The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market. By David H. Autor and David Dorn

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1 Overview

Although the canonical model has been used by several authors to explain the evolution of skill awards in the United States throughout the twentieth century, this model has limitations to explain two major features of the recent evolution of inequality that are the focus of this paper.

First, the strikingly non-monotone growth of employment by skill level between 1980 and 2005. Figure 1a shows employment changes in the United States during this period were strongly U-shaped in skill level, with relative employment declines in the middle of the distribution and relative gains at the tails. Second, the non-monotonicity of wage changes by skill percentile in this same period. Figure 1b shows wage growth is strikingly U-shaped in skill percentiles, with the greatest gains in the upper tail, modest gains in the lower tail, and substantially smaller gains toward the median.

Taking into account this two concerns, this paper tries to explain the forces behind the changing shape of low education, low wage employment in the US labor market. Autor and Dorn -henceforth, AD- argue that the twisting of the lower tail of the employment and earnings distributions is substantially accounted for by rising employment and wages in service occupations. To understand the rapid rise of employment and wages in service occupations the authors propose that polarization is driven by the interaction between two forces: consumer preferences, which favor variety over specialization; and non-neutral technological progress, which greatly reduces the cost of accomplishing routine.

To reach these conclusions the authors use two general equilibrium models. The first model assumes that technological progress takes the form of an ongoing decline in the cost of computerizing routine tasks, which can be performed both by computer capital and low-skill ("noncollege") workers in the production of goods. This model gives rise two focal cases which are supported by the data. On one hand, the continuously falling price of automating routine tasks causes wages in manual tasks to exceed wages in routine tasks, therefore Low-skill labor flows accordingly from goods to services. On the other hand, employment polarization is accompanied by wage polarization whereby the ratio of wages paid to manual relative to abstract tasks is either constant or increasing.

The second model is a spatial equilibrium model which establishes that as the price of computer capital falls, labor markets with greater initial specialization in routine tasks will experience: First, greater adoption of information technology, coinciding with the displacement of labor from routine tasks; second, greater reallocation of low-skill workers from routine task-intensive occupations to service occupations; third, larger increases in wages for both high-skill abstract and low-skill manual labor (i.e., wage polarization), driven by the q-complementarity between information technology and abstract tasks in production and the gross complementarity between goods and services in consumption, and finally, larger net inflows of high-skill labor, driven by the interaction between differential adoption of computer capital in initially routine task-intensive labor markets and q-complementarity between computer capital and high-skill labor.

The results presented on this paper could be interpreted causally if we trust on the Instrumental Variable Identification presented to estimate the effect of routine employment share on the variation of service employment. I think we can accept it given that the instrument is constructed using data from 30 years before, and that eliminates correlations with any contemporaneous innovations, therefore exclusion restrictions is supported. An ideal research design for this issue would be to randomly assign shocks of labor demand of high routine occupations to several community zones and evaluate the effect over the level of service employment, however this is not feasible.

Placing this paper in context, the authors expanded the analysis of Autor et al. (2003)-henceforth, ALM-adopting a general equilibrium model of “routine-task” replacing technological change. ALM showed that within industries, occupations, and education groups, computerization is associated with reduced labor input of routine manual and routine cognitive tasks. Using data from 16 European countries, Goos et al. (2009, 2014) found that the routinization hypothesis of ALM is the most important factor behind the observed shifts in employment but that offshoring does play a role. Furthermore, high-paying occupations expanded relative to middle-wage occupations in the 1990s and 2000s, and in low-paying occupations expanded relative to middle-wage occupations. Even when the authors argue that while the rapid growth of low-wage, low-education service occupations since 1980 may appear inconsistent with the conventional narrative in which low-skill occupations sharply contracted in the 1980s and expanded thereafter Autor et al. (2008), the reconciliation of these facts is found in Figure 2, which plots the evolution of employment in the set of occupations that comprised the lowest skill quintile of employment in 1980.

After the publication of this paper, some surveys still support some of the conclusions of the authors while others propose that automation could complement labor. One one hand, Leonardi (2015) using Consumer Expenditure Survey data shows that more educated workers demand more high-skill-intensive services and, to a lesser extent, more very low-skill-intensive services. Furthermore, Bárány and Siegel (2018) document that job polarization has started as early as the 1950s in the United States: middle-wage workers have been losing both in terms of employment and average wage growth compared to low and high-wage workers. At more aggregate level, Graetz and Michaels (2017) study recoveries from 71 recessions in 28 industries and 17 countries from 1970-2011 and found that Industries that used more routine tasks, and those more exposed to robotization, did not recently experience slower employment recoveries. Finally, Brynjolfsson et al. (2018) in a more disaggregated level, build measures of ”Suitability for Machine Learning” (SML) and apply it to 18,156 tasks in O*NET. They found most occupations include at least some SML tasks; few occupations are fully automatable using ML; and realizing the potential of ML usually requires redesign of job task content.

On the other hand, David (2015) propose that automation also complements labor, raises output in ways that leads to higher demand for labor. Furthermore, he proposes that this polarization is unlikely to continue very far into future since the interplay between machine and human comparative amplify the comparative advantage of workers in supplying problem-solving skills and creativity. Supporting this idea,Gaggl and Wright (2017) study the short-run causal effect of Information and Communication Technology (ICT) adoption on employment and wage distribution in UK. They exploit a natural experiment generated by a tax allowance on ICT investments and find that the primary effect of ICT is to complement nonroutine, cognitive-intensive work. Finally, Acemoglu and Restrepo (2018) propose a model where another powerful force is balancing the implications of automation: the creation of new tasks in which labor has a comparative advantage.

