Is Job Polarization ICT-Driven? Evidence from the U.S.[*]

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Abstract

This paper investigates the effects of automation on job polarization. Automation, which has been facilitated due to the decline of the price of ICT capital, has been claimed to be one of the main causes for the job polarization observed in many countries such as the U.S. since the mid-1980s. Using the U.S. Census data, we test whether this claim, or the "ICT-driven hypothesis," is empirically supported. Our results indicate that between 1980 and 2007 the increase in the usage of ICT capital is not statistically associated with changes in the employment and wage bill share of routine workers, although there is heterogeneity across industries. The main findings imply that ICT capital per se might not be the main factor driving job polarization in the U.S.

JEL classification: D24, J23, O33

Keywords: Labor demand, Job polarization, Routine worker, ICT capital, ICT-driven hypothesis, U.S. labor market

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1 Introduction

Has automation of tasks reshaped the employment structure of the U.S.? This paper aims to provide an answer to this old but important question in the context of job polarization. In particular, the emergence of job polarization, a phenomenon where jobs requiring routine tasks have disappeared while those requiring non-routine tasks have increased, has been attributed to various factors; automation due to the decline of the price of ICT (information and communication technology) capital (routine-replacing technology change, Acemoglu and Autor (2011)), offshoring (Goos, Manning, and Salomons (2014)), the rise of multinational firms (Ahn, Hur, and Yoon (2019)), or/and different initial conditions (Autor and Dorn (2013); and Shim and Yang (2018)). Among several alternative hypotheses, we examine if the "ICT-driven hypothesis," a hypothesis that has been widely accepted in the literature, is really supported by the U.S. data.

The hypothesis is straightforward to understand: While machines (physical capital) have replaced workers performing tasks that are routine or codifiable, they have raised the demand for workers in non-routine jobs that require manual force or cognitive ability (Autor, Levy, and Murnane (2003); and Acemoglu and Autor (2011)). Figure 1 visualizes this hypothesis. The sharp decline of the routine share (employment of routine workers divided by all employed workers, Figure 1a) and that of relative price of ICT capital (price of information processing equipment and software relative to that of personal consumption expenditure, Figure 1b) are jointly observed between 1980 and 2007, which provides a rationale for the hypothesis.

In order to test if the ICT-driven hypothesis is supported by U.S. data, we adopt Michaels, Natraj, and Reenen (2014)'s empirical strategy. We empirically evaluate the relationship between the wage bill share (or the employment share) of each occupation group and the growth rate of ICT capital. If the ICT-driven hypothesis holds in the U.S., the wage bill share of the routine (resp. non-routine) occupation group would have a negative (resp. positive) relationship with the growth rate of ICT capital since such a group would be replaced (resp. complemented) by ICT capital. Specifically, we use the U.S. Census data and the EU KLEMS data, which have information on ICT and non-ICT capital at the industry

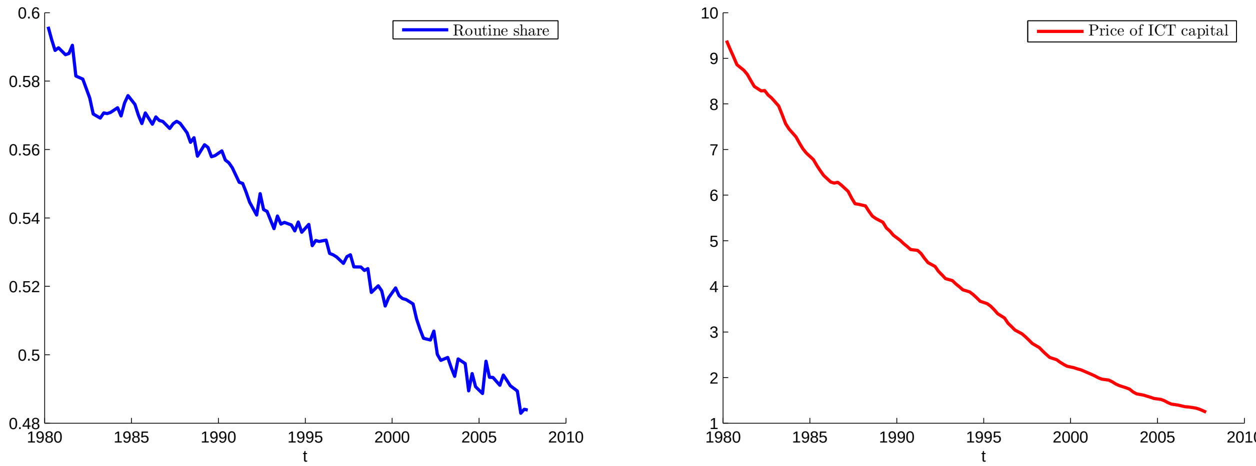

Figure 1a: Routine Share

Figure 1b: Price of ICT Capital

Figure 1: ICT-Driven Hypothesis

Data: Current Population Survey (CPS) Merged Outgoing Rotation Groups (MORG) (Shim and Yang (2016)) and Bureau of Economic Analysis.

