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DISCUSSION PAPER SERIES

IZA DP No. 17003

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ABSTRACT

The Role of Technological Change in the Evolution of the Employment to Output Elasticity*

The employment to output elasticity has risen from 0.65 during the 1960s and 1970s to 1.25 in the last two decades. We study the role of recent technological change in the evolution of this elasticity along the business cycle. Using the Covid-19-induced shock and an instrumental variable approach as sources of identification, we find that recent technologies augment the employment to output elasticity. We find that employment in sectors characterized with occupations with a high risk of automation are the most affected and that this effect is larger in sectors that have undergone a technology-capital deepening process in the last decades.

JEL Classification: O33, E32, J23

Keywords: technological change, automation, employment to output elasticity, labor markets

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Introduction

The employment to output elasticity has risen from 0.65 during the 1960s and 1970s to 1.25 in the last two decades. We study the role of recent technological change in the evolution of this elasticity along the business cycle. Using the Covid-19-induced shock and an instrumental variable approach as sources of identification, we find that recent technologies augment the employment to output elasticity. We find that employment in sectors characterized with occupations with a high risk of automation are the most affected and that this effect is larger in sectors that have undergone a technology-capital deepening process in the last decades.

A long tradition in macroeconomics, dating back to Okun (1962), has studied the co-movement of output and labor, either unemployment or employment. Empirical evidence shows that employment to output elasticity has been increasing monotonically over time since the sixties in the USA. The aggregate elasticity, estimated using nationwide quarterly data, goes from 0.65 during the 60s and 70s to 1.25 in the last two decades. Understanding this behavior is crucial because an increase in the employment to output elasticity can lead to instability and negative consequences for workers, such as an increase in the use of temporary contracts, a reduction in investment in human capital at the workplace, less job security, and destruction of specific human capital (Jacobson and Sullivan, 1993; Blanchard and Landier, 2002; Card and DiNardo, 2002; Lachowska et al., 2020).

In this paper we offer an explanation for this secular trend in the employment to output elasticity. We argue that the downward trajectory in technology-capital prices[1], coupled with the substitution between technology-capital and occupations characterized by a significant share of routine tasks, explain the increasing amplitude of the employment cycle. The mechanism is as follows: during the initial phase of the crisis, firms reduce production, cutting flexible inputs such as labor. Subsequently, time-to-build and the irreversibility of investment in technology-capital[2] imply that firms are left with excess technology-capital, necessitating further cuts in employment, primarily in occupations with a higher elasticity of substitution with technology capital – that is, in occupations characterized by routine tasks or at risk of automation (OaRA)–. During the rebound in output, the opposite should occur, albeit to a lesser extent due to adjustment costs and declining ICT prices. The higher the technology-capital deepening, the greater this effect, and hence the employment to output elasticity.

Figure 1a illustrates the cyclical component of output and labor from 1960 to the present. The figure reveals that during the initial period of the sample (i.e. the 60s) output experienced greater fluctuations compared to employment during recessions. However, as we approach the end of the timeline (i.e. 2020's), the situation reverses, with employment exhibiting more significant oscillations than output.[3] Figure 1b illustrates a

[1]Since the sixties, the investment in Information and Communication Technology, software and R&D (hereafter technology-capital -ICT-) increases monotonously from less than 15% of total investment in non residential fixed capital in 1960 to 50% in 2020. Data from ST.Louis FED: Software, Research and Development, Nonresidential Information Processing Equipment, and total Private Nonresidential Fixed Investment (PNFI).

[2]See Pindyck (1991) for a discussion about capital adjustment costs. The argument does not require that time-to-build or investment irreversibility is higher for ICT capital.

[3]A simple OLS regression shows that employment to output elasticity has increased from 0.67 in during the period 1960-1999 to 1.05 since the year 2000. See Table 1 in Appendix

significant rise in the share of investment in information processing equipment concerning total equipment over the course of these six decades, increasing from 16% to 35%.[4] Investment in new technologies can account for the secular increase in the employment to output elasticity. Investment irreversibility,[5] and occupations with a high elasticity of substitution with new technology capital are two sufficient conditions to explain a portion of this secular trend. A negative shock disproportionately reduces the level of employment in occupations that closely substitute for technology capital, which cannot be adjusted due to irreversibility. As it is straight forward to see in a simple model, this effect increases with the stock of technology capital.[6] The increasing investment in technology capital in recent decades further emphasizes the need to study employment to output elasticity.

Empirically, this paper examines the impact of recent technological change on the elasticity of employment to output throughout the business cycle, utilizing the Covid-19 pandemic as a natural experiment.

Between the first and second quarter of 2020, the cyclical component of employment fell by 12.7%, while the cyclical component of real GDP fell by 8.7%. In just one year, the aggregate economic activity recovered. The benefits of utilizing COVID-19 shocks as a source of exogenous variation are counterbalanced by the challenges of studying employment during a period marked by contractions in both labor demand and supply.

[4]Furthermore, the proportion of investment in software relative to total intellectual property products has seen a substantial surge, rising from 1% to 41% (BEA Table 5.3.5. Private Fixed Investment by Type).

[5]See Pindyck (1991).

[6]See Appendix for details on the model.

Our identification strategy assumes that demand factors, either product demand or input shortages, predominantly drive employment fluctuations. The Covid-19 pandemic, by its exogenous nature, large yet short impact on output, coupled with the innate irreversibility and time-to-build properties of technology capital, provides us with a unique opportunity to identify demand shocks to labor. This perspective is reinforced by recent research by Guerrieri et al. (2022) that demonstrate that the primary supply shock induced by the pandemic subsequently instigates a demand shock. These findings suggest that changes in the demand side primarily drove the decline in output during the COVID-19 crisis. As a result, a significant portion of the fluctuations in employment can be attributed to the exogenous demand shock caused by the pandemic. However, it is important to note that the COVID-19 pandemic also implied a large labor supply shock, which is considered, and controlled for, in our analysis. We consider several supply-side related variables, such as telework (working from home), coworker proximity, and sex, aiming to isolate the labor's demand shock. Nonetheless, we acknowledge that additional supply shocks are occurring during the pandemic that we need to control, including fear and worries causing shifts in employment, containment and closure policies, restrictions in movement, and different responses to health and sanitary restrictions. We control for as many relevant factors as are available (coworker proximity, telework, ICT capital penetration in the last decade, among others) plus time and sector-fixed effects.