These tasks increase the demand for labor and tend to raise the labor share. But new tasks require new skills, and especially when the education sector does not keep up with the demand for new skills, a mismatch between skills and technologies is bound to complicate the adjustment process.

2 Replication

For the replication process I used the data which was available on David Dorn's webpage. For replication of Table 7, David Autor kindly provided me the dataset, but I will extend this analysis on my extensions with an updated dataset. All the results on the tables and figures are exactly the same as in the paper, only the format and presentation of both are different.

2.1 Data Sources and Measuring the "Routine Employment Share"

This analysis draws on the Census Integrated Public Use Micro Samples for the years 1950, 1970, 1980, 1990, and 2000, and the American Community Survey (ACS) for 2005. Worker sample consists of individuals who were between age 16 and 64 and who were working in the year preceding the survey.

The authors use a definition of local labor markets based on the concept of Commuting Zones (CZs) developed by Tolbert and Sizer (1996), this contains county level commuting data from the 1990 Census to create 741 clusters of counties, these are based primarily on economic geography. To create the main dependent variable they proceed in two steps. First, the authors create a summary measure of routine task-intensity (RTI) by occupation, calculated as:

$$RTI_k = \ln(T^R_{k,1980} * - \ln(T^M_{k,1980} - \ln(T^A_{k,1980}) \tag{1}$$

where T^R_k, T^M_k , T^A_k are the routine, manual, and abstract task inputs in each occupation k in 1980. The authors created RTI at the geographic level in two steps. First, they use the RTI index to identify the set of occupations that are in the top employment-weighted third of routine task-intensity in 1980, called as routine-intensive occupations. Figure 2 shows routine intensity is inversely U-shaped in occupational skill. The fraction of occupations flagged as routine-intensive is lowest at the 1st and 80th percentiles of the skill distribution and rises smoothly from both locations to a maximum at approximately the 30th skill percentile.

Second, they calculate for each commuting zone j a routine employment share measure, RSH_{jt} equal to:

$$RSH_{jt} = \left(\sum_{k=1}^{K} L_{jkt}[RTI_k > RTI^{P66}] \right) \left(\sum_{k=1}^{K} L_{jkt} \right)^{-1} \tag{2}$$

where L_{jkt} is the employment in occupation k in commuting zone j at time t, and 1[.] takes the value of one if the occupation is routine intensive by their definition.

For computer adoption implications they use a measure of geographic computer penetration developed by Doms and Lewis (2006), this measure counts the number of personal computers per employee at the firm level by CZ´s.

2.2 Main Results

Now I will present how AD test their model's four empirical implications concerning computer adoption and displacement of routine tasks; reallocation of noncollege labor into service occupations; wage and employment polarization; and geographic mobility.

First, one prediction of the model establishes that commuting zones with a greater initial routine employment share should differentially adopt information technology , for instance computers, in response to its declining price and differentially displace labor from routine tasks. Thus, AD estimate models predicting computer adoption (PCs per worker) across commuting zones of the form:

$$\Delta PC_{jst} = \delta_t + \beta_0 \times RSH_{jst_0} + \gamma_s + \epsilon_{jst} \tag{3}$$

the dependent variable is the change in the Doms-Lewis measure of computer adoption over decade t_0 to t_1 in commuting zone j in state s, RSH_{jst_0} is that commuting zone's share of routine employment at the start of the decade. Panel A of Table 4.1 shows that the RSH variable is highly predictive of computer adoption. Likewise, panel B confirms that commuting zones with initially higher routine task specialization saw larger subsequent declines in routine-intensive occupations. Consistent with the conceptual model, columns 2 and 3 find that the decline in routine employment is substantially larger for noncollege workers than for college workers.

Second, according to the model rapid rise in service employment should be most pronounced in initially routine task-intensive labor markets because the potential for displacement of noncollege labor from routine activities is greatest in these locations. AD regress the change in the noncollege service occupation share on the start of the period routine employment share by decade for the period 1950 through 2005:

$$\Delta SVC_{jst} = \delta_t + \beta_1 RSH_{jst_0} + \epsilon_{jst} \tag{4}$$

Table 4.2 shows that this relationship is only weakly evident prior to the 1980s and has the opposite sign during the 1950s and 1960s. The relationship becomes highly significant in the 1980s and its magnitude increases further in the 2000s.

Then the authors considered that host of human capital, demographic, and local labor market factors may explain differences across commuting zones in the growth of service employment. Therefore they expand the equation (4) to estimate:

$$\Delta SVC_{jst} = \delta_t + \beta_1 RSH_{jst_0} + X'_{jst_0}\beta_2 + \gamma_s + \epsilon_{jst} \tag{5}$$

This new regression covers the interval 1980–2005, and includes a full set of time period effects, state effects, as well as the start-of-period values of the new seven additional explanatory variables. Table 4.3 panel A shows after including these variables that the coefficient of RSH variable remains robustly significant and large. For instance, column 2 and 3 show that greater relative supply of college-educated individuals predicts rising service employment among noncollege workers, as does a greater stock of foreign born residents. From Column 4 they conclude that service employment grows less rapidly in areas with higher unemployment and a larger manufacturing employment share. In column 5 they show that a greater share of senior citizens in the population may raise service employment, besides, higher female labor force participation might be expected to raise demand for services. Finally, from column 6 they propose that larger fraction of workers for whom the minimum wage will become binding significantly dampens the growth of service occupation employment.