level. Industry variation is then exploited for the identification of our variables of interest. While we closely follow Michaels, Natraj, and Reenen (2014), there are two important deviations from their analysis. First, we classify workers according to "occupations," while their classification of workers relies on "educational attainment." Our classification strategy makes our analysis consistent with the previous research on job polarization, which describes polarization according to job (occupation) characteristics (see Acemoglu and Autor (2011), for instance). This distinction is important because classification under each criterion (occupation or educational attainment) does not necessarily match each other. For instance, about 70% of high school dropouts, who are classified as the low skill group when educational attainment is used for classification, have routine jobs. Also, 70% of workers with a high school diploma or some college degree, classified as the middle-skilled in Michaels, Natraj, and Reenen (2014), have routine jobs. This implies that the two criteria might not exactly match.[1] Second, we focus on the U.S. so that we can exploit the rich information contained in the Census data.

From the benchmark OLS regression, we find that during the sample period (1980–2007), an increase in the usage of ICT capital does not significantly affect the wage bill share or employment share of routine workers, while it has a positive relationship with the shares of cognitive workers and manual workers.

[1] Statistics come from authors' calculation using the CPS MORG. Data are available upon request.

This result seems to partially support the ICT-driven hypothesis. However, the OLS regression might suffer from endogeneity and measurement problems. We try to overcome this issue by performing an instrumental variable (IV) regression, similarly to Michaels, Natraj, and Reenen (2014). When the routine share in 1980 or the labor unionization rate in 1983 are utilized as IVs, this finding becomes much weaker; we cannot observe robust evidence supporting the ICT-driven hypothesis.[2] We also show that this result is robust to sub-sample analysis including full-time workers and male workers.

We further test if there exist differential effects across sectors by introducing an interaction term between each industry and ICT capital to the main regression. Our finding indicates that the effect of changes in ICT capital is heterogenous across industries. For instance, in the banking sector, which is usually believed to be one of the sectors most affected by developments in IT technology, the wage bill share and employment share of routine workers have statistically and significantly decreased as ICT capital has increased. Since the banking sector's ICT intensity has increased by 50% per year, we can expect a great decrease in the wage bill share and employment share of routine workers in this sector. On the other hand, the demand for cognitive workers has increased, which suggests that the ICT-driven hypothesis can be industry-specific. On the contrary, the retail trade sector and service sector have experienced increases in the wage bill share and employment share of routine workers. The non-durable manufacturing sector and transportation sector do not seem to be related with the change in ICT capital over time.

Our findings indicate that at least in the U.S., ICT capital might not be the sole factor driving job polarization as results from our OLS and IV regressions do not strongly support the ICT-driven hypothesis. Rather, our findings can be interpreted as suggestive of the importance of other factors underlying job polarization; for example, Shim and Yang (2018) show that the heteregenous aspect of job polarization across industries is the consequence of initial conditions, interindustry wage differentials in particular, that industries faced in the early 1980s. According to their analysis, the positive correlation between ICT capital growth (per worker) and the degree of job polarization is the result of a firm's optimal response to the existing wage structure.

[2] In addition, the F-statistic is very low in most of our empirical specifications. We will come back to this issue later.

The structure of our paper is the following. Section 2 will introduce the variables, data, and empirical methodology. Section 3 will display the results. Finally, section 4 will conclude.