In addition, we control for the reverse causality from labor supply to output using sector demand shocks as instruments. We use the standard Bartik (1991)'s Shift-Share methodology and construct sector's activity instrument as the "The Use of Commodities by Sectorâ input-output matrix times sectors and final demand activity, sectors demand activity are themselves instrumented by each sector final demand. Each sector's final demand is composed of personal consumption expenditures, four subcategories of investment, exports, federal defense and non-defense expenditures, and State and local government expenditures.

In short, our strategy aims to identify demand shocks using the exogenous nature of the Covid-19 pandemic jointly with an IV approach while controlling for labor supply-side-related variables.

We employ disaggregated data on sector employment and occupational characteristics, automation risks, and economic activity. In our main econometric model, we use data from 60 sectors defined at their 2-3-4 digits NAICS classification in 51 territories (50 states and The District of Columbia) during the period 2018q1 and 2021q4. We find that moving from a sector with the average risk of automation Ã la Autor et al. (2003)'s routine task index to one with one standard deviation higher increases output elasticity of employment from 0.49 to 0.61. The elasticity increases in 0.11 if the latter sector is also characterized by one standard larger increase in technology capital deepening in the last two decades. We interpret these results as a consequence of firms' initial response to the crisis, which entailed simultaneous reductions in flexible inputs, such as labor, in reaction to a decrease in demand. The resulting surplus of technology capital led to further contractions in employment, in occupations with a greater elasticity of substitution with technology capital, such as OaRAs.[7]

[7]Flexible inputs have to adjust whereas capital remains constant and even may continue to grow

Then, we test the hypothesis that as output rebounds, employment in OaRAs would follow suit but to a lesser extent than other occupations due to adjustment costs and the downward trend in ICT prices. We find that after the output rebound, employment in OaRAs reacted faster, and that, by the end of 2021, its share remained, depending on the model, 0.16-0.25 percentage points lower than its level before the pandemic started. Finally, we test for heterogeneous effects by sex. After controlling for occupation and sector, we do find that female employment is, on average, more affected by the pandemic, but this result is only statistically significant at 10%.

Moreover, during the recent economic downturn, the relationship between employment and output showed a noteworthy difference compared to past recessions. Specifically, in the downward phase, the employment to output elasticity stood at 1.3, marking a significant increase of 0.24 points in comparison to the figure seen during the Great Recession, which was already relatively high at 1.06 when compared to earlier recessions. To provide context, the employment to output elasticities in the 1980, 1981, and 1991 recessions were significantly lower, measuring at 0.56, 0.46, and 0.57, respectively. Crivelli et al. (2012) and Gorg et al. (2018) also report increasing employment to output elasticity over time.

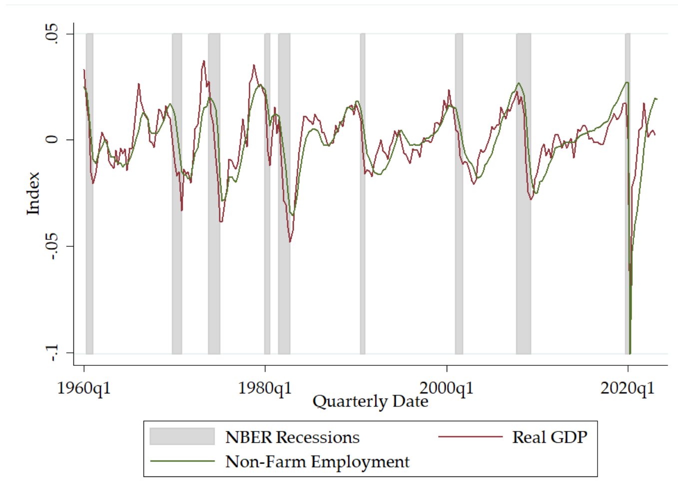
These results are consistent with our argument that the output elasticity of employment has been increasing and that OaRAs are a key factor explaining this phenomenon. Our results contribute to the growing literature regarding the labor-market consequences of the deployment of technology capital (e.g. Autor et al. (2003); Goldin and Katz

due to irreversible investment and time built. See, for example, Pindyck (1988).

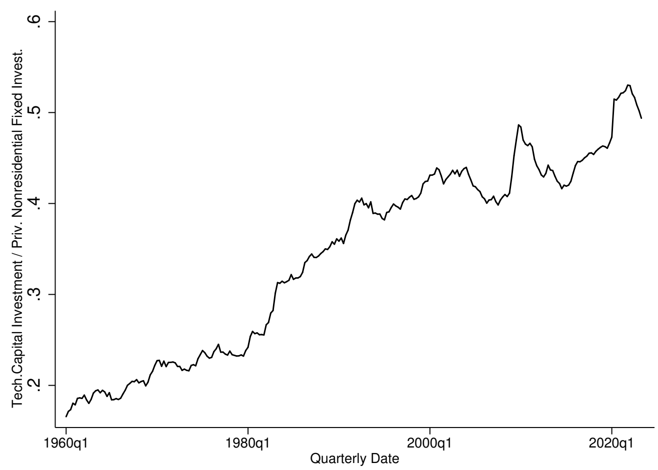
(2009); Autor and Dorn (2013); Brynjolfsson and McAfee (2014); Frey and Osborne (2017); Arntz et al. (2017); Pedemonte et al. (2018); Graetz and Michaels (2018); Acemoglu and Restrepo (2018, 2019); Egana-delSol and Joyce (2020); Egana-delSol et al. (2022,?)) and the literature documenting the impact of economic crises on the labor market and technology adoption (e.g. Caballero and Hammour (1994); Kopytov et al. (2018); Jaimovich and Siu (2020); Hershbein and Kahn (2018)). The contribution of our work stems from exploring the repercussions throughout the business cycle and strengthening the identification strategy through the inclusion of a natural experiment in concert with a vastly used Instrumental Variable approach.