Third, the authors were worried about what causes RSH to vary across commuting zones. Their theoretical model attributes this variation to stable differences in production structure across CZs. Therefore, they propose a decomposition of $RSH_{jst_0} = RSH^*_j + \nu_{jt_0}$ and consider an augmented version of the equation (4):

$$\Delta SVC_{jst} = \delta_t + \beta_1 RSH_{jst_0} + \beta_2 \nu_{jt_0} + \gamma_s + \epsilon_{jst} \tag{6}$$

RSH_j^* represents the long-run, quasi-fixed component of industrial structure while ν_{jt_0} is any unobserved, time-varying attribute that affects CZs' routine occupation shares. They argue that ν_{jt_0} might reflect a cyclical spike in the demand for a CZ's manufacturing outputs, which draws low-skilled workers temporarily from services into manufacturing. This cyclical fluctuation would lead to biased OLS estimates of β_1.

To solve this potential bias, they propose an instrument which provides a predicted value for the routine employment share in each commuting zone, which depends only on the local industry mix in 1950 and the occupational structure of industries nationally in 1950:

$$\widetilde{RSH}_j = \sum_{i=1}^{I} E_{i,j,1950} \times R_{i,-j,1950} \tag{7}$$

They argue that this instrumental variable is valid for RSH because it is determined three decades prior to 1980, it is expected to be correlated with the long-run component of the routine occupation share RSH^* but uncorrelated with contemporaneous innovations to RSH reflected in ν. Table 4.3 panel B repeats estimates for the growth of noncollege service employment. The 2SLS estimates are precisely estimated and are larger in magnitude than their OLS counterparts. For instance in column 7 the 2SLS point estimate is 0.149 versus 0.111 in the OLS model.

Finally, the spatial model predicts that polarization of both employment and wages should be more pronounced in routine task-intensive labor markets. The authors verify this on employment and wage changes in all six major occupation groups.

Panel A in Table 4.4 shows changes in noncollege employment by major occupational category. The estimates demonstrate that noncollege employment differentially contracted in all of these occupational categories in routine-intensive commuting zones between 1980 and 2005. The employment share declines were particularly pronounced in productive and operator occupations among males, and in clerical and sales occupations among females.

Panel B in Table 4.4 shows whether there were differential wage changes among noncollege workers in routine-intensive labor markets . The authors estimated the next equation :

$$\ln w_{ijskt} = \gamma_{jk} + \lambda_k \{RSH_{J,1980} \times 1[t = 2005]\} + X_i^{'}\beta_t + \delta_{kt} + \phi_{st} + \epsilon_{ijkt} \tag{8}$$

Where i denotes workers, j denotes commuting zones, s denotes states, k denotes occupations, and t denotes time (1980, 2005). The term $\lambda_k\{RSH_{J,1980} \times 1[t = 2005]\}$ measures the impact of a CZ's routine-intensity in 1980 on wage growth during 1980–2005. The results establish that routine task-intensive labor markets saw rising employment and earnings of noncollege workers in non-routine intensive occupations combined with declining employment, and in some cases declining wages, in routine-intensive occupations. Among all occupational categories, service occupations stand out for sharp gains in employment shares and wages among noncollege workers.

Panel C in Table 4.4 was not originally estimated by the authors, but it will be important for my extensions. For occupations with low routine content, natives experienced rising earnings only for the coefficient in column 3 which is significant.For immigrants the effects appear to be negative but non significant too. However, in the case of service occupations immigrants experienced higher increase on earnings compared to natives.

3 Extension

3.1 Extension I: Extending analysis until 2015

Table 4.5 pretend to replicate the results in Table 7 panel B of David and Dorn (2013) for an extended period until 2015. The third row of Panel A shows the main analysis from 1980 to 2005 as the authors did, so this is our baseline. The first row presents the results for the updated dataset from 1980 to 2015. Overall, most of the estimates do not change. The larger differences appear on columns 3 and 4. For Administrative support and retail sales occupations the coefficient is 0.02 smaller while for manager, finance, public safety occupations the coefficient is 0.03 smaller too. Therefore, after ten years these results establish that routine task-intensive labor markets saw rising earnings of noncollege workers in non-routine intensive occupations combined with ,in some cases, declining wages in routine-intensive occupations.

Panel B of Table 4.5 presents the wage estimates by sex. For males, some coefficient are smaller than the estimates from the authors. On one hand, for low routine occupations, the groups 2 and 3 have smaller coefficient but both are non significant as the authors' findings. For service occupations the coefficient is 0.002 smaller and significant. On the other hand, for high routine occupations the larger change appears on the Administrative , support an retail sales occupations which is 0.013 smaller. For Females, some coefficient experienced pronounced changes on the coefficients. On one hand, the bigger changes appear on the low routine occupations, for all the columns in this group the coefficients are 0.04 smaller. On the other hand, for high routine occupations the changes are really small. In sum, among males and females I did not find huge difference in the coefficients when I analyse the equation for a longer period. In sum, it is still true that wages decline were particularly pronounced in machine operator and assemblers occupations among males, and in precision production and craft occupations among females.