2 Data and Empirical Methodology

2.1 Data and Variables

This paper uses (1) the Decennial Census and American Community Survey (henceforth Census) and (2) the EU KLEMS from the years 1980 to 2007. This is in line with the literature that uses data up to 2007 in order to exclude the effects of the Great Recession.[3] Our analysis uses industry and occupation-level micro data and the Census' sample is large enough for each cell to have an adequate sample size thereby enabling a thorough analysis (Acemoglu and Autor (2011)).[4]

For the empirical analysis, we drop farmers and the armed forces and only include wage and salary workers.[5] Since the dependent variable is labor market outcomes, we limit the sample age to 16-64 years old. As is well-known, the occupation codes for the Census have changed every 10 years, and hence we use the consistent occupation code proposed by Dorn (2009) to consolidate the different occupation codes (see Dorn (2009) and Shim and Yang (2016) for details). We particularly classify workers into three groups, following the literature on job polarization (Autor (2010)):

- Non-routine cognitive occupations: Managers; Professionals; and Technicians
- Routine occupations: Sales; Office and administration; Production, crafts, and repair; and Operators, fabricators, and laborers
- Non-routine manual occupations: Protective services; Food preparation and building and grounds cleaning; and Personal care and personal services

[3] In particular, the great recession that occurred at the end of 2007 disproportionately affected the employment of routine occupations (Jaimovich and Siu (2018)). In addition, according to recent studies (Beaudry, Green, and Sand (2016)), the trend of job polarization has shown a different phase since the mid-2000s and our "ICT-driven" hypothesis tests the previous trend (i.e., before the mid-2000). The previous literature is also based on data before the financial crisis and hence we use the same sample period to preserve comparability with previous findings.

[4] We use the 5% population sample from the 1980 and the 2007 Census.

[5] We exclude the sample on agriculture because there are many undocumented workers in the agriculture sector and so data on wages are often inaccurate (Autor (2010)).

After we classify industries into 60 groups, we create variables for the employment share (the number of workers in a particular occupation group divided by the number of total workers) and wage bill share (the labor income of a particular occupation group divided by the total labor income) of cognitive, routine, and manual workers for each industry. Data on value added, total capital, ICT capital, and non-ICT capital are obtained from the EU KLEMS and then we create variables regarding ICT and non-ICT capital for each industry.[6]

Table 1 shows summary statistics for key variables, in particular ICT (non-ICT) capital per worker and share of ICT (non-ICT) capital. ICT capital intensity, compared to non-ICT capital, has dramatically risen between 1980 and 2007, and the rise in ICT capital might have led to a reduction of non-routine occupations. Time series evidence in Figure 1 shows that over the period of 1980 and 2007, the proportion of routine workers has steadily decreased. ICT capital intensity and its growth rate over the sample period vary across industries and the initial intensity seems to matter; an industry with a high share of ICT capital in 1980 has experienced a lower growth rate.

Table 1: Descriptive Statistics for ICT and Non-ICT Capital

	ICT capital per worker		Non-ICT capital per worker	
	Mean	Standard deviation	Mean	Standard deviation
1980	2.42	8.43	143.09	243.26
2007	41.77	52.86	236.84	413.02
	ICT capital share		Non-ICT capital share	
	Mean	Standard deviation	Mean	Standard deviation
1980	0.02	0.06	0.98	0.06
2007	0.19	0.13	0.81	0.13

Note: There are 60 industries. ICT (or non-ICT) capital per worker is calculated by dividing capital asset by total employment in each industry, and ICT (non-ICT) capital share is calculated by dividing capital by total asset in each industry.

In Table 2, we report the changes in the employment share and wage bill share for each occupation group between 1980 and 2007, which clearly shows evidence of job polarization: First, the employment share and wage bill share of routine workers was 60% and 57%, respectively in 1980. These shares

[6] The 29 industry codes of the EU KLEMS differ from those of the 60 sectors of the Census. This study matches the industry code of the EU KLEMS to that of the Census' 60 sectors. The reason why we do not do the opposite is because the 29 sectors of EU KLEMS is too small for industry-level analysis. When using only 29 sectors as in the EU KLEMS, there is no significant difference in the results. Refer to the Appendix A for details regarding the industry classification.

dropped to 47% and 39%, respectively in 2007. On the contrary, cognitive workers' employment share increased by 6.4% point, while their wage bill share increased by 13% point. Manual workers' shares increased by 7% and 6% point, respectively between the same period. Hence, as is well-known in the literature, job polarization is evident in the U.S. for both measures (employment share and wage bill share). This paper aims to systematically analyze whether this phenomenon is associated with the change in the usage of ICT capital.

Table 2: Employment and Wage Bill Share by Occupation Groups

	Employment Share			Wage Bill Share		
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
1980	26.5	59.9	13.6	35.8	56.9	7.3
2007	32.9	46.7	20.3	48.7	38.6	12.8
Δ (2007-1980)	6.4	−13.2	6.7	12.9	−18.4	5.5

Note: Each number denotes %.

