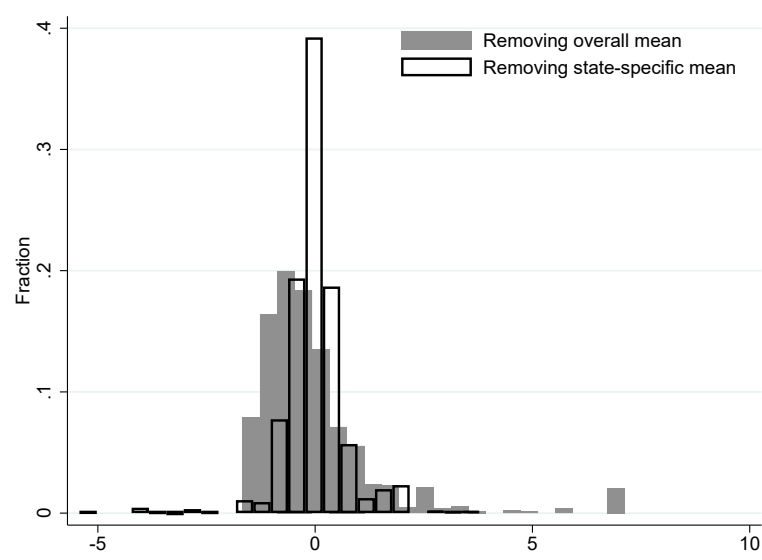
Notes. This figure shows the variation in initial industrial shares by state. This figure is constructed using data from the 1970 census.

Figure A.6: Robot Exposure in Selected States and Industries



Notes. These figures show the variation underlying the robot exposure variable. Panel A shows the initial industry’s share of employment in Louisiana and Michigan. Panel B shows the adjusted penetration of robots in each industry.

Figure A.7: Robot Exposure across Commuting Zones after Removing State Effects



Notes. This figure shows the variation in the robot exposure across commuting zones before and after removing state fixed effects.

Table A.1: Crosswalks between 1990 Census Bureau industrial classification and IFR Industries

IFR Industry	Census Industry Code	Number of Groups
<i>Manufacturing:</i>		
Food and Beverages	100-130	10
Textiles	132-152, 220-222, and 450-472	6
Paper and Printing	160-172	5
Petrochemicals	180-192 and 200-212	10
Wood and Furniture	231, 241, and 242	3
Minerals	250-262	5
Basic Metals	270-272, 280, and 301	5
Metal Products	281-300	6
Industrial Machinery	310-312, 320, 331, and 332	6
Electronics	321-350 and 371-381	10
Automotive	351	1
Miscellaneous Manufacturing	391 and 392	2
<i>Nonmanufacturing:</i>		
Agriculture	10-32 and 2030	6
Mining	40-42 and 50	4
Construction	60	1
Shipbuilding and Aerospace	352-370	4
Services	400-442, 500-842, 870-890, and 892	101
Utilities	450-452 and 470-472	6
Education and Research	850-860 and 891	4

Notes. This table shows the crosswalks between the industry codes in the 1970 census and that in the IFR data.

Table A.2: Robot Exposure

	Mean	Standard Deviation	Observations	
			N	Aggreg. Level
Robots per thousand workers	2.09	1.35	49	States
Adjusted penetration of robots per thousand workers (overall)	4.77	8.46	19	
Adjusted penetration of robots per thousand workers...				
<i>Manufacturing</i>				
Automotive	32.94			
Petrochemicals	21.46			
Metal Products	8.01			
Industrial Machinery	1.01			
Food and Beverages	5.20			
Basic Metals	5.70			
Electronics	3.46			
Miscellaneous Manufacturing	-1.20			IFR industries
Minerals	2.66			
Wood and Furniture	3.65			
Shipbuilding and Aerospace	2.83			
Textiles	1.06			
Paper and Printing	0.61			
<i>Nonmanufacturing</i>				
Mining	2.69			
Education and Research	0.30			
Agriculture	0.16			
Utilities	0.02			
Construction	0.07			
Services	0.00			

Notes. This table provides descriptive statistics for the main measure of exposure to robots, displaying the variation in the adjusted penetration of robots across industries.

B Long-Run Labor Market Pre-Trends

Table B.1: Labor Market Pre-Trends 1970-1990:
State Level

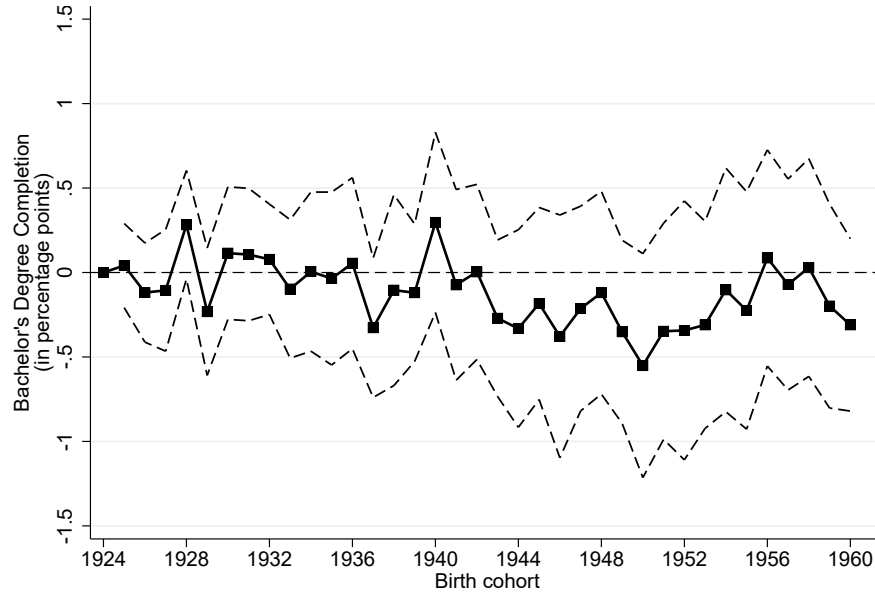
	Long differences, 1970-1990					
	Employment to population ratio (1)	Manufacturing employment to population ratio (2)	Employment to population ratio (include public sector and self-emp.) (3)	Non-participation rate (4)	Unemployment rate (5)	Log wages (6)
Robot penetration	0.001 [0.0016]	0.0013 [0.0012]	0.0003 [0.0013]	-0.0014 [0.0016]	0.0009 [0.0013]	-0.0061 [0.0048]
R^2	0.371	0.797	0.508	0.544	0.584	0.717
Observations	48	48	48	48	48	7070
Baseline covariates	✓	✓	✓	✓	✓	✓

Notes. This table reports the results from estimating the change in labor market outcomes between 1970 and 1990 on the robot penetration. The unit analysis is a state. Baseline covariates include: 1970 state college enrollment, 1970 state demographics (log of population, the share of the population over 65 years of age, the share of the population under 5 years of age, the share of blacks, and the share of population that is urban), 1970 state industry shares (the share of manufacturing employment, and the share of light manufacturing employment), exposure to Chinese imports, and the share of employment in routine jobs. The specification in column (6) is estimated at the demographic cell $\times$ state level, where demographic cells are defined by age, gender, education, and race. All regressions are weighted by population in 1970. Robust standard errors in brackets are clustered at the state level.