Finally, panel C in Table 4.5 shows no many differences with respect to Table 4.4. For occupations with low routine content, natives experienced rising earnings only for the coefficient in column 3 which is significant but now this coefficient is lower by 0.04 units. In the case of service occupations, immigrants experienced higher increase on earnings compared to natives but again this coefficient is lower than the previous table by 0.04 units.

3.2 Extension II: Impact of Immigrant Share on Labor Market Outcomes by Occupation

To analyse the impact of immigrant share on labor market outcomes by occupations I will extend the methodology applied by Borjas (2003). Let y_{ijot} denote the mean value of a particular labor market outcome for native men who have education $i(i = 1,..,4)$, experience $j(j = 1,...,8)$, occupation $o(o = 1,..,6)$ and are observed at time t (t = 1980, 1990, 2000, 2005, 2015). I estimate the model :

$$\begin{aligned} y_{ijot} =& \beta * Immigrant_{ijot} + s_i + x_j + \pi_t + r_o + (s_i * x_j) + (s_i * \pi_t) \\ &+ (x_j * \pi_t) + (r_o * x_j) + (r_o * \pi_t) + (r_o * s_i) + \epsilon_{ijot} \end{aligned} \tag{9}$$

where s_i , x_j , π_t and r_o are vectors of fixed effects indicating the group´s education attainment, the group´s work experience, the time period and occupations classified by routine content respectively. The dependent variables are the mean of log annual earnings, the mean of log weekly earnings, and the mean of fraction of time worked. The standard errors are clustered by education-experience-occupation cells to adjust for possible serial correlation.

The first row of Table 4.6 presents the basic estimates for the coefficient β. When the dependent variable is the log of annual earnings of native workers, the coefficient is -0.109, with a standard error of 0.045. We need to translate this coefficient to an elasticity. Given that by 2015 immigration had increased the number of labor force by 17.35 percent, the wage elasticity for annual earnings is -0.27(or -.109*0.39). That means that a 10 percent supply shock reduces annual earnings by about 2 percent. Table 4.6 indicates that immigration has an even stronger effect on weekly earnings, but small an positive effect on fraction of time worked.

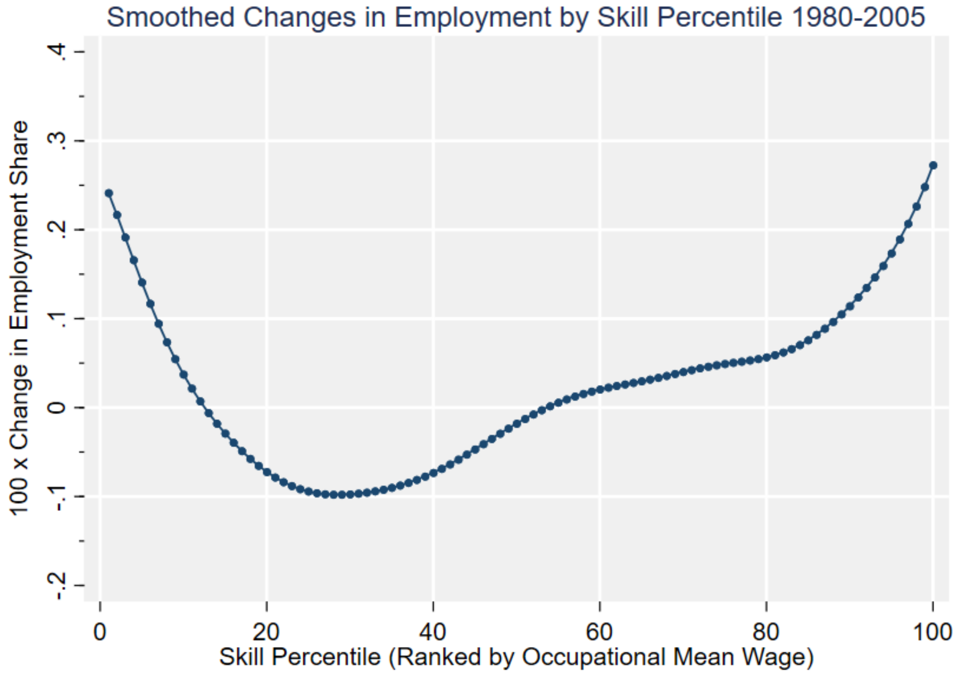
I also estimated the regression model within occupations that were classified by routine content as in David and Dorn (2013), to determine whether the results are being driven by particular occupation groups.

Table 4.7 shows the impact of immigration on the outcome variables by occupations group. Panel A shows mixed results. For low routine occupations the impact of immigration on annual earnings is negative for occupations in columns 2 and 3, but these coefficients are not significant. For high routine occupations, there is a positive impact on annual earnings and these effects are significant, the higher positive effect is on administrative support and retail sales occupations. which is 0.764. These results are quite similar for weekly earnings.