Figure 1: Cyclical Component of Employment and Output, and Share Tech.Investment

((a)) Cyclical component of output and labor



((b)) Share of investment on ICT



Panel A illustrates the cyclical fluctuations in output and labor in the USA from 1960 to the present. The shaded areas in gray represent economic cycles when recessions, as defined by the NBER, occurred. The figure reveals that in the early part of the time frame of the data, output showed more pronounced variations during recessions than employment did. However, as we approach the end of the timeline, the situation reverses, with employment experiencing more significant fluctuations than output. Moving on to Panel B, it depicts the evolution of the relationship between investment in Information and Communication Technology (ICT) and investment in fixed capital. It's evident that there has been a substantial increase in the importance of ICT investment over time. [Source] FRED and NBER Business Cycle Dating.

Data

In this section, we describe the different indicators and the data-sets used in our analysis.

Employment

We use quarterly employment data from the Quarterly Census of Employment and Wages (QCEW). The program, constructed by the Bureau of Labor Statistics (BLS), publishes a quarterly count of employment and wages reported by employers covering more than 95 percent of U.S. jobs, available at the state and national levels by sector. We aggregate employment data to the "Production Account Codes" (PAC) sectors from the Bureau of Economic Analysis (BEA) and BLS Integrated Sector-level Production Account for the United States. The BEA/BLS data aggregate the private US economy into 61 sectors defined at 2-3-4 digits NAICS 2007 (although we end up using only 60 sectors). From now on, we call PAC sectors the BEA/BLS Integrated Sector-level sector. The data covers the time frame from 2018q1 through 2021q4.[8]

To split employment by gender and to expand the period until 2022q2, we use quarterly employment data from "The Current Employment Statistics" (CES) constructed by the BLS. The CES program provides estimates of employment information by gender on a national basis and in considerable sector detail at 3-4 digits NAICS 2002. We aggregate data at the PAC level.

[8]QCEW data is available until 2022q4. We do not use the last two quarters because they classified sectors using NAICS rev 2022.

Risk of automation

To identify Occupations at Risk of Automation *OaRAs*, we construct a Routine Task Index Ã la Autor et al. (2003) (hereafter ALM). For robustness, we also use Frey and Osborne (2017)'s risk of automation.

ALM claim that routine tasks, both cognitive and manual, are prone to be replaced by new technologies. By contrast, non-routine cognitive analytic, interpersonal, and manual/physical tasks are difficult to automate. We borrow ALM's method to classify 795 occupations according to the number of routine and non-routine tasks performed in 2010. These authors identify four types of tasks: routine cognitive, routine manual, non-routine analytic, and non-routine interactive (i.e. interpersonal). Using ALM's codes, we constructed the previous four type of tasks' indices using the O*NET 23 database and occupation employment data from the "Occupational Employment and Wage Statistics" 2018 (OES), produced by the BLS. The indices are normalized to have a mean 0 and a variance 1.

We constructed the Routine Task Index for each occupation as follows:

$$\text{Rout.Task Index}_o = \sum_{\tau:\ \text{Rout}} T_\tau^o - \sum_{\tau:\ \text{Non Rout}} T_\tau^o, \tag{1}$$

Here, T_τ^o represents the index for task τ within occupation o. It's worth noting that two of the tasks are routine, while the remaining four are classified as non-routine tasks, which are further categorized into non-routine cognitive and non-routine manual tasks.

Following the insights of ALM and Autor and Dorn (2013), who suggest that both cognitive and manual routine tasks are prone to automation, we interpret the Routine Task Index as a proxy for the likelihood that occupation o faces a risk of automation. For each PAC sector, we calculate the employment-weighted average of Rout.Task Index$_o$, denoted as ROUT_j, where we use employment data at the occupation level from OES 2018. This serves as our primary measure of sector j's share of employment that may be vulnerable to automation:

$$\text{ROUT}_j = \sum_o \left(\frac{\text{Emp}_{oj}}{\text{Emp}_j}\right) \text{Rout.Task Index}_j^o$$

Frey and Osborne (2017) claim that computerization (widely referred as automation) can be extended to any non-routine task that is not subject to any engineering bottlenecks with respect to computerization. Hereafter, they use an econometric method to assign the risk of automation probability (FO.RISK_o) to 702 occupations defined at the three- to six-digit level of the Occupational Employment Statistics 2010 BLS definition (OES 2010). For each PAC sector, we computed the employment-weighted average of occupation risk of automation.

Coworker proximity, telework, and female employment

To correct for the impact of Covid-19 on the supply side of employment, we consider, at each occupation, the risk of getting Covid-19 at work by using the Beland et al. (2020) index, and the possibility to work from home by using the Dingel and Neiman

(2020) index.[9] For each PAC sector, we computed the employment-weighted average of each variable: "Coworker Proximity" (PROX_j) and "Remote Work" (RWORK_j). Recent evidence suggests that the Covid-19 pandemic had an asymmetric gender effect on employment (Alon et al., 2020). We also control for the sector share of female employment in 2018 (ShWomen_j).

New Technology Capital: Sector ICT Penetration

We compute PAC sector technology capital penetration per worker in the last two decades as the twenty years real change of "Communications equipment", "Computer hardware" and "Software Capital" divided by the average employment in 1998 and 2018 ($\Delta ICT/L_j$) . We use PAC sector data from the BEA/BLS Integrated Sector-level Production Account for the United States. Because quantity variables are indices, we construct the ICT_{jt} quantity index as the sum of "Communications equipment", "Computer hardware" and "Software Capital" indices weighted by capital compensations in 2012 (the baseline year).

$$\Delta\text{ICT}/\text{L}_j = 2\frac{\text{ICT}_{j2018} - \text{ICT}_{j1998}}{\text{L}_{j2018} + \text{L}_{j1998}}$$

Sector Production

To measure economic activity we use the quarterly output by sector from the Bureau of Economic Analysis, ending in $2022q2$. This data is available for 60 PAC sectors.

[9] For robustness, we also use Beland et al. (2020) index of remote work.