C Additional Results and Robustness Checks

C.1 Longer Pretrends in College Attainment

Figure C.1: Falsification: Longer Pretrends from 1990 Census

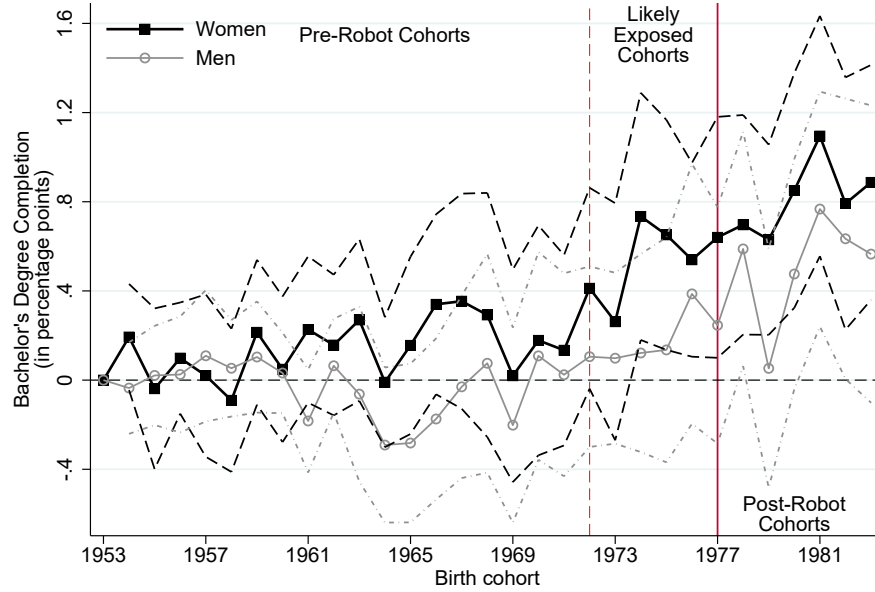


Notes. This figure presents the results from a falsification exercise using data from the 1990 Census. It plots estimates of the interaction between the robot exposure variable and indicators for birth years, using the flexible model (3). The covariates include those from column 5 of Table 1. Baseline state characteristics are constructed using the 1970 Census. See notes to column (5) of Table 1 for details on sample and specification. The dashed lines represent 95 percent confidence intervals based on standard errors clustered at the state-of-birth level.

C.2 Gender Differences

Appendix Figure C.2 explores heterogeneous effects with respect to gender. We do not observe statistically meaningful differences in the estimated coefficients between males and females. At first glance, this lack of heterogeneous effects could seem surprising, given that the labor market impacts of robots on males tend to be somewhat larger (though not always statistically significant). However, a possible interpretation is that the educational responses to a same change in labor market conditions may be larger for females than males. This is in line with the recent evidence by (Charles et al., 2018) documenting that a labor market shock, which similarly affected male and female employment opportunities, had larger effects on female education. This interpretation is also consistent with the rapid growth in female schooling during our study period.

Figure C.2: Flexible Estimates by Gender



Notes. This figure plots estimates of the interaction between the robot exposure variable and indicators for birth years, using the flexible model (3) separately by gender. The covariates include those from column 5 of Table 1. See notes to column (5) of Table 1 for details on sample and specification. The dashed lines represent 95 percent confidence intervals based on standard errors clustered at the state-of-birth level.

C.3 Weighted versus Unweighted Regressions

Because the underlying variation that we exploit is across states and birth cohorts, the use of individual-level data in the analysis effectively weights state-cohort cells by population size. As discussed by Solon et al. (2015), such weighting is appropriate in the presence of heteroskedasticity. Otherwise, it is thought to be counterproductive. We follow their practical recommendations and report both weighted and unweighted estimates. To estimate the unweighted version of model (2), we first estimate a regression of bachelor’s degree attainment against individual-level characteristics (gender, race) and then collapse the residuals into state-of-birth and year-of-birth cells. We then estimate model (2) using these state-cohort level data. Appendix Table C.1 shows that the unweighted estimate is extremely similar to the weighted one (0.48 versus 0.44) but notably less precise, confirming the strengths of our main approach.

Table C.1: Childhood Exposure Effects on Bachelor Completion (in % pts)
(Weighted vs. Unweighted Estimates)

	Dependent variable is Bachelor’s degree completion		
	Data collapsed by state-birth-year cells		
	Baseline (1)	Weighted (2)	Unweighted (3)
Robot penetration $\times$ post	0.4828 [0.1338]	0.4849 [0.1568]	0.4407 [0.2108]
R^2	0.673	0.978	0.962
Mean Dep. Variable	32.51	32.51	32.51
Observations	15372069	1519	1519
Baseline covariates	✓	✓	✓

Notes. This table presents weighted and unweighted estimates. Column (1) repeats the baseline results for ease of comparison. To obtain the results displayed in columns (2) and (3), we first estimate a regression of bachelor’s degree completion on gender and race indicators. We then collapse the residuals into state-of-birth and year-of-birth cells. These collapsed residuals are used as the dependent variable of interest. Column (2) estimates equation (2) weighing the observations by cell group size. Column (3) estimate equation (2) without weighing the observations. Baseline covariates correspond to those reported in column (5) of Table 1. See notes to Table 1 for details. Robust standard errors in brackets are clustered at the state-of-birth level.