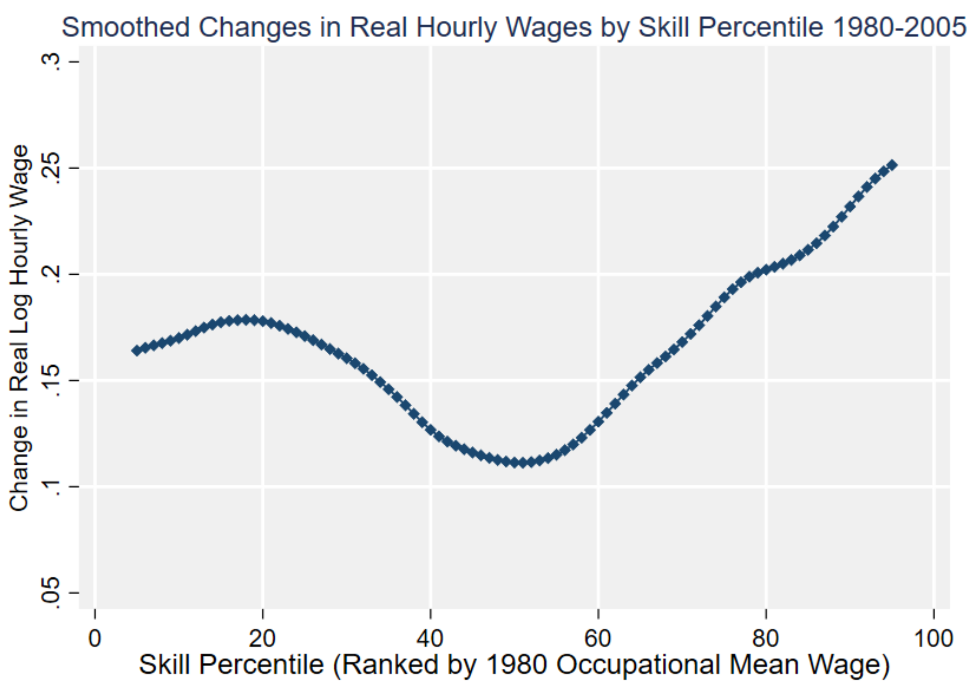
But when I analyse for non college workers interesting results appear. Panel B of Table 4.7 shows that immigration has a negative effect on labor outcomes for those who are working on transport, construction and mechanical occupations. This result is in line with what Peri and Sparber (2009) found, they concluded that immigrants with little educational attainment have a comparative advantage in manual and physical tasks, therefore immigration could create wage losses among less-educated native workers for this kind of occupations. The coefficient is even bigger for those who are in managerial, technical and public safety occupations. For high routine occupations the relation appear to be positive but they are not significant. I also found that there is a positive correlation between immigration and wages for service occupations. This could represent what Peri and Sparber (2009) found about how native workers shifted to occupations more intensive in language skills and less intensive in physical skills , therefore the relative compensation paid to communication skills rises, rewarding natives who progressively move to language-intensive jobs. For a more detailed analysis I should describe the variation on service occupation in each period of time and describe labor supply movements from natives.

Finally, Panel C of Table 4.7 estimates the main equation just for workers with some college education. For occupations in column 3 the coefficients are also negative, but for occupations as transportation and construction now the coefficients are positive and significant. Even, in service occupations the coefficients are higher and also significant. For occupations with high routine content the coefficient are positive and significant , and the higher estimates are on precision production and retail sales occupations. In sum, just for managerial and public safety occupations immigration creates a negative effect on wages, while in all other occupations the relation is positive, and this result is in line with Card (2009) findings who stated that High school–equivalent and college-equivalent workers are imperfect substitutes, with an elasticity of substitution on the order of 1.5–2.5.

4 Figures and Tables



(a) Panel A



(b) Panel B

Figure 1: Smoothed Changes in Employment and Hourly Wages, 1980–2005

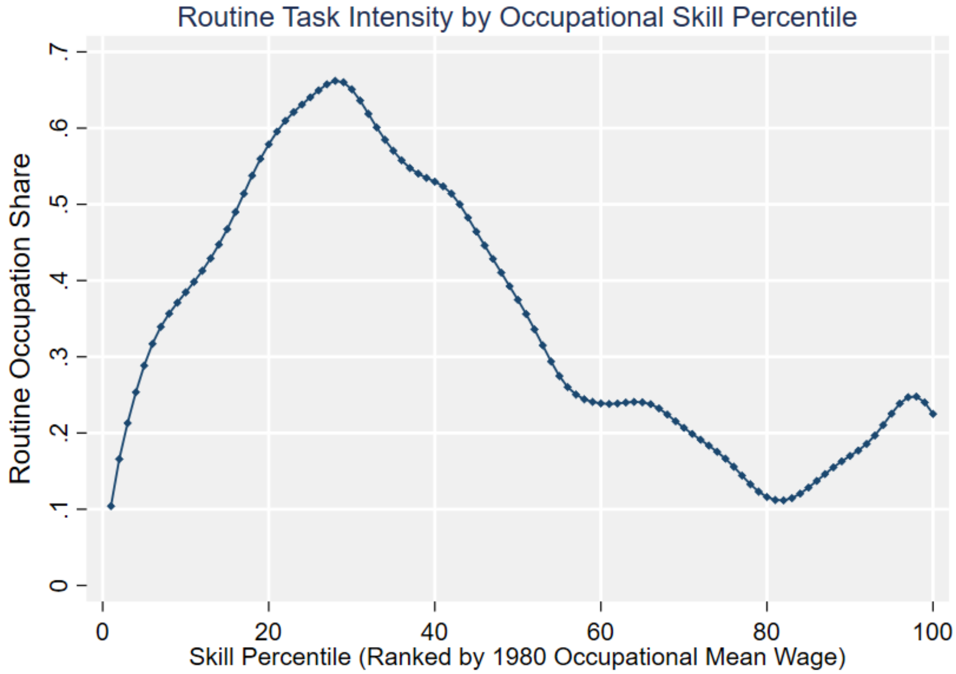


Figure 2: Share of Routine Occupations by Occupational Skill Percentile

Table 4.1: Computer Adoption and Task Specialization within Commuting Zones, 1980–2005