Other variables

For robustness, in some econometrics exercises, not reported in the main text, we control for state-level work restrictions and childcare/school closures during the Covid-19 pandemic. We use monthly data from Oxford University's data set of state policies implemented to fight the Covid-19 pandemic (Hale et al., 2021). We take a three-month moving average of restrictions to account for the fact that restrictions take time to affect employment.

Summary Statistics and Employment evolution by sectors' characteristics

Table 1 presents the summary statistics of (ln) sector total employment and (ln) state sector local employment, (ln) sector production, and the share of women sector employment. We do not report the summary statistics of sector routine task index a la ALM (ROUT_j), sector proximity of coworkers a la Beland et al. (2020) (PROX_j), the teleworkable index a la Dingel and Neiman (2020) (RWORK_j), and the ICT capital penetration in the last two decades ($\Delta\mathrm{ICT/L}_j$), because we normalize them to have zero mean and standard deviation one. The correlation between sector routine task index (ROUT_j), and both coworker proximity (PROX_j) and the possibility of doing telework (RWORK_j), are -0.09 and -0.55, respectively. The correlation between PROX_j and RWORK_j is -0.43. These results suggest that these variables should capture different

Table 1: Summary Statistics and Pairwise Correlations

Panel A: *Summary Statistics*

	(1)	(2)	(3)	(4)	(5)
Variable	Obs	Mean	Std.Dev.	Min	Max
(ln) Emp.*	960	13.58	1.68	5.97	16.59
(ln) PY *	960	5.75	1.12	2.71	8.33
Sh.Women*	960	0.36	0.18	0.10	0.84
(ln) Emp.**	46,036	9.14	1.96	0.85	14.36

Panel B: *Pairwise Correlations*

	(1)	(2)	(3)	(4)	(5)
	ROUT	RWORK	PROX	$\Delta ICT/L_0$	ShW
ROUT	1.00				
RWORK	-0.67	1.00			
PROX	-0.11	-0.43	1.00		
$\Delta ICT/L$	-0.39	0.30	0.06	1.00	
Sh.Women	-0.42	0.37	0.32	0.36	1.00

Notes:* Sector-Data has 60 disaggregated sectors and 16 quarters.
** State-Sector-Data covers 51 territories (states and the District of Columbia), and the same 60 sectors during 16 quarters.

Source: Employment from Quarterly Census of Employ- ment and Wages (QCEW). Share of women from CES-BLS. Routine Task Index (ROUT) is constructed using ALM methodology and ONET 23 data. Coworker proximity (PROX) and remote work (RWORK) are from Beland et al. (2020) and Dingel and Neiman (2020), respectively. Sector Output ((ln)PY) and Sector ICT penetration (ΔICT/L) are from BEA/BLS Integrated Sector-level Production Account.

aspects of the impact of Covid-19 on employment.[10]

Figure 2 reports the evolution of employment for different subgroups. At the end of every trend line, we can see the contraction and rebound of employment for each of these groups occurring during the Covid-19 pandemic.

Figure 2a reports the evolution of employment in sectors with a share of employees

[10]There is a negative correlation between the routine index and ICT penetration. This result shows sectors that invested more in ICT in the last decades today have less employment in occupations at risks of automation.

in Routine Tasks below the 2019 sector median (black line) and above (grey line). The red line illustrates the share of employment in sectors with a large share of OaRA. The loss of employment in OaRAs is concentrated during the first phase of the pandemic. Employment in all sectors fell during the first quarter of 2020, although this fall is two times larger for sectors with a large share of jobs in OaRAs (-18% versus -9%). Since May, the same is true for the recovery. The raw evolution of employment in sectors with high and lower shares of jobs in OaRAs is in line with the hypothesis that occupations characterized by routine tasks, and therefore prone to automation, have larger elasticity of substitution with technology-capital.

Figure 2b reports the evolution of employment in sectors with the female share of employment above the median (gray line) and below (black line). During the initial phase of Covid-19 pandemic, employment in sectors characterized with a large share of female employment fell by 16%, where in the rest of sectors employment fell by only 8%. Rebound in former sectors is large, although by the end of the sample employment in these sector remain below in relative term.

Figure 2c reports the evolution of sector with coworker proximity below (black line) and above (grey line) the median sector. In line with the hypothesis that workers are afraid to work in places were the risk of contagion is high, employment falls more in the first part of the pandemic in sector above the median and also rebounds more after that. The evolution of employment is in line with research that shows that the single cue of

Figure 2: Employment in Sectors by Routine Task, Share of Female Emp., Co-Worker Proximity and Telework.