C.4 Alternative Constructions of Exposure to Robots

Table C.2: Exposure Effects on Bachelor's Degree (in % pts)
(Alternative Definitions of Robot Exposure)

	Alternative constructions of robot penetration				
	Baseline	Employment	Include Germany	Include all European countries with data	Unadjusted definition
		shares in 1990			
	(1)	(2)	(3)	(4)	(5)
Robot penetration $\times$ post	0.4828 [0.1338]	0.7817 [0.2683]	0.3497 [0.1035]	0.3225 [0.0985]	0.3371 [0.0947]
Rescaled coefficient	0.4828	0.4806	0.4559	0.4006	0.4969
R^2	0.673	0.673	0.673	0.673	0.673
Mean Dep. Variable	32.51	32.51	32.51	32.51	32.51
Observations	15372069	15372069	15372069	15372069	15372069
Baseline covariates	✓	✓	✓	✓	✓

Notes. This table presents results from alternative ways to construct the measure of exposure to robots. For ease of comparison, the table also reports rescaled coefficients. The rescaled coefficients are obtained by dividing the point estimates by the ratio of the standard deviations of the baseline to alternative measures of robot penetration. Column (1) repeats the baseline estimates reported in column (5) of Table 1. Column (2) uses the 1990 rather than the 1970 census to construct the initial industrial composition of employment in each state. Column (3) includes Germany to construct the adjusted penetration of robots. Column (4) uses data from all European countries to construct the adjusted penetration of robots. Column (5) uses the unadjusted penetration of robots to construct the overall measure of robot exposure. See notes to Table 1 for details on the sample and specification. Robust standard errors in brackets are clustered at the state-of-birth level.

C.5 Outlier Analysis

Table C.3: Exposure Effects on Bachelor's Degree (in % pts)
(Outlier Analysis)

	Baseline	Exclude 3-sigma outliers	Exclude 2-sigma outliers	Exclude 1-sigma outliers	Exclude 0.5-sigma outliers	Exclude highly influential observations (Cook's distance)
	(1)	(2)	(3)	(4)	(5)	(6)
Robot penetration $\times$ post	0.4828 [0.1338]	0.4861 [0.1347]	0.4715 [0.1319]	0.4717 [0.1257]	0.5484 [0.1215]	0.5017 [0.1074]
R^2	0.673	0.689	0.732	0.783	0.832	0.849
Mean Dep. Variable	32.51	32.49	32.45	32.39	32.47	32.47
Observations	15372069	15367892	15350905	15270926	14979839	14665860
Baseline covariates	✓	✓	✓	✓	✓	✓

Notes. This table evaluates the robustness to outliers. Column (1) repeats the baseline results reported in column (2) of Table 1. Columns (2)-(5) exclude observations that are 3, 2, 1, and 0.5 standard deviations away from the residual mean respectively. Column (6) excludes observations that shift the baseline estimate at least to $4/N$ (Cook's distance). See notes to Table 1 for details on the sample and specification. Robust standard errors in brackets are clustered at the state-of-birth level.

C.6 Decomposing Variation: Rotemberg Weights

We next investigate the relative importance of each industry for our results by computing the “Rotemberg” weights, as recommended by Goldsmith-Pinkham et al. (2020). Here the concern is that the positive effects on college attainment we find are completely driven by a particular industry, which would suggest that the results may be the product of unobservable shocks differentially affecting regions disproportionately specialized in certain types of industries. The Rotemberg weights decompose the Bartik difference-in-differences estimator into a weighted sum of estimates that use each industry share, along with the robot penetration in each industry, as a separate source of variation. Let x_{ist} and $\tilde{y}_{ist}$ denote *Robot penetration_s × Post_t* and the outcome variable after removing the basic set of fixed effects and the rest of the control variables. Let also z_{ijst} denote $\ell_{sj} \cdot \text{Robot penetration}_j \times \text{Post}_t$, which is the robot exposure variable separately for each industry after filtering out the baseline covariates. Finally, let μ_j be the adjusted penetration of robots in each industry. In this case, the Rotemberg weights can be computed as follows:

$$\begin{aligned} \beta &= \sum_j \alpha_j \tilde{\beta}_j \\ \text{where} \quad \tilde{\beta}_j &\equiv \left(\sum_i z_{ijst} \cdot x_{ist} \right)^{-1} \sum_i z_{ijst} \cdot \tilde{y}_{ist} \\ \alpha_j &\equiv \left(\sum_j \mu_j \sum_i z_{ijst} \cdot x_{ist} \right)^{-1} \mu_j \sum_i z_{ijst} \cdot x_{ist} \end{aligned}$$

Under this framework, $\tilde{\beta}_j$ is obtained in a 2SLS regression where the measure of robot exposure based only on industry j is used as an instrumental variable for the overall robot exposure variable. The weights $\{\alpha_j\}$ sum to one, but not all need to be positive.

Appendix Table C.4 reports the Rotemberg weights. We find that the automotive industry has the largest share of the overall weight, with a weight above 80 percent. This is what one could expect given that the trends in robot adoption of this industry are almost of incomparable magnitude to that of any other industry. But most importantly, the automotive industry is not the only reason why we observe the positive effects of robots on college attainment. As shown in the table, the estimated coefficient β is in fact larger when we exclude the automotive industry.

Table C.4: Exposure Effects on Bachelor's Degree
(Rotemberg Weights)

	Rotemberg weights		Estimate of β (in % pts) excluding each industry in row (Baseline covariates)
	Raw data	Baseline covariates	
	(1)	(2)	(3)
Automotive	0.8496	1.0125	1.1618
Plastics and Chemicals	0.1060	0.0826	0.5252
Basic Metals	0.0367	-0.0130	0.4550
Metal Products	0.0291	-0.0130	0.4625
Industrial Machinery	0.0080	-0.0015	0.4920
Electronics	0.0024	-0.0189	0.4817
Minerals	0.0021	-0.0011	0.4834
Paper and Printing	0.0001	0.0001	0.4901
Utilities	0.0000	0.0000	0.4820
Education and Research	-0.0003	0.0001	0.4838
Construction	-0.0003	-0.0001	0.4798
Miscellaneous Manufacturing	-0.0006	-0.0004	0.4831
Agriculture	-0.0008	-0.0007	0.4771
Mining	-0.0047	-0.0011	0.4963
Wood and Furniture	-0.0051	-0.0152	0.4866
Shipbuilding and Aerospace	-0.0061	-0.0174	0.4938
Textiles	-0.0070	0.0091	0.4844
Food and Beverages	-0.0092	-0.0221	0.4608

Notes. This table decomposes the baseline coefficient β into a weighted sum of estimates that use each industry share, along with the robot penetration in each industry, as a separate source of variation. Columns (1) and (2) presents Rotemberg weights for all industries, following Goldsmith-Pinkham et al. (2020). Column (3) shows the estimated coefficient when each industry is excluded from the overall measure of robot exposure. See notes to Table 1 for details on the sample and specification.