2.2 Empirical Methodology

For the empirical analysis, we closely follow Michaels, Natraj, and Reenen (2014): In order to derive our empirical specification, we first consider the following short-run variable cost function:

$$Cost = C\left(W^C, W^R, W^M; K^{ICT}, K^{nonICT}; Y\right), \tag{1}$$

where W indicates hourly wages and superscripts indicate occupation groups (C: cognitive workers, R: routine workers, and M: manual workers). K indicates capital and superscripts are for ICT and non-ICT capital, respectively. Finally, Y is value-added.

Assuming quasi-fixed capital stocks, exogenous factor prices due to perfect competition, and a translog functional form for the cost function, we can express each worker type's wage bill share as follows:

$$Share^{C} = \phi_{CC} \ln\left(W^{C}/W^{M}\right) + \phi_{RC} \ln\left(W^{R}/W^{M}\right) + \phi_{IC} \ln\left(K^{ICT}/Y\right) + \phi_{NC} \ln\left(K^{nonICT}/Y\right) + \phi_{YC} \ln Y, \tag{2}$$

$$Share^{R} = \phi_{CR} \ln\left(W^{C}/W^{M}\right) + \phi_{RR} \ln\left(W^{R}/W^{M}\right) + \phi_{IR} \ln\left(K^{ICT}/Y\right) + \phi_{NR} \ln\left(K^{nonICT}/Y\right) + \phi_{YR} \ln Y, \tag{3}$$

$$Share^{M} = \phi_{CM} \ln\left(W^{C}/W^{M}\right) + \phi_{RM} \ln\left(W^{R}/W^{M}\right) + \phi_{IM} \ln\left(K^{ICT}/Y\right) + \phi_{NM} \ln\left(K^{nonICT}/Y\right) + \phi_{YM} \ln Y, \tag{4}$$

where $Share^{x} = W^{x}N^{x}/\sum_{j=C,R,M} W^{j}N^{j}$ indicates the wage bill share and N^{x} means the total working hours of each occupation group $x \in \{C, R, M\}$. If ICT capital drives job polarization, we expect to observe $\phi_{IR} < 0$ and $\phi_{IC} > 0$.

Though equations (2) – (4) are our benchmark models, we will (i) capture relative wage terms using time fixed effects and (ii) account for industry heterogeneity through industry fixed effects. Hence, our equation becomes

$$Share^{x}_{i,t} = \tau_t + \eta_i + \phi_{Ix} \ln\left(K^{ICT}/Y\right)_{i,t} + \phi_{Nx} \ln\left(K^{nonICT}/Y\right)_{i,t} + \phi_{Yx} \ln Y_{i,t}, \tag{5}$$

where i and t refer to industry and year, respectively.

In order to account for trends and minimize measurement error, we take the first difference of equation (5) and obtain the following specification:

$$\Delta Share^{x}_{i,t} = constant + \phi_{Ix}\Delta\left(K^{ICT}/Y\right)_{i,t} + \phi_{Nx}\Delta\left(K^{nonICT}/Y\right)_{i,t} + \phi_{Yx}\Delta \ln Y_{i,t} + u_{i,t}. \tag{6}$$

By taking differences for each variable, equation (6) uses the periodic growth rate. We use levels instead of logarithms because the variable differences are large for the sample period and using logs caused a huge discrepancy with the real growth rate.

3 Empirical Findings

3.1 Main Results In this section, we present the main findings from estimating equation (6). Table 3 shows results obtained from the OLS regression. Here, the dependent variable is the change in wage bill share for each occupation group between 1980 and 2007. Columns 1 and 2 are estimates for cognitive workers, 3 and 4 for routine workers, and 5 and 6 for manual workers, respectively. While the intensity of ICT capital, measured by ICT capital per value-added, is our main independent variable, we further consider non-ICT capital per value-added and log of value-added in the estimation. These two variables are included in the estimation as both factors can affect the cost structure of the firm (equation (1)) thereby potentially affecting the coefficients of interest. We use the changes in those variables as in equation (6). Coefficients are identified by utilizing industry variation.

The most interesting finding from Table 3 is that the relationship between wage bill share and ICT capital (and non-ICT capital) is not significant for all three occupation groups, even though the signs are consistent with the prediction. While there is a statically significant positive relationship between ICT capital and manual workers (column 5), this relationship disappears when we further control for other variables (column 6). On the contrary, the growth of value-added has a statistically significant relationship with the wage bill share of the routine group at the 1% level. This finding indicates that the empirical findings of Michaels, Natraj, and Reenen (2014), in support of the ICT-driven hypothesis that the growth of ICT capital is associated with job polarization, is not observed when we (1) focus on the U.S. and (2) classify workers according to their occupation rather than education.