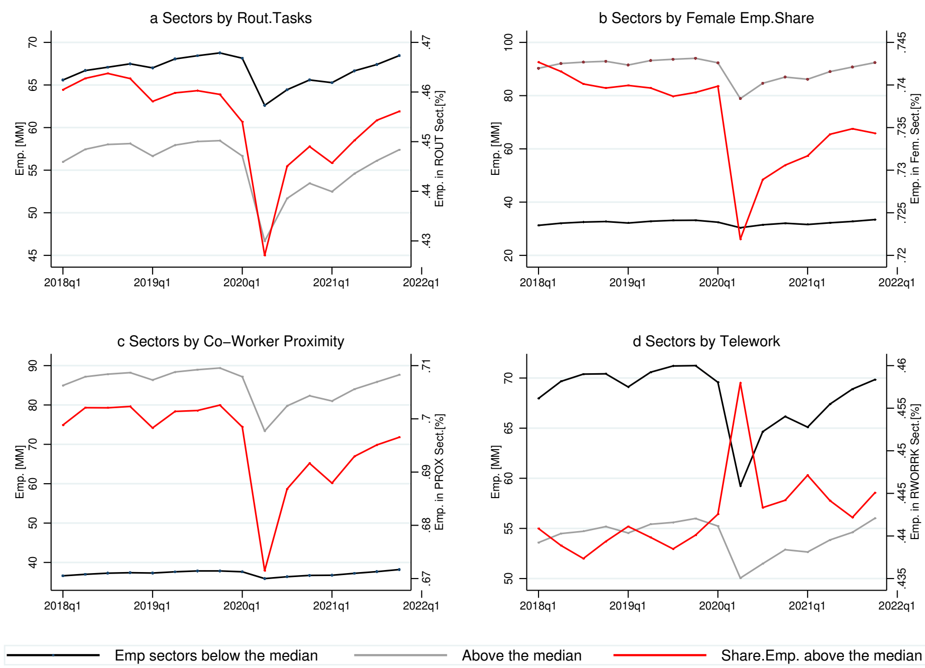


Figure 2 shows the evolution of employment in sectors with weighted average of Routine Task Index Ã la ALM above and below the median sector. Figure b shows the evolution of sectors with the share of female work above and below the median. Figure c shows the evolution of employment in sectors with a weighted average of Beland et al. (2020) Coworker Proximity Index above and below the median sector. Figure d shows the evolution of employment in sectors with weighted average of Teleworkeable Index Ã la Dingel and Neiman (2020) above and below the median sector. Source. Bureau of Labor Statistics, ALM, Dingel and Neiman (2020), and Beland et al. (2020).

daily new cases can drive risk perception.[11] The total number of deaths per million was 0.003 in February 2020, then jumps to 16.102 in March and 185.95 in April. These are exactly the two months we observe a large fall in the number of employees in sectors above the coworker proximity median. In May, when the number of deaths per month started to fall, employment in these sectors also reverted to their negative trend. The

[11]Harman (2021) studies the risk perception and the evolution of time-series Covid-19 data (in particular the cumulative number of deaths).

share of sectors above the median continues to recover faster until October 2021 and then their share stops growing. Between May and mid-October, cases were falling; however, they started to increase again after this month.[12]

Figure 2d presents employment in sectors with the share of employment prone to telework above the median sector (grey line) and below (black line). Reassuring previous results in the literature, Figure 2d indicates that sectors with a large share of employment in occupations with teleworkable tasks in 2009 experienced a lower decline in employment at the beginning of the pandemic, and they maintained a relatively higher level of employment by the end of the sample.

Empirical Strategy and Results

Empirical Strategy

Given the limitations associated with using COVID-19 as a natural experiment, our empirical approach complement the Covid-19 shock with an identification method designed to separate the influence of demand shocks on employment given the characteristics of the Covid-19 pandemic.

We begin exploiting the exogenous nature of the pandemic, which has had a large but short-lived impact on output. Time-to-build properties of technology capital, provides us with a unique opportunity to identify demand shocks affecting labor markets of different occupations keeping constant the trajectory of capital (ICT and total).

[12]Data for the number of deaths per month are from Our World in Data.

In the first set of results, we exploit national cross-sector variation in the share of employment in occupations prone to computerization/automation (ROUT_j) to identify the effect of the surge of ICT-software investment across sectors. Additionally, we explore the variations across sectors of ($\Delta\mathrm{ICT/L}_j$) penetration between 1998 and 2018, before the Covid-19 pandemic, on employment to output elasticity.

$$
\begin{aligned}
ln(\mathrm{Emp}_{jt}) = {} & \beta_{\mathrm{PY}} \ln(\mathrm{PY}_{jt}) + \beta_{\mathrm{PY}}^{\mathrm{ROUT}}\ \mathrm{ROUT}_j \cdot \ln(\mathrm{PY}_{jt}) + \\
& + \beta_{\mathrm{PY}}^{\mathrm{ROUT},\Delta\mathrm{ICT/L}}\ \Delta\mathrm{ICT/L}_j \cdot \mathrm{ROUT}_j \cdot \ln(\mathrm{PY}_{jt}) \\
& + \beta_{\mathrm{PY}}^{\Delta\mathrm{ICT/L}}\ \Delta\mathrm{ICT/L}_j \cdot \ln(PY_{jt}) \\
& + \beta^{\mathrm{X}}\mathrm{X}_{jt} + \mathrm{ROUT}_j \cdot \mathrm{D}_t^{post} + \mathrm{D}_j + \mathrm{D}_t + \epsilon_{jt}
\end{aligned}
\tag{2}
$$

Where j corresponds to one of the 60 sectors and t to one of the 16 year-quarters periods covered. The dependent variable is the logarithm of employment [$\ln(\mathrm{Emp}_{jt})$]. The independent variables of interest are the double interaction between the Routine Task Index (ROUT_j) and the logarithm of sector output ($\ln(\mathrm{PY}_{jt})$), and the triple interaction between Routine Task Index, (ln) sector output and our sector ICT penetration index in the last two decades ($\Delta\mathrm{ICT/L}_j$). To capture the idea that employment in occupations at risk of automation, characterized by routine tasks, may recover to a lower level after output rebound because of firing costs and the upward trends of ICT capital penetration, we include ROUT_j times a dummy equals to one after October 2020 (D_t^{post}).[13]

[13] Sector and state-sector dummies controls for ROUT_j and $\Delta(\ln)\mathrm{ICT/L}_j$.

As we mentioned above, Covid-19 pandemic has introduced various supply shocks, such as fear and concerns leading to shifts in employment, containment and closure policies, restrictions on movement, and diverse responses to health and sanitary measures. We incorporate several control variables to account for supply-side factors that may confound our results. These controls include working from home (RWORK_j), coworker proximity (PROX_j) and the initial share of female employment ($\mathrm{ShWomen}_j$) times year-quarter dummies. Moreover, we employ time (D_t) and sector (D_j) fixed effects to control for time-varying and sector-specific characteristics that may influence employment dynamics.

Although we include control variables to account for supply-side factors, that the literature claims are important during the pandemic, our estimation may be still bias due to reverse causality, i.e., the potential influence of unobserved labor supply shocks correlated to our sector Routine Index. To control for this unobserved labor supply component of the Covid-19 output collapse, we adopt a well-established Instrumental Variable (IV) approach. Specifically, we control for these variations by utilizing a sector product demand Bartik (1991) Shift-Share instrument. First, we construct a sector i's activity proxy $\overrightarrow{IIV_t}$ as the share of each commodity used by each final use $[FD]$,[14] from

[14]We exclude from the final demand "Imports of goods and services" and "Change in inventories" columns.