C.7 Additional Covariates

Table C.5: Exposure Effects on Bachelor's Degree (in % pts)
(Additional Covariates)

	Dependent variable is Bachelor's degree completion			
	(1)	(2)	(3)	(4)
Robot penetration $\times$ post	0.4828 [0.1338]	0.5221 [0.1238]	0.4152 [0.1628]	0.4819 [0.1561]
R^2	0.673	0.673	0.674	0.674
Mean Dep. Variable	32.51	32.51	32.51	32.51
Observations	15372069	15372069	15372069	15372069
1990 employment-to-pop. ratio ($\times$ birth-year FE)		✓		✓
1990-2008 change in demographics ($\times$ birth-year FE)			✓	✓
Baseline covariates	✓	✓	✓	✓

Notes. This table explores the robustness of the baseline estimates to additional controls. The sample is limited to individuals over age 30 at survey time and born in one of the States covering the mainland of the United States. All regressions include the baseline controls included in column (5) of Table 1 (see footnotes to that table for details). Robust standard errors in brackets are clustered at the state-of-birth level.

C.8 Robust Inference

Our baseline analysis uses standard errors clustered at the state-of-birth level. In this section, we evaluate the robustness of our results to alternative inference approaches. First, we use standard errors clustered at the state level but adjust them by the effective sample size implied by the relative importance of each observation, as suggested by [Young \(2016\)](#). Second, because we are using a shift-share identification strategy, a particular concern is that standard procedures to inference may result in smaller standard errors if residuals are spatially correlated across areas with similar sectoral shares ([Borusyak et al., 2022](#)). Therefore, we evaluate the robustness of the results using the inference procedures proposed by [Adao et al. \(2019\)](#) and [Borusyak et al. \(2022\)](#) that address cross-region correlation in residuals in shift-share designs. Finally, we present results from a specification that uses standard errors two-way clustered at the state-of-birth and birth-year level, which account for possible serial and spatial correlation in a flexible manner. As shown in Table C.6, the results are in general very similar to our baseline.

Table C.6: Exposure Effects on Bachelor’s Degree (in % pts)
(Robustness to Alternative Inference Procedures)

	Alternative inference procedures				
	Baseline	Clustered by state + Young (2016) effective d.o.f.-adj.	Borusyak et al. (2022) robust SE	Adao et al. (2019) robust SE	Twoway clustering by state + birth year
	(1)	(2)	(3)	(4)	(5)
Robot penetration×post	0.4828 [0.1338]	0.4828 [0.1447]	0.4828 [0.1216]	0.4828 [0.1103]	0.4828 [0.1341]
R^2	0.673	0.673	0.673	0.673	0.673
Mean Dep. Variable	32.51	32.51	32.51	32.51	32.51
Observations	15372069	15372069	15372069	15372069	15372069
Baseline covariates	✓	✓	✓	✓	✓

Notes. This table evaluates the robustness of the baseline results in Table 1 to alternative inference approaches: *i*) standard errors clustered at the state level but adjusted by the effective sample size implied by the relative importance of each observation, as suggested by [Young \(2016\)](#); *ii*) inference procedures proposed by [Adao et al. \(2019\)](#) and [Borusyak et al. \(2022\)](#) that address cross-region correlation in residuals in shift-share designs; *iii*) two-way clustering by state-of-birth and birth year. See notes to Table 1 for details on the sample and specification.

C.9 Preexisting Trends and Mean Reversion

Table C.7: Childhood Exposure Effects on Bachelor Attainment (in % pts)
(Mean Reversion, Pre-cohort Trends and Within-Region Variation)

	Dependent variable is Bachelor's degree completion				
	(1)	(2)	(3)	(4)	(5)
Robot penetration $\times$ post	0.4828 [0.1338]	0.5022 [0.1430]	0.5022 [0.1430]	0.4807 [0.1344]	0.4701 [0.1996]
R^2	0.673	0.673	0.673	0.509†	0.674
Mean Dep. Variable	32.51	32.51	32.51	32.51	32.51
Observations	15372069	15372069	15372069	15372069	15372069
1970 state college level ($\times$ birth-year FE)		✓			
1970-1990 change in state college level ($\times$ birth-year FE)			✓		
State-specific pre-cohort trends				✓	
Region-of-birth $\times$ birth-year FE					✓
Baseline covariates	✓	✓	✓	✓	✓

Notes. This table explores the robustness of the baseline estimates to additional controls for mean reversion (columns 2-3), pre-cohort linear trends (column 4), and region-of-birth $\times$ birth-year fixed effects (column 5). The sample is limited to individuals who are over age 30 at survey time and born in one of the States covering the mainland of the United States. Robot penetration is the intensity of exposure to robots in one's state of birth, as described in Section 2. All regressions include the baseline controls included in column (3) of Table 1 (see footnotes to that table for details). The regions are defined by the US Census Bureau: the Northeast, the Midwest, the South, and the West. Robust standard errors in brackets are clustered at the state-of-birth level.

† note that the R^2 in column (4) is not comparable with that of the other columns given the two-step procedure described in Section 4.1.

Table C.8: Childhood Exposure Effects on College Attainment (in % pts)
(Controlling for Other Labor Market Shocks, and Social Reforms)

	Dependent variable is Bachelor's degree completion									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Robot penetration×post	0.4828 [0.1338]	0.4826 [0.1483]	0.4844 [0.1310]	0.5116 [0.1393]	0.484 [0.1374]	0.5047 [0.1222]	0.4512 [0.1346]	0.4839 [0.1341]	0.4456 [0.1197]	0.6123 [0.1418]
R^2	0.673	0.673	0.673	0.673	0.673	0.673	0.673	0.673	0.673	0.674
Mean Dep. Variable	32.51	32.43	32.51	32.51	32.51	32.51	32.51	32.51	32.51	32.43
Observations	15372069	15274531	15372069	15372069	15372069	15372069	15372069	15372069	15372069	15274531
<i>Adding controls for:</i>										
Mexican import competition		✓								✓
Offshoring			✓							✓
IT capital				✓						✓
Computer technology					✓					✓
1980-82 recession						✓				✓
War on poverty programs							✓			✓
Medicaid								✓		✓
School finance reforms									✓	✓
Baseline covariates	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes. This table reports estimates that evaluate the robustness of our baseline results to controlling for other labor market shocks and social reforms. Column (1) repeats the baseline specification reported in column (5) of Table 1 (see footnotes to that table for details). Column 2 includes interactions between birth-year fixed effects and the exposure in Mexican import competition in the state of birth. Column (3) controls for interactions between birth-year fixed effects and a Bartik measure of exposure to offshoring in the state of birth. Column (4) controls for interactions between birth-year fixed effects and the exposure to information technology capital in the state of birth. Column (5) controls for interactions between birth-year fixed effects and the exposure to computer technology in the state of birth. Column (6) controls for interactions between birth-year fixed effects and the measure of exposure to the 1980-82 recession in the state of birth (Stuart, 2022b). Column (7) includes the fraction of childhood years exposed to war-on-poverty programs for each birth cohort in the state of birth: Head Start, Food Stamp, and Community Health Centers. Column (8) includes the fraction of childhood years exposed to Medicaid in the state of birth. Column (9) adds the fraction of school-going ages (5 to 17) exposed to a school finance reform in the state of birth. The measures of exposure to Mexican imports, offshoring, IT capital, and computer technology are measured as in Acemoglu and Restrepo (2020b). Robust standard errors in brackets are clustered at the state-of-birth level.