(Dependent variables: 10 × annual change in adjusted PCs per employee, 10 × annual change in employment share of routine occupations)

	1980–1990 (1)	1990–2000 (2)	1980–2000 (3)
Panel A. ***Adjusted PCs per employee, 1980–2000***			
Share of routine occs-1	0.695***	0.490***	0.619***
	(0.061)	(0.076)	(0.044)
R^2	0.577	0.332	0.385
	All workers	College	Noncollege
Panel B. ***Share routine occupations,1980–2005***			
Share of routine occs-1	-0.254***	-0.153***	-0.295***
	(0.023)	(0.024)	(0.018)
R^2	0.433	0.206	0.429

Notes: N = 675, N = 660, and N = 1,335 in the three columns of panel A, and N = 2,166 (3 time periods × 722 commuting zones) in panel B. Adjusted number of PCs per employee is based on firm-level data on PC use which is purged of industry-establishment size fixed effects (Doms and Lewis 2006). The PC variable is unavailable for a small number of commuting zones that account for less than 1 percent of total US population. All models include an intercept, state dummies, and in multi-period models, time dummies. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population.

Table 4.2: Routine Employment Share and Growth of Service Employment 1950–2005

(Dependent variable: 10 × annual change in share of noncollege employment in service occupations)

	1950–1970 (1)	1970–1980 (2)	1980–1990 (3)	1990–2000 (4)	2000–2005 (5)
Panel A. ***OLS estimates***					
Share of routine occs-1	-0.133***	0.042	0.083***	0.084*	0.354***
	(0.020)	(0.032)	(0.028)	(0.045)	(0.110)
Constant	0.026***	-0.035***	-0.015*	-0.003	-0.051
	(0.003)	(0.009)	(0.008)	(0.014)	(0.033)
Panel B. ***Summary measures***					
R^2	0.52	0.44	0.52	0.59	0.33
Mean growth	0.006	-0.004	0.026	0.024	0.037
SD growth	(0.015)	(0.016)	(0.013)	(0.015)	(0.035)

Notes: N = 722 commuting zones. Robust standard errors in parentheses are clustered on state. All models include state dummies and are weighted by start of period commuting zone share of national population.

Table 4.3: Routine Employment Share and Growth of Service Employment within Commuting Zones, 1980–2005: Stacked First Differences, OLS and 2SLS Estimates

(Dependent variable: 10 × annual change in share of noncollege employment in service occupations)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. ***OLS estimates***							
Share of routine occs$_{-1}$	0.105***	0.066*	0.066**	0.110***	0.110**	0.069*	0.111***
	(0.032)	(0.036)	(0.029)	(0.031)	(0.049)	(0.035)	(0.034)
College/noncollege pop$_{-1}$		0.012***					0.011**
		(0.004)					(0.005)
Immigr/noncollege pop$_{-1}$			0.042**				0.025**
			(0.017)				(0.011)
Manufact/empl$_{-1}$				-0.056***			-0.036***
				(0.015)			(0.011)
Unemployment rate$_{-1}$				-0.067			-0.313***
				(0.069)			(0.068)
Female empl/pop$_{-1}$					-0.044		-0.200***
					(0.039)		(0.037)
Age 65+/pop$_{-1}$					-0.114***		-0.061***
					(0.035)		(0.020)
Share workers with wage$_t$ < min wage$_{t+1}$						-0.134***	-0.197***
						(0.020)	(0.029)
R^2	0.179	0.189	0.196	0.195	0.191	0.196	0.265
Panel B. ***2SLS: lagged levels***							
Share of routine occs$_{-1}$	0.192***	0.118***	0.148***	0.162***	0.218***	0.174***	0.149***
	(0.035)	(0.046)	(0.044)	(0.031)	(0.054)	(0.035)	(0.056)
R^2	0.169	0.186	0.189	0.192	0.182	0.184	0.264
Panel B. ***2SLS: ten year changes***							
Share of routine occs$_{-1}$	0.192***	0.173***	0.152***	0.170***	0.180***	0.174***	0.112**
	(0.035)	(0.043)	(0.032)	(0.035)	(0.035)	(0.035)	(0.044)
R^2	0.169	0.174	0.188	0.232	0.186	0.184	0.265

Notes: N = 2,166 (3 time periods × 722 commuting zones). All models include an intercept, time dummies, and state dummies. In panels B and C, share of routine occupations is instrumented by interactions between the 1950 industry mix instrument and time dummies; see text for details. Covariates in panels A and B are identical. Covariates in columns 2–5 and 7 of panel C are equal to contemporaneous decadal change in the covariates used in panels A and B. Robust standard errors in parentheses are clustered on state. Models are weighted by start of period commuting zone share of national population.