In order to show the robustness of our finding, Table 4 presents results using the employment share as the dependent variable instead of the wage bill share. When using the employment share, ICT capital intensity has a significant effect only on the share of cognitive workers, but no significant effect

Table 3: Main Analysis with Wage Bill Share

	(1) Cognitive	(2) Cognitive	(3) Routine	(4) Routine	(5) Manual	(6) Manual
$\Delta\left(K^{ICT}/Y\right)$	8.525	9.668	−1.519	−4.285	30.989	19.195
	(8.999)	(8.211)	(7.430)	(8.961)	(12.897)**	(15.140)
$\Delta\left(K^{n-ICT}/Y\right)$		−0.047		0.249		−0.406
		(0.302)		(0.526)		(0.563)
$\Delta \ln Y$		66.405		161.402		−267.993
		(90.199)		(59.221)***		(127.356)
Constant	3.334	−1.019	−8.059	−15.335	−5.218	12.553
	(2.670)	(5.077)	(2.287)***	(3.233)***	(3.508)	(9.396)
R^2	0.02	0.04	0.00	0.07	0.15	0.27

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

on routine or manual workers, providing a consistent result with Table 3. Both Tables 3 and 4 show that it is difficult to conclude that there is a relationship between the change in ICT capital and job polarization.

Table 4: Main Analysis with Employment Share

	(1) Cognitive	(2) Cognitive	(3) Routine	(4) Routine	(5) Manual	(6) Manual
$\Delta\left(K^{ICT}/Y\right)$	11.148	14.746	−3.860	−4.299	13.668	2.631
	(7.988)	(7.116)**	(6.732)	(7.022)	(12.746)	(14.513)
$\Delta\left(K^{n-ICT}/Y\right)$		0.706		−0.162		−0.638
		(0.446)		(0.457)		(0.598)
$\Delta \ln Y$		124.497		−2.964		−193.572
		(55.101)**		(48.450)		(142.274)
Constant	2.444	−4.657	−4.115	−4.123	−1.422	11.247
	(2.248)	(3.380)	(1.693)**	(2.762)	(3.420)	(9.214)
R^2	0.05	0.12	0.01	0.01	0.03	0.10

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We further add the initial wage bill share and employment share in 1980 in order to remove the tendency for mean reversion, but there is little difference. As another robustness check, we also consider the union participation rate of each industry in 1983 as an additional control variable[7] as unions might

[7] Data on union membership rates by industry start from 1983 (Hirsch and Macpherson (2003)). We also use the union membership rate as an IV for ICT intensity in the next section.

have a strong effect on wages or employment security. However, the results hardly change.[8]

While the ICT-driven hypothesis is not strongly supported in the benchmark analysis, the effect of ICT capital on job polarization might vary across industries. To capture this heterogenous effect, we estimate the following equation:

$$\Delta Share^{x}_{i,t} = constant + \phi_{Ix}\Delta\left(K^{ICT}/Y\right)_{i,t} + \phi_{IxD}\Delta\left(K^{ICT}/Y\right)_{i,t} \times sector_i + \phi_{Nx}\Delta\left(K^{nonICT}/Y\right)_{i,t}$$
$$+ \phi_{NxD}\Delta\left(K^{nonICT}/Y\right)_{i,t} \times sector_i + \phi_{Yx}\Delta \ln Y_{i,t} + u_{i,t}, \quad (7)$$

where $sector_i$ is a dummy variable indicating a certain sector such as finance, mining and construction, manufacturing, transportation and utility, wholesale and retail trade, service, and professional industries. If industry i is affected by technical change more than other industries, estimated ϕ_{IxD} or ϕ_{NxD} will be statistically different from 0.

Table 5 shows the key results based on equation (7). For ease of presentation, we only report the effect of ICT intensity on routine workers. The most notable finding is that the effects of ICT capital on routine employment are heterogenous. Replacement of routine workers with ICT capital is evident in some industries, for example, the finance industry. The finance industry has a coefficient of –33 and is significant at the 1% level. Hence, in that industry, the wage bill share of routine workers decreases by 25 percentage points (=8.416-33.414) when ICT intensity rises by 1 percentage point between 1980 and 2007. However, some other industries such as the service industry have experienced the opposite; routine employment has increased with ICT capital during the same period.