C.10 Robots and Exposure to Other Programs

We examine the extent to which cohort exposure to robots predicts the probability of childhood exposure to Community Health Centers, Head Start, Food Stamp, Medicaid and School Finance Reforms. As in [Goodman-Bacon \(2021\)](#), we consider ages 0 to 9 as the relevant window of exposure for Community Health Centers, Food Stamp and Medicaid, and ages 3 to 4 for Head Start. For the school finance reforms, we use the ages 5 to 17 as the relevant window of exposure (as in [Jackson et al. \(2016\)](#)). For each of these programs, we generate a variable measuring the fraction of the relevant years that a given cohort was exposed to the reform or program. We then estimate our baseline specification (2) using these measures of program exposure as dependent variables. Table C.9 documents that the post-robot cohorts from states with greater robot penetration are not significantly more likely to have been exposed to these programs in childhood.

Table C.9: Robots and Exposure to Safety Net Programs and School Finance Reforms

	Fraction of relevant years of exposure to...				
	Community Health Centers	Head Start	Food Stamp	Medicaid	School Finance Reforms
	(1)	(2)	(3)	(4)	(5)
Robot penetration $\times$ post	0.0246 [0.0181]	0.0023 [0.0156]	0.0028 [0.0138]	-0.005 [0.0137]	-0.0575 [0.0371]
R^2	0.915	0.866	0.967	0.975	0.892
Mean Dep. Variable	0.210	0.150	0.520	0.580	0.300
Observations	15372069	15372069	15372069	15372069	15372069
Baseline covariates	✓	✓	✓	✓	✓

Notes. This table estimates the effects of robots on the share of childhood years exposed to each program and reform. As in [Goodman-Bacon \(2021\)](#), we consider ages 0 to 9 as the relevant window of exposure for Community Health Centers, Food Stamp, and Medicaid, and ages 3 to 4 for Head Start. For the school finance reforms, we use the ages 5 to 17 as the relevant window of exposure (as in [Jackson et al. \(2016\)](#)). See notes to Table 1 for details on the sample and specification. Robust standard errors in brackets are clustered at the state-of-birth level.

Table C.10: Exposure Effects on Bachelor's Degree (in % pts)
(Controlling Flexibly for Other Social Reforms)

	Controlling for birth-cohort FE x adoption year of...						All simultaneously
	Baseline	Community Health Centers	Head Start	Food Stamp	Medicaid	School Finance Reforms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Robot penetration $\times$ post	0.4828 [0.1338]	0.4819 [0.1345]	0.554 [0.1417]	0.51 [0.1294]	0.4736 [0.1316]	0.5678 [0.1543]	0.5814 [0.1558]
R^2	0.673	0.673	0.673	0.673	0.673	0.673	0.674
Mean Dep. Variable	32.51	32.51	32.51	32.51	32.51	32.51	32.51
Observations	15372069	15372069	15372069	15372069	15372069	15372069	15372069
Baseline covariates	✓	✓	✓	✓	✓	✓	✓

Notes. This table demonstrates the robustness of the baseline estimates to controlling flexibly for the timing of war-on-poverty programs, Medicaid, and School Finance reforms. Columns (2)-(6) repeat the baseline specification, but separately include birth-cohort fixed effects interacted with the year of each program or adoption across states. See notes to Table 1 for details on the sample and specification. Robust standard errors in brackets are clustered at the state-of-birth level.

C.11 Supply-Side Responses

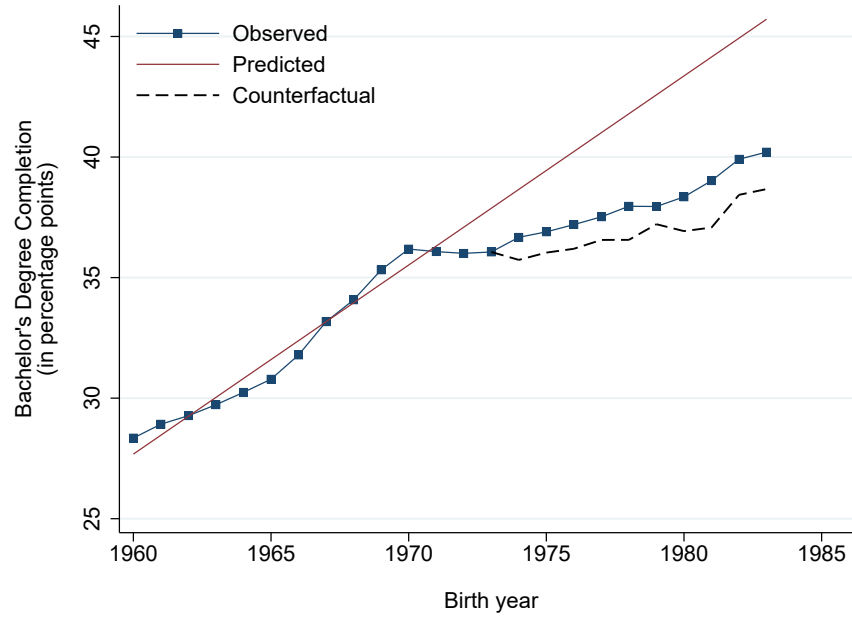
Table C.11: Robots and Supply-Side Responses

	Log-differences 1990-2008:			
	Average net tuition and fees costs	Per capita revenue from state and local appropriations	Per capita revenue from state and local grants	Per capita Government transfers in education and training assistance
	(1)	(2)	(3)	(4)
Robot penetration	0.0015 [0.0099]	0.0014 [0.0288]	0.0059 [0.0323]	-0.017 [0.045]
R^2	0.0001	0.0001	0.0002	0.319
Mean Dep. Variable	1.13	0.35	1.63	1.06
Observations	49	49	49	49
Baseline covariates	✓	✓	✓	✓

Notes. This table reports results from estimating equation (6): $\Delta Y_{s,90-08} = \alpha + \gamma Robots_s + \mathbf{Z}'_s \Omega + \xi_s$. The unit of analysis is a state. All regressions control for the baseline demographic and socioeconomic state characteristics described in Table 1. Standard errors are robust to arbitrary forms of heteroskedasticity.