US Input-Output Use Table 2019, times the final demand shift $[IFD]$.[15]

$$
\begin{aligned}
\overrightarrow{IIV_t} &= [FD] \times [IFD]' \\
\overrightarrow{IV_t} &= [[USE] + [I]] \times \overrightarrow{IIV_t}
\end{aligned}
\tag{3}
$$

$[USE]$ accounts for intermediate demand of commodities (70 x 70 matrix)[16] and $[FD]$ for the final demand from household consumption, government, exports, investment (70 x 9 matrix).[17] $[IFD]$ is the quarterly nominal "Gross Domestic Product" index open in 9 categories. $\overrightarrow{IIV_t}$ is an standard Shift-Share instrument where we use the Input-Output matrix to construct the initial share of each sector final demand. The shift component of the instrument comes from the final demand of households, governments, firms, and foreign countries. This is a good instrument only for sector in which the final demand is an important component. To account for this problem we compute $\overrightarrow{IV_t}$ which includes the inputs demand from sectors that was induced itself from the final demand ($[I]$ is the identity matrix.). Following Goldsmith-Pinkham et al. (2020) analysis of Bartik (1991) methodology, we think about the shares as the instruments. The sector shares measures the differential exogenous exposure to common shocks: changes

[15] The instrument is the sum of multiple Bartik (1991) Shift-Share instruments. For the production of each commodity we sum the share of the commodity demanded by each component of the US final demand times its (log) change. "The Use of Commodities by Industries(sectors) - BEA Summary 2021" data includes the use of commodities by sectors $[USE]$ and final demand $[FD]$. We normalized the "Total commodity Output" matrix ($[[USE], [FD]]$) (minus imports and change in inventories) to sum 1 by column.

[16] We merge sectors "Hospitals-62" and "Nursing and residential care facilities-63".

[17] $[USE]$ and $[FD]$ comes from "The Domestic Supply of Commodities by Industries - Sector" at BEA. FD includes "Personal consumption expenditures", "Nonresidential private fixed investment in structures","Nonresidential private fixed investment in equipment","Nonresidential private fixed investment in intellectual property products", "Residential private fixed investment", "Exports of goods and services", "Federal national defense","Federal national nondefense", and "State and local".

in the final commodities demands due to Covid19 pandemic.[18] Table 2, in the online Appendix , reports the regression between sector quarterly (ln) output, (ln) change of employment and (ln) wages, and the (ln) of $\overrightarrow{IV_t}$ for the period 2018q1 and 2021q4. All models include PAC sector and time fixed effects. First, when the dependent variable is (ln) sector output, the estimated coefficient for the instrument is 1.744 and highly significant (F test 60.56). We save the residual *Resid*. This is the component of sector output that is orthogonal to the instrument. The orthogonal component should include the labor supply component of the Covid-19 shock. Second, we regress (ln) sector employment on (ln) sector activity instrumented by $\overrightarrow{IV_t}$ first and second instrumented with the orthogonal component (*Resid*). As we should expect, both coefficients are positive and significant, and both instruments have a large *F Cragg-Donald* statistics. Finally, we use as the dependent variable (ln) wage. The demand component of the shock, the instrument, should have a positive and significant coefficient, whereas the orthogonal component should be negative or not significant. The estimated coefficient for (ln) activity instrumented with by $\overrightarrow{IV_t}$ is positive (0.434) and highly significant. The estimated coefficient when we instrument using the orthogonal component (*Resid*) is not statistically different from zero. These results reassure us that our instrumental variable is capturing the demand component of the Covid-19 shock.[19]

By employing this robust empirical strategy, which combines the IV approach with thorough controls for supply-side factors and the inclusion of fixed effects, we aim to

[18] It is hard to argue that the pre Covid19 sector shares from the "Use input-output table" are correlated with how Covid19 affected the supply of labor of different sectors.

[19] Results in levels are qualitatively identical.

discern the effects of the Covid-19 pandemic on employment and unravel the role of technology in shaping employment dynamics during and after crises.

We conduct robustness checks and heterogeneous estimations using state-sector employment data [$\ln(\text{Emp}_{sjt})$], and including additional controls for labor sector supply shocks at the state level: state-time fixed effects or School lockdown and state work restriction. We consider both the main effect and the interacted effect with the initial share of female employment. Although we have state-sector data of employment we only have production and its instrumental variable at the national-sector level. To control for the lack of state-sector-time product data, we use standard errors clustered at the sector-time level.

Results

Employment to Output Elasticities: National-Sector and State-Sector Level

In this subsection, we report our main results using (ln) national or state sector employment between 2018q1 and 2021q4. In all specifications, we instrument (ln) sector output [$(\ln)\text{PY}_{jt}$] using our shift sharing IV described in Equation (3).[20] Table 2 reports our estimates of Equation (2) using both national-sector and sector-sector employment data. In all models, independent variables are normalized to have a zero mean and a standard deviation equals to one.

[20] We instrument $(\ln)PY$ and $\text{ROUT}_j \times (\ln)\text{PY}$ using IVVA2_j and $\text{ROUT}_j \times \text{IVVA2}_j$, respectively.

Table 2: Employment elasticity of Output and Routine Tasks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(ln) Emp.	(ln) Emp.	(ln) Emp.	(ln) Emp.	(ln) Emp.	(ln) Emp.	(ln) Emp.
ROUT x (ln)PY	0.193	0.181	0.198	0.192	0.260	0.248	0.260
	(0.072)***	(0.075)**	(0.088)**	(0.072)***	(0.088)***	(0.076)***	(0.088)***
(ln) PY	0.312	0.305	0.053	0.352	0.126	0.355	0.126
	(0.061)***	(0.069)***	(0.070)	(0.061)***	(0.064)**	(0.061)***	(0.064)**
ROUT x Post2020q4	-0.017	-0.016	-0.023	-0.016	-0.025	-0.018	-0.025
	(0.009)*	(0.010)*	(0.012)**	(0.009)*	(0.011)**	(0.009)**	(0.011)**
Δ ICT/Emp.x (ln)PY				0.078	0.111	0.089	0.111
				(0.035)**	(0.030)***	(0.036)**	(0.030)***
ROUT Δ ICT/Emp.x (ln)PY						0.109	0.097
						(0.035)***	(0.030)***
Obs.	960	960	46,028	960	46,028	960	46,028
F Cragg-Donald	29.55	21.61	21.10	15.56	11.83	11.75	11.83
Sample-Sector	National	National	State	National	State	National	State