Table 4.4: Routine Employment Share and Change in Occupational Employment Shares and Wage Levels within Commuting Zones, 1980–2005: 2SLS and Reduced Form OLS Estimates

(Dependent variable: 10 × annual change in share of noncollege employment by occupation; log real hourly wage)

	I. Occupations with low routine content			II. Occupations with high routine content		
	(1)	(2)	(3)	(4)	(5)	(6)
	Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance, public safety	Administrative support, retail sales	Precision production, craft workers	Machine operators, assemblers
Panel A. ***OLS estimates***						
All Share of routine occs_{-1}	0.192***	0.248***	0.028	-0.277***	-0.085***	-0.107**
	(0.035)	(0.037)	(0.029)	(0.038)	(0.017)	(0.044)
Males Share of routine occs_{-1}	0.210***	0.246***	-0.043	-0.055*	-0.145***	-0.213***
	(0.027)	(0.046)	(0.036)	(0.030)	(0.026)	(0.046)
Females Share of routine occs_{-1}	0.253***	0.248***	0.117***	-0.431***	-0.028**	0.087
	(0.073)	(0.037)	(0.030)	(0.062)	(0.012)	(0.055)
Panel B. ***log hourly wages of noncollege workers***						
All Share of routine $\text{occs}_{80}\times 2005$	0.381***	0.023	0.433***	0.337***	-0.078	-0.388***
	(0.091)	(0.099)	(0.113)	(0.082)	(0.109)	(0.085)
Males Share of routine $\text{occs}_{80}\times 2005$	0.346***	0.015	0.287*	0.187*	-0.075	-0.374***
	(0.132)	(0.097)	(0.149)	(0.098)	(0.140)	(0.106)
Females Share of routine $\text{occs}_{80}\times 2005$	0.328***	0.310*	0.618***	0.468***	-0.223	-0.415***
	(0.095)	(0.183)	(0.117)	(0.092)	(0.139)	(0.105)
Panel C. ***log hourly wages: Natives - Immigrants***						
Natives Share of routine $\text{occs}_{80}\times 2005$	0.085	0.077	0.520***	0.377***	0.047	-0.429***
	(0.085)	(0.112)	(0.122)	(0.078)	(0.110)	(0.107)
Immigrants Share of routine $\text{occs}_{80}\times 2005$	0.498**	-0.066	-0.200	-0.052	0.044	0.021
	(0.194)	(0.193)	(0.333)	(0.251)	(0.330)	(0.223)

Notes: Panel A: Each coefficient is based on a separate 2SLS regression with N = 2,166 (3 time periods × 722 commuting zones). Models include an intercept, state dummies, and time dummies, and are weighted by start of period commuting zone share of national population. The routine occupation share is instrumented by interactions between the 1950 industry mix measure interacted with time dummies. Robust standard errors in parentheses are clustered on state. Panel B: Each row presents coefficients from one pooled OLS reduced form regression with N = 5,363,963/2,844,441/2,519,522 in rows i/ii/iii. Panel C: Each row presents coefficients from one pooled OLS reduced form regression with N = 321,659/321,659 in rows i/ii. Observations are drawn from the 1980 Census and 2005 ACS, and exclude self-employed and farm workers. The instrument (share of routine occupations predicted by industry structure in 1950) is interacted with a dummy for the observations of year 2005. All models include an intercept, commuting zone-occupation group fixed effects, time trends for occupation groups and states, an interaction between the time dummy and the share of workers in an occupation group whose 1980 wage was below the federal or state minimum wage of 2005, nine dummies for education levels, a quartic in potential experience, dummies for married, nonwhite, and foreign-born, and interactions of all individual level controls with the time dummy. Pooled sex models also include a female dummy and its interaction with the time dummy. Hourly wages are defined as yearly wage and salary income divided by the product of weeks worked times usual weekly hours. Robust standard errors in parentheses are clustered on commuting zones. Observations are weighted by each worker's share in total labor supply in a given year.

Table 4.5: Routine Employment Share and Change in Wage Levels within Commuting Zones, 1980–2015: Reduced Form OLS Estimates

(Dependent variable: log real hourly wage of noncollege workers)

	I. Occupations with low routine content			II. Occupations with high routine content		
	(1)	(2)	(3)	(4)	(5)	(6)
	Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance, public safety	Administrative support, retail sales	Precision production, craft workers	Machine operators, assemblers
Panel A. ***log hourly wages 1980-2015***						
Share of routine occs$_{80}$×2015	0.352***	0.015	0.401***	0.316***	-0.089	-0.393***
	(0.087)	(0.096)	(0.105)	(0.076)	(0.105)	(0.082)
Share of routine occs$_{2005}$×2015	-0.128	-0.352***	-0.181	-0.258**	-0.243	-0.174
	(0.125)	(0.107)	(0.122)	(0.106)	(0.182)	(0.166)
Share of routine occs$_{80}$×2005	0.381***	0.023	0.433***	0.337***	-0.078	-0.388***
	(0.091)	(0.099)	(0.113)	(0.082)	(0.109)	(0.085)
Panel B. ***log hourly wages by gender***						
Males Share of routine occs$_{80}$×2015	0.332***	0.007	0.264*	0.174*	-0.082	-0.374***
	(0.125)	(0.092)	(0.141)	(0.089)	(0.134)	(0.102)
Females Share of routine occs$_{80}$×2015	0.288***	0.277	0.570***	0.436***	-0.241*	-0.429***
	(0.092)	(0.181)	(0.106)	(0.086)	(0.135)	(0.103)
Panel C. ***log hourly wages: Natives - Immigrants***						
Natives Share of routine occs$_{80}$×2015	0.070	0.062	0.485***	0.356***	0.032	-0.441***
	(0.082)	(0.109)	(0.115)	(0.073)	(0.107)	(0.105)
Immigrants Share of routine occs$_{80}$×2015	0.447**	-0.086	-0.180	-0.064	0.010	0.002
	(0.186)	(0.179)	(0.292)	(0.228)	(0.305)	(0.209)