D Implications for Aggregate Trends in College Attainment

Figure D.1: Trends in Bachelor Attainment



Notes. This figure shows the observed and counterfactual trends in bachelor's degree completion rates by birth cohort. The counterfactual bachelor attainment is calculated using the estimates obtained from the flexible specification (3), as described in Section 7. The solid line is the predicted bachelor attainment rate on a linear trend that is fit to the 1960-1971 birth cohorts.

E Model Appendix

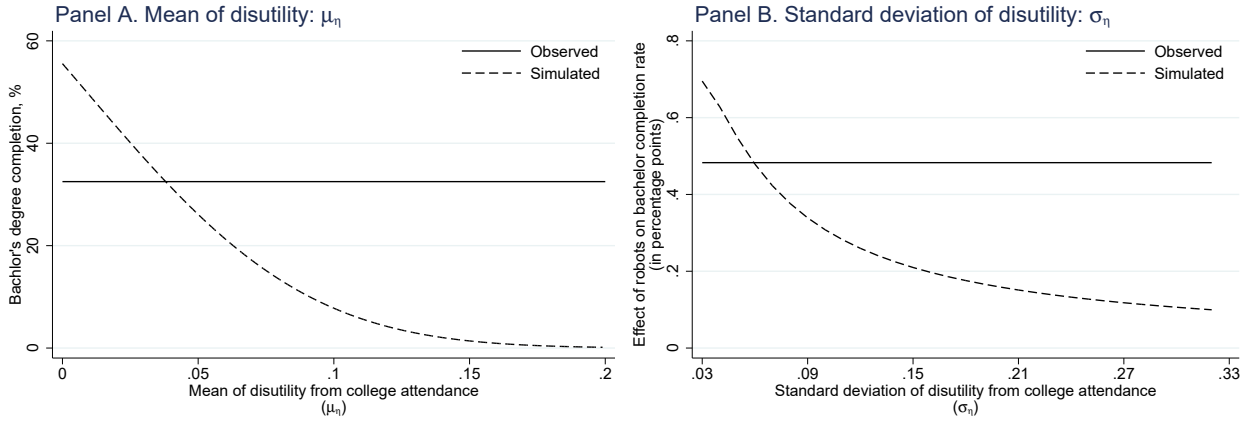
E.1 Identification

While the parameters are estimated simultaneously, it is useful to discuss the moments that best identify each of them. The mean of the disutility parameter, μ_η , is pinned down by seeking the values consistent with the baseline college attainment rate. Holding all else equal, the simulated college attainment rate declines monotonically as μ_η increases. On the other hand, the response of college attainment to robots provides information to identify the parameter σ_η . For values of σ_η close to zero, college attendance is either a rare or universal phenomenon for low or high values of μ_η , scenarios that are inconsistent with the data.¹ For a less extreme value of μ_η , such that the model matches the baseline bachelor attainment perfectly, values of σ_η close to zero imply an unrealistically large college response to robots.² It follows that there needs to be sufficient dispersion in the disutility from attending college for the model to rationalize the data. For values of σ_η that are not very close to zero, the predicted college response is monotonically decreasing in σ_η , with a unique value matching the model's moments to the empirical ones. Figure E.1 illustrates this visually.

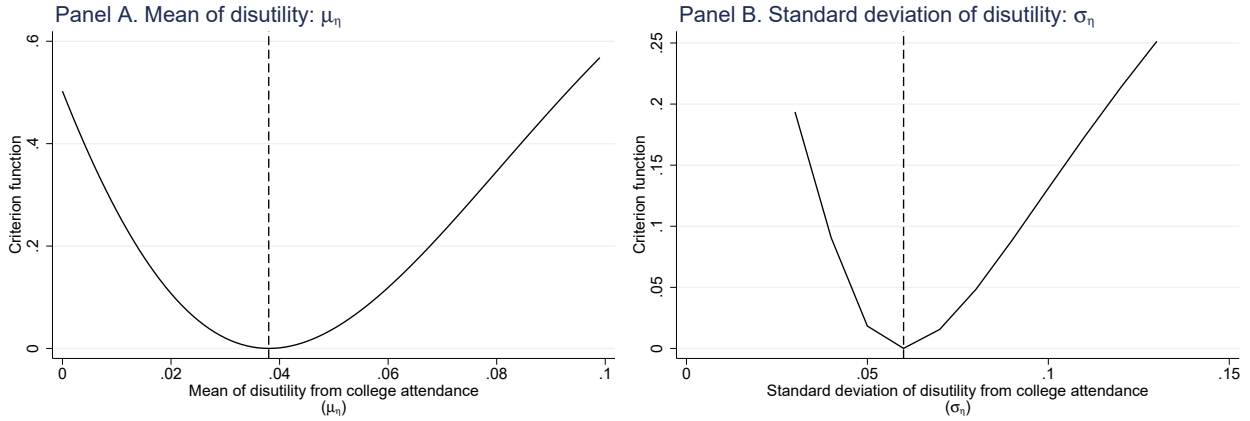
Figure E.2 plots the value of the criterion function for different values of a given parameter, holding the other fixed at its estimated value. As one can infer from the figure, the targeted moments provide relevant identification information. The criterion function is strictly convex around the estimated parameters and consequently the coefficients are uniquely identified.

¹Intuitively, for low values of μ_η , college attendance becomes nearly universal for a value of σ_η close to zero, as few individuals receive disutility shocks sufficiently high to counterbalance the benefits of going to college. The opposite holds for high values of μ_η .

²In particular, when $\mu = 0.0097$ and σ_η ranges between 0.0001 and 0.0002, the model closely replicates the baseline bachelor's degree completion rate. However, the predicted reduced-form coefficient of the effects of robots on college attainment is 30 times as large as the one observed empirically.

Figure E.1: Identification of the Structural Parameters

Notes. These figures illustrate the identification of the structural parameters with respect to the observed and simulated moments. The x -axis is the respective parameter of interest, which we vary while fixing the other parameter to its estimated value. The y -axis represents the corresponding observed and simulated moments. The solid lines indicate the observed value in the data, while the dashed ones indicate the value simulated from the estimated model. Each parameter is identified by finding the point on the x -axis where the solid and dashed lines intersect.