Notes: Robust standard errors in parenthesis for National-sector level results and clustered at sector-time level for State-Sector employment results. * p < 0:10;** p < 0:05; *** p < 0:01. (ln) Emp. is the National or State sector level of employment at PAC aggregation level (60 sectors). (ln) PY is Sector's output at PAC aggregation level (60 sectors). ROUT is the Sector weighted by the employment average of the Routine Task Index. Δ(ln)ICT/EMP is the (ln) technology-capital deepening process in the last 20 years ending in 2018. All regressions include RWORK, PROX, and ShWomen, times year-quarter dummies, but Column 1 does not include ShWomen times year-quarter dummies.

All models using National-Sector data include sector and time fixed-effects, and models using States-Sector data include State-Sector and Stare-times fixed effects. columns.

As expected, the log activity variable [(ln) PY] is positive and statistically significant in all models. This elasticity is larger for sectors with higher routine task index. In Column 1, which utilizes National level data, the employment elasticity of Output stands at 0.31, but for sectors exhibiting a one-standard-deviation larger ROUT index, this elasticity escalates to 0.51 (i.e. 0.312+0.193). Furthermore, we discover some tentative evidence suggesting that employment levels in sectors with a substantial share of initial employment susceptible to automation exhibit a slower recovery, although this coefficient only reaches statistical significance at the 10% level.

Column 2 essentially replicates the previous model but introduces ShWomen $\times$ t alongside RWORK and PROX $\times$ times. Remarkably, the results remain similar.

Moving on to Column 3, our approach shifts to State-Sector employment data, while also incorporating state-sector and State-time fixed effects. Here, the coefficient for ROUT$\times$(ln) PY remains similar at 0.198 retaining its high level of statistical significance. The coefficient for ROUT$\times Post2020q4$ decreases its prior magnitude to -0.023, and more relevant, it becomes significant at the 5% level.

Columns 4 and 5 introduce our proxy for ICT sector penetration in the last two decades, interacting with (ln) PY. The estimated coefficients for this variable are both positive, amounting to 0.078 and 0.111 in the National and State sector datasets, respectively. Notably, in Column 5, we observe that sectors with both a one-standard-deviation higher ROUT and ΔICT/L$_j$ penetration display a larger employment elasticity to output, amounting to 0.37 compared to the average sector.

In our final two columns, we delve into the triple interaction effects of ROUT $\times$

$(\Delta\text{ICT}/\text{L}_j) \times (\ln)$ PY. These coefficients are positive and equal to 0.11 and 0.10, respectively. This particular finding underscores that sectors characterized by high ROUT and substantial ICT penetration in recent decades exhibit a significantly larger employment elasticity in comparison to the broader sectoral economy. Specifically, a sector with a one-standard-deviation higher share of ROUT and $\Delta\text{ICT}/\text{L}_j$ yields an elasticity of 0.60 $(0.26 + 0.13 + 0.11 + 0.10)$, in contrast to the 0.13 elasticity of the average sector.

Heterogeneity and Robustness Checks

The primary objective of this subsection is to investigate potential asymmetric outcomes with regard to female and male employment. It is worth noting that the QCEW dataset lacks gender-specific employment information. Consequently, for the examination of female and male employment patterns, we rely on the CES dataset, which offers data at the National sector level spanning from the first quarter of 2018 to the second quarter of 2022.

In Table 3, specifically in Column 1, we essentially replicate the model presented in Column 6 of Table 2 using our CES database. Notably, the results obtained here exhibit a qualitative similarity to the previous findings.

In Column 2, we repeat the same model but focus specifically on female employment. While the results align with the previous model, there are slight variations in the coefficients. Particularly, the ROUT $\times$ (ln)PY coefficient appears slightly larger, and the triple interaction term is nearly half the magnitude observed for the entire sample. It's noteworthy that the sum of all terms interacting with (ln) PY, which essentially represents the employment elasticity of output for a sector with one standard deviation larger ROUT and Δ(ln)ICT/EMP compared to the average sector, does not exhibit statistical differences when compared to the sum of interacted terms in Column 1.

Moving on to Column 3, we shift our attention to male employment. The outcomes are akin to those observed in Column 1, with no statistically significant differences in the sum.

Interestingly, when we utilize the natural logarithm ratio of female and male employment as the dependent variable (Column 4), we have that female within occupations susceptible to automation may have a higher employment elasticity, regardless this is only statistically significant at the 10% level. Moreover, after the pandemics, female employment on occupations susceptible to automation is 0.021 lower than male employment.

In our previous set of results, the focus was primarily on ICT penetration, yet a lingering question remains - could our findings be linked to total capital penetration rather than specifically to technology-related capital? To explore this hypothesis, we turn our attention to the last three columns of our analysis.

In Column 5, we revisit the model presented in Column 1, but this time we introduce controls for variables related to total capital, specifically, the product of the change in natural logarithm of capital and output [$\Delta(\ln)\mathrm{K/Emp}_j \cdot (\ln)\mathrm{PY}_j$], along with the triple interaction term [$\mathrm{ROUT}_j \cdot \Delta(\ln)\mathrm{K/EMP}_j \cdot (\ln)\mathrm{PY}_j$]. Remarkably, all the coefficients of interest retain their magnitudes and statistical significance. It's noteworthy that the