We further note that there is significant difference in the estimates when the wage bill share or employment share are used. For wage bill shares, mining and construction, and manufacturing industries have negative estimates. In the case of mining and construction, the coefficient is about -69, two times the size of the finance sector. This means that the share of routine workers in the mining and construction industry has decreased more rapidly in the last 30 years than other industries. For other

[8] Results are available upon request.

Table 5: Differential Effects on Routine Share across Industries

	(1) Wage Bill Share	(2) Employment Share
Finance	−33.414(10.141)***	−29.749(8.591)***
Mining and Construction	−68.759(20.960)***	−4.404(17.283)
Manufacturing (Non-durable)	−15.333(29.023)	−39.396(27.161)
Manufacturing (Durable)	−40.825(17.373)**	−18.294(17.015)
Transportation and Utility	7.690(18.076)	8.007(14.830)
Wholesale and Retail Trade	29.979(5.831)***	21.237(5.496)***
Service	59.954(14.366)***	42.312(10.253)***
Professional	30.170(8.405)***	10.385(9.986)

Note: 1. For expositional clarity, we only report ϕ_{IMD} for routine workers that is obtained by estimating equation (7) industry by industry.
2. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

industries such as wholesale and resale trade, service, and professional sectors, the intensity of ICT capital has a positive relationship with the routine wage bill share. For instance, the coefficient for service is about 60 and significant at the 1% level. While mining and construction, and manufacturing industries have significantly negative coefficients when using wage bill shares as dependent variables, they do not have significant coefficients when using the employment share. Wholesale and retail trade, and service sectors retain their positive coefficients as in the case of the wage bill share.[9]

3.2 Additional Analysis

In this section, we provide further empirical analyses to show the robustness of our findings.

3.2.1 IV Analysis

As the variables we use in the main analysis are jointly determined at the equilibrium, it is natural to argue that there might exist possible endogeneity as well as measurement errors for the variables used in the estimation. In order to resolve theses issues, in this subsection we use an instrumental variables (IV) approach exploiting the industry-specific initial levels. Following Michaels, Natraj, and Reenen (2014), we first use each industry's initial (i.e., 1980) routine share as an IV.[10] The idea is that industries that had a higher share of routine workers in 1980 would have had

[9] Industry coefficients may depend on industry characteristics. Refer to Shim and Yang (2018) for further analysis.

[10] Michaels, Natraj, and Reenen (2014) also use initial ICT intensity in the U.S. as an IV for other countries' subsequent ICT increases, but we only focus on the U.S. and our main variable of interest is composed of initial ICT capital. Thus, it is not appropriate to use initial ICT intensity as an IV.

a greater incentive to invest in ICT capital to lower production costs by substituting labor force with the dramatic fall in ICT prices since 1980 (Shim and Yang (2018)). In other words, industries that intensively used routine workers would be more eager to employ ICT capital in the wake of falling ICT prices. We report the results from our IV estimation in Table 6.

Table 6: Results with 1980 Routine Share as IV

	Wage Bill Share			Employment Share		
	(1) Cognitive	(2) Routine	(3) Manual	(4) Cognitive	(5) Routine	(6) Manual
$\Delta\left(K^{ICT}/Y\right)$	10.774	33.317	93.420	−5.536	41.493	59.790
	(17.457)	(36.677)	(38.056)**	(27.300)	(38.328)	(32.582)*
$\Delta\left(K^{n-ICT}/Y\right)$	−0.034	0.773	1.411	0.462	0.475	0.761
	(0.364)	(0.839)	(1.234)	(0.498)	(0.880)	(1.108)
$\Delta \ln Y$	68.609	106.839	11.079	82.067	−69.411	21.336
	(92.320)	(87.696)	(222.038)	(90.178)	(96.641)	(221.433)
Constant	−1.355	−20.637	−13.641	1.502	−10.581	−8.925
	(6.635)	(7.734)***	(16.245)	(9.898)	(7.420)	(15.277)
F-Stat	6.41					

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The ICT-driven hypothesis is still not supported by the IV approach. The sign of the estimated coefficient for the growth of ICT capital per value-added is positive, which is the opposite of what we expected, though it is not statically significant. While there exists a positive relationship between ICT intensity and changes in manual share, it is not consistent with the ICT-driven hypothesis as the routine share does not decline with higher ICT intensity. In addition, the F-statistic for the IV is only about 6, and hence we cannot say our IV is suitable. We would like to emphasize that this result is similar to Michaels, Natraj, and Reenen (2014); they also report insignificant coefficients for the IV regression and a low F-statistic.