Figure E.2: Minimum Distance, Model

Notes. These figures show the impact of varying one parameter at time on the criterion function, holding the other parameter fixed at its estimated value. The x -axis is the respective parameter of interest, while the y -axis represents the value of the criterion function.

E.2 Sensitivity Tests

Table E.1: Estimated Parameters for the Structural Model:
Alternative Curvature Coefficients

Description	Parameter	Estimate	Target moment	Data	Model
<i>Panel A: $\gamma = 1$ (log utility)</i>					
Mean of disutility from college attendance	μ_η	3.899 [0.296]	Bachelor completion (% pts.)	32.506	32.2655
Standard deviation of disutility from college attendance	σ_η	4.4878 [0.2988]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4941
<i>Panel B: $\gamma = 2$</i>					
Mean of disutility from college attendance	μ_η	0.00037 [5e-05]	Bachelor completion (% pts.)	32.506	32.5136
Standard deviation of disutility from college attendance	σ_η	0.00076 [1e-05]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4691

Notes. This table shows the robustness of the results to assuming alternative values for the curvature parameter of the utility function. The estimates are obtained using the simulated method of moments. The estimation sample consists of all youths aged 18 in the 1990 census, when they are ready to make college decisions. For a vector of possible values of structural parameters ψ , we simulate a value η_i for each individual i based on the cumulative normal distribution function $F(\cdot)$ and then solve for their college decision under a scenario with and without robots. For the latter scenario, the corresponding updated earnings profiles are simulated using the estimates of κ_{sa} obtained in the first step. The parameters are estimated by minimizing the distance between the target empirical moments and simulated moments as predicted by the model for a given vector of free parameters. The target moments are the bachelor attainment rate and the reduced-form effect of robots on bachelor attainment reported in column (5) of Table 1. The estimated coefficients and respective standard errors are reported in the third column. The empirical and simulated moments are reported in the last two columns. Standard errors reported in brackets are obtained through a bootstrap of the structural estimation.

Table E.2: Estimated Parameters for the Structural Model:
Alternative Interest Rates

Description	Parameter	Estimate	Target moment	Data	Model
<i>Panel A: annual interest rate=1%</i>					
Mean of disutility from college attendance	μ_η	0.06404 [0.00256]	Bachelor completion (% pts.)	32.5062	32.7336
Standard deviation of disutility from college attendance	σ_η	0.08282 [0.0025]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.5105
<i>Panel B: annual interest rate=2%</i>					
Mean of disutility from college attendance	μ_η	0.0563 [0.00245]	Bachelor completion (% pts.)	32.5062	32.4832
Standard deviation of disutility from college attendance	σ_η	0.07682 [0.00242]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4901
<i>Panel C: annual interest rate=3%</i>					
Mean of disutility from college attendance	μ_η	0.04852 [0.00241]	Bachelor completion (% pts.)	32.5062	32.5621
Standard deviation of disutility from college attendance	σ_η	0.07211 [0.00239]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4784
<i>Panel D: annual interest rate=4%</i>					
Mean of disutility from college attendance	μ_η	0.04219 [0.00247]	Bachelor completion (% pts.)	32.5062	32.4195
Standard deviation of disutility from college attendance	σ_η	0.06658 [0.00251]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4869

Notes. This table shows the robustness of the results to assuming alternative values for the annual interest rate. Note that the interest rate per period is equal $4(\times)$ the annual interest rate, since each period corresponds to 4 years. The estimates are obtained using the simulated method of moments. The estimation sample consists of all youths aged 18 in the 1990 census, when they are ready to make college decisions. For a vector of possible values of structural parameters ψ , we simulate a value η_i for each individual i based on the cumulative normal distribution function $F(\cdot)$ and then solve for their college decision under a scenario with and without robots. For the latter scenario, the corresponding updated earnings profiles are simulated using the estimates of κ_{sa} obtained in the first step. The parameters are estimated by minimizing the distance between the target empirical moments and simulated moments as predicted by the model for a given vector of free parameters. The target moments are the bachelor attainment rate and the reduced-form effect of robots on bachelor attainment reported in column (5) of Table 1. The estimated coefficients and respective standard errors are reported in the third column. The empirical and simulated moments are reported in the last two columns. Standard errors reported in brackets are obtained through a bootstrap of the structural estimation.

Table E.3: Estimated Parameters for the Structural Model:
Alternative Repayment Periods

Description	Parameter	Estimate	Target moment	Data	Model
<i>Panel A: loans last 4 periods</i>					
Mean of disutility from college attendance	μ_η	0.03871 [0.0024]	Bachelor completion (% pts.)	32.5062	33.1295
Standard deviation of disutility from college attendance	σ_η	0.06567 [0.0025]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4869
<i>Panel B: loans last 6 periods</i>					
Mean of disutility from college attendance	μ_η	0.03945 [0.00246]	Bachelor completion (% pts.)	32.5062	32.371
Standard deviation of disutility from college attendance	σ_η	0.06347 [0.0024]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4937
<i>Panel C: loans last 8 periods</i>					
Mean of disutility from college attendance	μ_η	0.04091 [0.0025]	Bachelor completion (% pts.)	32.5062	32.5159
Standard deviation of disutility from college attendance	σ_η	0.06776 [0.00245]	Reduced-form effect of robots on bachelor completion (% pts.)	0.4828	0.4669

Notes. This table shows the robustness of the results to assuming alternative repayment periods. The estimates are obtained using the simulated method of moments. The estimation sample consists of all youths aged 18 in the 1990 census, when they are ready to make college decisions. For a vector of possible values of structural parameters ψ , we simulate a value η_i for each individual i based on the cumulative normal distribution function $F(\cdot)$ and then solve for their college decision under a scenario with and without robots. For the latter scenario, the corresponding updated earnings profiles are simulated using the estimates of κ_{sa} obtained in the first step. The parameters are estimated by minimizing the distance between the target empirical moments and simulated moments as predicted by the model for a given vector of free parameters. The target moments are the bachelor attainment rate and the reduced-form effect of robots on bachelor attainment reported in column (5) of Table 1. The estimated coefficients and respective standard errors are reported in the third column. The empirical and simulated moments are reported in the last two columns. Standard errors reported in brackets are obtained through a bootstrap of the structural estimation.