Notes: Panel A: Each row presents coefficients from one pooled OLS reduced form regression with N = 5,641,064/1,026,995/5,363,963 in rows i/ii/iii. Panel B: Each row presents coefficients from one pooled OLS reduced form regression with N = 3,015,761/2,625,303 in rows i/ii. Panel C: Each row presents coefficients from one pooled OLS reduced form regression with N = 5,269,322/371,742 in rows i/ii. Observations are drawn from the 1980 Census, 2005 and 2015 ACS, and exclude self-employed and farm workers. The instrument (share of routine occupations predicted by industry structure in 1950) is interacted with a dummy for the observations of years 2005 and 2015. All models include an intercept, commuting zone-occupation group fixed effects, time trends for occupation groups and states, an interaction between the trend and the share of workers in an occupation group whose 1980 and 2015 wage was below the federal or state minimum wage of 2005, nine dummies for education levels, a quartic in potential experience, dummies for married, nonwhite, and foreign-born, and interactions of all individual level controls with the tren. Pooled sex models also include a female dummy and its interaction with the trend. Hourly wages are defined as yearly wage and salary income divided by the product of weeks worked times usual weekly hours. Robust standard errors in parentheses are clustered on commuting zones. Observations are weighted by each worker's share in total labor supply in a given year.

Table 4.6: Impact of Immigrant Share on Labor Market Outcomes of Native Education-Experience-Routine Occupation Groups, 1980–2015: Reduced Form OLS Estimates

(Dependent variables:log annual earnings, log weekly earnings, fraction of time worked)

	(1) Log annual earnings	(2) Log weekly earnings	(3) Fraction of time worked
Immigrant share	-0.109**	-0.124***	0.014***
	(0.046)	(0.045)	(0.002)
N	960	960	960

Notes: The table reports the coefficient of the immigrant share variable from regressions where the dependent variable is the mean labor market outcome for a native education-experience-occupation group at a particular time. Standard errors are reported in parentheses and are adjusted for clustering within education-experience-occupation cells. All regressions have 960 observations. All regression models include education, experience, occupation and period fixed effects, as well as interactions between all of them.

Table 4.7: Impact of Immigrant Share on Labor Market Outcomes of Native Education-Experience-Routine Occupation Groups, 1980–2015: Reduced Form OLS Estimates

(Dependent variables:log annual earnings, log weekly earnings, fraction of time worked)

	I. Occupations with low routine content			II. Occupations with high routine content		
	(1)	(2)	(3)	(4)	(5)	(6)
	Service occs	Transport, construct, mechanics, mining, farm	Managers, prof, tech, finance, public safety	Administrative support, retail sales	Precision production, craft workers	Machine operators, assemblers
Panel A. ***OLS estimates***						
Mean log annual earnings	0.026	-0.015	-0.027	0.764***	0.260*	0.164***
	(0.039)	(0.052)	(0.045)	(0.140)	(0.134)	(0.039)
Mean log weekly earnings	0.033	-0.014	-0.031	0.744***	0.259*	0.161***
	(0.039)	(0.053)	(0.044)	(0.135)	(0.135)	(0.039)
Mean fraction of time worked	-0.007***	-0.001	0.003	0.018**	0.001	0.003
	(0.002)	(0.003)	(0.002)	(0.009)	(0.004)	(0.002)
Panel B. ***OLS estimates-Non College***						
Mean log annual earnings	0.116*	-0.166**	-0.274***	0.155	0.142	0.049
	(0.063)	(0.072)	(0.086)	(0.198)	(0.244)	(0.082)
Mean log weekly earnings	0.129*	-0.157*	-0.270***	0.147	0.148	0.050
	(0.061)	(0.073)	(0.085)	(0.196)	(0.244)	(0.080)
Mean fraction of time worked	-0.011***	-0.008	-0.004	0.007	-0.006	-0.002
	(0.003)	(0.006)	(0.004)	(0.007)	(0.006)	(0.003)
Panel C. ***OLS estimates-Some College***						
Mean log annual earnings	0.492***	0.464**	-0.270**	0.845***	1.777***	0.177**
	(0.131)	(0.158)	(0.105)	(0.239)	(0.290)	(0.073)
Mean log weekly earnings	0.506***	0.466**	-0.277**	0.848***	1.798***	0.179**
	(0.132)	(0.160)	(0.103)	(0.238)	(0.291)	(0.073)
Mean fraction of time worked	-0.013	-0.002	0.006	-0.003	-0.019***	-0.002
	(0.007)	(0.006)	(0.008)	(0.009)	(0.006)	(0.006)

Notes: The table reports the coefficient of the immigrant share variable from regressions conditioned by the routine occupation group. Standard errors are reported in parentheses and are adjusted for clustering within education-experience cells. All regressions in Panel A have 160 observations, except for those reported in Panel B and Panel C. Observations are drawn from the 1980-1990-2000 Census,2005 and 2015 ACS, and exclude self-employed and farm workers.All regression models include education, period fixed effects, as well as interactions between education and experience fixed effects, period fixed effects, and experience and period fixed effects.

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