We further use the union membership rate in 1983 as an alternative IV for subsequent increases in ICT capital, which was not used as an IV in Michaels, Natraj, and Reenen (2014).[11] The idea behind this IV is similar to the previous one: The industry has a greater incentive to replace workers with the alternative production factor, ICT capital in our case, if it faces high union membership rate (Shim and

[11] Union data at the industry level are available only from 1983. See Hirsch and Macpherson (2003) for details.

Yang (2018)). We re-estimate equation (6) and report the key results in Table 7. It is easy to observe that our findings are robust to the alternative IV. Although the signs of the IV estimates are the same as the OLS, the F-statistic is still low and the estimates are not precise at all.

Table 7: Results with 1983 Union Membership Rate as IV

	Wage Bill Share			Employment Share		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$\Delta\left(K^{ICT}/Y\right)$	96.759	−92.789	68.149	238.924	−52.185	18.309
	(189.800)	(120.500)	(59.211)	(475.212)	(71.478)	(55.474)
$\Delta\left(K^{n-ICT}/Y\right)$	1.002	−0.982	0.792	3.407	−0.828	−0.254
	(1.885)	(1.726)	(1.653)	(4.710)	(1.046)	(1.628)
$\Delta \ln Y$	240.009	289.828	−83.935	569.366	66.522	−134.625
	(351.611)	(230.162)	(210.201)	(805.458)	(135.034)	(216.897)
Constant	−27.466	−2.854	−4.723	−72.731	2.629	5.714
	(55.787)	(16.551)	(17.742)	(136.801)	(10.174)	(17.356)
F-Stat	5.95					

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

3.2.2 Full-time and Male Workers

In this section, we further present results for robustness checks by restricting the sample to full-time workers and male workers. If there are other factors that change the structure of the labor market, it could potentially affect our findings. We address this concern by performing sub-group analyses: We first restrict our sample to full-time workers because (1) the share of part-time workers, that exhibits different employment patterns from full-time workers, may vary across industries and (2) there is a secular trend for the share of part-time workers[12]. We then focus on male workers in order to rule out (1) the effect of the relatively high variation of female workers in the labor market (Castro and Coen-Pirani (2008)) and (2) long-term trends that can possibly affect the outcome variables that we are interested in.

Results reported in Tables 8 and 9 all confirm that our findings in the benchmark analysis are not driven by compositional differences across industries.

[12]Source: World Bank (https://data.worldbank.org/indicator/SL.TLF.PART.ZS?locations=US).

Table 8: Robustness Check with Full-Time Workers

	Wage Bill Share			Employment Share		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cognitive	Routine	Manual	Cognitive	Routine	Manual
$\Delta\left(K^{ICT}/Y\right)$	10.035	−2.539	18.016	16.884	−6.360	7.304
	(8.486)	(8.711)	(13.792)	(7.177)**	(7.272)	(13.287)
$\Delta\left(K^{n-ICT}/Y\right)$	−0.080	0.159	−0.391	0.534	−0.229	−0.425
	(0.293)	(0.519)	(0.559)	(0.340)	(0.456)	(0.571)
$\Delta \ln Y$	47.645	152.299	−351.396	103.265	20.884	−287.452
	(89.377)	(56.477)***	(140.828)**	(57.772)*	(44.364)	(150.912)*
Constant	−0.369	−15.813	19.227	−5.210	−5.220	18.323
	(4.964)	(2.974)***	(10.200)*	(3.481)	(2.416)**	(9.547)*
R^2	0.04	0.07	0.33	0.14	0.02	0.21

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Robustness Check with Male Workers

	Wage Bill Share			Employment Share		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\left(K^{ICT}/Y\right)$	6.987	6.201	4.613	13.091	0.118	−0.547
	(7.901)	(8.370)	(10.392)	(6.711)*	(6.019)	(8.988)
$\Delta\left(K^{n-ICT}/Y\right)$	−0.558	0.366	−0.008	−0.115	−0.032	0.220
	(0.350)	(0.519)	(0.533)	(0.347)	(0.371)	(0.493)
$\Delta \ln Y$	−82.188	181.488	−345.208	−15.663	59.044	−263.300
	(84.742)	(85.076)**	(144.212)**	(71.848)	(51.361)	(156.181)*
Constant	2.905	−16.326	25.696	−2.929	−5.269	21.248
	(4.843)	(3.558)***	(9.256)**	(3.650)	(2.489)	(9.172)
R^2	0.06	0.09	0.25	0.07	0.02	0.19

Note: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4 Conclusion

This paper investigates the extent to which automation has affected workers in the U.S. since the early 1980s. Automation has been believed to bring about job polarization in developed countries. The drop in the price of ICT capital led many industries to adopt automation in their production and this has replaced workers. Workers in jobs that require repetitive and codifiable tasks have been most easily replaced by ICT capital and hence are more vulnerable to automation.