F Mathematical Appendix

F.1 Proof of Proposition 1

Final goods are produced by a representative firm combining high-skill labor, low-skill labor of younger workers, low-skill labor of older workers, and capital. Firms operate in competitive markets and the price of the final good is normalized to one. Given prices p and w_j of factors, the firm chooses inputs to maximize profits:

$$\max_{\ell_j, K} \{\pi \equiv Q(\ell_j, K) - \sum_{j \in \chi} w_j \ell_j - pK\} \quad (\text{F.1})$$

Given the assumption that $Q(\cdot)$ is a CES production function of the form given by equation (10), the first-order conditions become:

$$w_j = a_j^{\frac{\varepsilon-1}{\varepsilon}} Q^{1/\varepsilon} \ell_j^{-1/\varepsilon} \quad (\text{F.2})$$

$$p = a_K^{\frac{\varepsilon-1}{\varepsilon}} Q^{1/\varepsilon} K^{-1/\varepsilon}$$

To obtain the equilibrium impact of automation on the price of labor, we differentiate the log of the first-order condition for ℓ_j :

$$d \ln w_j = \frac{\varepsilon-1}{\varepsilon} d \ln a_j + \frac{1}{\varepsilon} d \ln Q - \frac{1}{\varepsilon} d \ln \ell_j \quad (\text{F.3})$$

The first term on the right-side hand of this equation represents a strictly negative displacement effect created by automation. The second term captures the gains in output from automation. The third term is a supply effect on the group of workers affected.

Because $\ln a_j = \varphi_j \nu$, we have that $d \ln a_j = \varphi_j d \nu$. To derive the productivity effect, we begin by taking logs of the production function:

$$\ln Q = \frac{\varepsilon}{\varepsilon-1} \ln \left[\sum_{j \in \chi} (a_j \ell_j)^{\frac{\varepsilon-1}{\varepsilon}} + (a_K K)^{\frac{\varepsilon-1}{\varepsilon}} \right]$$

Differentiating this expression with respect to ν yields:

$$d \ln Q = \left(\frac{\varepsilon}{\varepsilon-1} \right) \frac{1}{Q^{\frac{\varepsilon-1}{\varepsilon}}} \left[\left(\frac{\varepsilon-1}{\varepsilon} \right) \left(\sum_{j \in \chi} a_j^{-\frac{1}{\varepsilon}} \ell_j^{\frac{\varepsilon-1}{\varepsilon}} \frac{d a_j}{d \nu} + a_K^{-\frac{1}{\varepsilon}} K^{\frac{\varepsilon-1}{\varepsilon}} \frac{d a_K}{d \nu} \right) \right] d \nu$$

$$d \ln Q = \frac{1}{Q^{\frac{\varepsilon-1}{\varepsilon}}} \left(\sum_{j \in \chi} a_j^{-\frac{1}{\varepsilon}} \ell_j^{\frac{\varepsilon-1}{\varepsilon}} \frac{d a_j}{d \nu} + a_K^{-\frac{1}{\varepsilon}} K^{\frac{\varepsilon-1}{\varepsilon}} \frac{d a_K}{d \nu} \right) d \nu$$

$$d \ln Q = \left(\sum_{j \in \chi} a_j^{-\frac{1}{\varepsilon}} \frac{\ell_j^{\frac{\varepsilon-1}{\varepsilon}}}{Q^{\frac{\varepsilon-1}{\varepsilon}}} \frac{d a_j}{d \nu} + a_K^{-\frac{1}{\varepsilon}} \frac{K^{\frac{\varepsilon-1}{\varepsilon}}}{Q^{\frac{\varepsilon-1}{\varepsilon}}} \frac{d a_K}{d \nu} \right) d \nu$$

$$d\ln Q = \left(\sum_{j \in \chi} a_j^{-\frac{1}{\varepsilon}} \frac{\ell_j}{Q} \frac{\ell_j^{-\frac{1}{\varepsilon}}}{Q^{-\frac{1}{\varepsilon}}} \frac{da_j}{d\nu} + a_K^{-\frac{1}{\varepsilon}} \frac{K}{Q} \frac{K^{-\frac{1}{\varepsilon}}}{Q^{-\frac{1}{\varepsilon}}} \frac{da_K}{d\nu} \right) d\nu \quad (\text{F.4})$$

From the first-order conditions, we have:

$$\frac{\ell_j^{-\frac{1}{\varepsilon}}}{Q^{-\frac{1}{\varepsilon}}} = w_j a_j^{-\frac{\varepsilon-1}{\varepsilon}}$$

$$\frac{K^{-\frac{1}{\varepsilon}}}{Q^{-\frac{1}{\varepsilon}}} = p a_K^{-\frac{\varepsilon-1}{\varepsilon}}$$

Substituting into equation (F.4) yield

$$\begin{aligned} d\ln Q &= \left[\sum_{j \in \chi} a_j^{-\frac{1}{\varepsilon}} \frac{\ell_j}{Q} (w_j a_j^{-\frac{\varepsilon-1}{\varepsilon}}) \frac{da_j}{d\nu} + a_K^{-\frac{1}{\varepsilon}} \frac{K}{Q} (p a_K^{-\frac{\varepsilon-1}{\varepsilon}}) \frac{da_K}{d\nu} \right] d\nu \\ d\ln Q &= \left(\sum_{j \in \chi} \frac{w_j \ell_j}{Q} \frac{1}{a_j} \frac{da_j}{d\nu} + \frac{pK}{Q} \frac{1}{a_K} \frac{da_K}{d\nu} \right) d\nu \\ d\ln Q &= \left(\sum_{j \in \chi} \zeta_j \frac{1}{a_K} \frac{da_j}{d\nu} + \zeta_K \frac{1}{a_K} \frac{da_K}{d\nu} \right) d\nu \end{aligned} \quad (\text{F.5})$$

where ζ' s are factor share. The formal functional of the share parameters a' s described in the text implies:

$$\frac{1}{a_x} \frac{da_x}{d\nu} = \varphi_x$$

The term x indexes capital and labor factors. Let Φ denote the set containing both the capital and labor factors. Equation (F.5) becomes:

$$d\ln Q = \left(\sum_{x \in \Phi} \zeta_x \varphi_x \right) d\nu \quad (\text{F.6})$$

Replacing this result and $d\ln a_j = \varphi_j d\nu$ into equation (F.3):

$$d\ln w_j = \kappa_j d\nu - \frac{1}{\varepsilon} d\ln \ell_j$$

where

$$\kappa_j = \frac{\varepsilon-1}{\varepsilon} \varphi_j + \frac{1}{\varepsilon} \sum_{x \in \Phi} \zeta_x \varphi_x$$

which yields the desired result. ■

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