Using U.S. data, this paper analyzes whether the ICT-driven hypothesis is supported by the data.

Specifically, we closely follow Michaels, Natraj, and Reenen (2014) to empirically examine the relationship between wage bill shares (and employment shares) for each occupation group and ICT capital growth. The results show that between 1980 and 2007, there is no significant relationship between an increase in usage of ICT capital and a decline of routine employment. Instead, an increase in usage of ICT capital has a positive relationship with the shares of cognitive and manual workers, if any, showing a weak correlation between ICT capital and job polarization. We further show that this finding is robust to other specifications and samples, while there exist differential effects across industries.

Our finding casts a question on the hypothesis that the growth of ICT capital per se is the most important factor underlying job polarization. For example, Leonardi (2015) and Mazzolari and Ragusa (2013) argue that the spillover effect from the demand for goods can be an important driver of job polarization while Shim and Yang (2018) show that wage structure might be the source of the heterogeneous aspect of job polarization across industries. Hence, we leave the search for more relevant channels for job polarization as future work.

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A Appendix: Industry Classification

Table 10: Census Industry Classification

Number	Industry	IND1990 Code
1	Metal mining	40
2	Coal mining	41
3	Oil and gas extraction	42
4	Nonmetallic mining and quarrying, except fuels	50
5	Construction	60
6	Food and kindred products	100 − 122
7	Tobacco manufactures	130
8	Textile mill products	132 − 150
9	Apparel and other finished textile products	151 − 152
10	Paper and allied products	160 − 162
11	Printing, publishing, and allied industries	171 − 172
12	Chemicals and allied products	180 − 192
13	Petroleum and coal products	200 − 201
14	Rubber and miscellaneous plastics products	210 − 212
15	Leather and leather products	220 − 222
16	Lumber and woods products, except furniture	230 − 241
17	Furniture and fixtures	242
18	Stone, clay, glass, and concrete products	250 − 262
19	Metal industries	270 − 301
20	Machinery and computing equipments	310 − 332
21	Electrical machinery, equipment, and supplies	340 − 350
22	Motor vehicles and motor vehicle equipment	351
23	Other transportation equipment	352 − 370
24	Professional and photographic equipment and watches	371 − 381
25	Miscellaneous manufacturing industries / Toys, amusement, and sporting goods	390 − 392
26	Railroads	400
27	Bus service and urban transit / Taxicab service	401 − 402

28	Trucking service / Warehousing and storage	410 – 411
29	U.S. postal service	412
30	Water transportation	420
31	Air transportation	421
32	Pipe lines, except natural gas / Services incidental to transportation	422 – 432
33	Communications	440 – 442
34	Utilities and sanitary services	450 – 472
35	Durable goods	500 – 532
36	Nondurable goods	540 – 571
37	Lumber and building material retailing	580
38	General merchandiser (Note 2)	581 – 600
39	Food retail	601 – 611
40	Motor vehicle and gas retail	612 – 622
41	Apparel and shoe	623 – 630
42	Furniture and appliance	631 – 640
43	Eating and drinking	641 – 650
44	Miscellaneous retail	651 – 691
45	Banking and credit	700 – 702
46	Security, commodity brokerage, and investment companies	710
47	Insurance	711
48	Real estate, including real estate-insurance offices	712
49	Business services	721 – 741
50	Automotive services	742 – 751
51	Miscellaneous repair services	752 – 760
52	Hotels and lodging places	761 – 770
53	Personal services	771 – 791
54	Entertainment and recreation services	800 – 810
55	Health care	812 – 840
56	Legal services	841
57	Education services	842 – 861
58	Miscellaneous services (Note 3)	862 – 881
59	Professional services	882 – 893

60	Public administration	900 − 932

Note: 1. Numbers 6−15 are "nondurable manufacturing goods," 16−25 are "durable manufacturing goods," 26−32 are "transportation," 35−36 are "wholesale trade," 37−44 are "retail trade," 45−49 are "finance, insurance, and real estate," 49−51 are "business and repair services," and 55−59 are "professional and related services" industries.

2. General merchandiser includes hardware stores, retail nurseries and garden stores, mobile home dealers, and department stores.

3. Miscellaneous services include child care, social services, labor unions, and religious organizations.