Table 3: Employment Elasticity of Output by Gender and Regular Capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	(ln) Emp.	(ln) Emp.	(ln) Emp.	(ln) Female Emp.	(ln) Men Emp.	(ln) Fem/Male	(ln) Emp.
ROUT x (ln)PY	0.318	0.328	0.197	0.247	0.144	0.102	0.266
	(0.094)***	(0.105)***	(0.057)***	(0.067)***	(0.064)**	(0.053)*	(0.066)***
ROUT Δ ICT/Emp.x (ln)PY	0.188	0.182	0.042	0.030	0.029	0.001	0.136
	(0.076)**	(0.076)**	(0.021)**	(0.025)	(0.022)	(0.015)	(0.053)**
Δ ICT/Emp.x (ln)PY	0.007	0.057	0.092	0.095	0.111	-0.016	0.023
	(0.076)	(0.062)	(0.021)***	(0.029)***	(0.024)***	(0.019)	(0.042)
(ln) PY	0.281	0.075	0.167	0.185	0.154	0.031	0.021
	(0.076)***	(0.088)	(0.064)***	(0.101)*	(0.074)**	(0.079)	(0.095)
ROUT x Post2020q4	-0.020	-0.027	-0.002	-0.019	0.002	-0.021	-0.005
	(0.009)**	(0.011)**	(0.007)	(0.010)*	(0.009)	(0.009)**	(0.008)
ROUT Δ K/Emp. x (ln)PY	-0.122	-0.194					-0.154
	(0.162)	(0.166)					(0.113)
Δ K/Emp. x (ln)PY	0.251	0.115					0.222
	(0.169)	(0.133)					(0.087)**
Obs.	960	46,028	1,026	954	954	954	1,026
F Cragg-Donald	7.16	7.91	6.45	4.82	4.82	4.82	3.22
ROUT joint test			13.79	14.25	6.03	3.89	
Sample-Sector	National	State	National	National	National	National	National

Robust standard errors in parenthesis for National-Sector level results and clustered at sector-times levels for State-Sector level results. * p < 0:10;** p < 0:05; *** p < 0:01. (ln Emp.) is National or State sector quarterly level of employment at PAC aggregation level (60 sectors). (ln) PY is Sector's quarterly output at PAC aggregation level (60 sectors). ROUT is the Sector weighted by employment average of the Routine Task Index. Δ(ln)ICT/EMP is the (ln) technology-capital deepening process. All regressions include RWORK, PROX, and times year-quarter dummies.

new variables related to capital penetration exhibit an opposite sign when compared to the ones related to ICT penetration, but they do not differ significantly from zero. These findings lend support to our initial interpretation that we are indeed capturing an effect associated with new technologies and the risk of automation.

In Columns 6 and 7, we extend our analysis to encompass OCWS data, specifically focusing on models resembling those presented in Columns 6 and 7 of Table 2. Once again, we introduce controls for total capital times output [Δ(ln)K/Emp$_j$ $\times$ (ln)PY$_j$] and the triple interaction term [ROUT$_j$ $\times$ Δ(ln)K/EMP$_j$ $\times$ (ln)PY$_j$]. In both of these models, our results align with those found in Column 5. However, it's worth noting that in Column 6, the triple interaction term exhibits the same magnitude but loses its statistical significance. Nonetheless, the overarching pattern reinforces the idea that our findings are linked to new technologies and the risk of automation, rather than solely to total capital penetration.

For additional robustness, in nonreporting regression, we use Frey and Osborne (2017)'s risk of automation index instead of ROUT. The results are similar.

Conclusions

In this study, we investigate the influence of recent technologies on the elasticity of employment to output in the business cycle, with a focus on the progressively enhanced capacity of technology to substitute labor, thereby amplifying elasticity over time. We argue that, in response to the inception of a crisis, firms tend to reduce production, predominantly cutting flexible inputs such as labor. Factors like the time-to-build and the irreversibility of investments lead to a more pronounced reduction in employment in occupations where there exists a higher elasticity of substitution with technology capital.

Leveraging the shock induced by the Covid-19 pandemic and employing an Instrumental Variable methodology for identification, we observe that the employment to output elasticity is markedly higher than in prior crises. Moreover, our findings reveal that occupations vulnerable to automation bear the brunt of employment losses. This implies that they were more sensitive to fluctuations in economic activity, likely due to the ease with which technology can replace certain routine tasks. Interestingly, our results hint at a relatively slower recovery in sectors with a substantial share of initial employment susceptible to automation, a trend observed throughout the pandemic. Moreover, we find suggestive evidence that these effects are higher for female workers.

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APPENDIX

Cyclical component of output and labor

Table 1: Employment and Output cycle

	(1) Emp Cycle	(2) Emp Cycle	(3) Emp Cycle
GDP Cycle	0.672		0.238
	(14.84)**		(2.15)*
GDP Cycle X Post2000	0.401		
	(5.09)**		
Post2000	-0.000		
	(0.05)		
GDP Cycle X 1960s		0.657	
		(7.54)**	
GDP Cycle X 1970s		0.650	
		(11.20)**	
GDP Cycle X 1980s		0.701	
		(10.19)**	
GDP Cycle X 1990s		0.725	
		(6.60)**	
GDP Cycle X 2000s		0.862	
		(10.51)**	
GDP Cycle X 2010s		1.248	
		(11.65)**	
GDP Cycle X Share ICT inv			1.735
			(5.42)**
Share ICT inv			-0.005
			(0.97)
Constant	-0.000	0.000	0.002
	(0.04)	(0.05)	(0.99)
R^2	0.66	0.68	0.67
N	256	256	256

Robust standard errors. * $p < 0.05$; ** $p < 0.01$*Notes*: Log cyclical fluctuations in Real Gross Domestic Product (ST.Lous FED: GDPC1) and Total Nonfarm Employees (ST-Louis FED: PAYEMS) in the USA from 1960 to the present. We use the Hodrick-Prescott time-series filter to compute the cyclical component with a smoothing parameter 1600 for the period 1960q1-2022q4 (254 quarters). The "Share ICT inv" is the ratio between investment in Software, Research and Development and Nonresidential Information Processing Equipment (ST.Louis FED : B985RC1Q027SBEA + Y006RC1Q027SBEA +Y034RC1Q027SBEA) and Total Private Nonresidential Fixed Investment (ST.Louis FED :PNFI).

Table 2: Employment and Wages, and the Shift-Share Product Demand Instrument

	(1)	(2)	(3)	(4)	(5)
	(ln) PY	(ln) Emp.	(ln) Emp.	(ln) Wage	(ln) Wage
(ln) IV PY	1.744				
	(0.224)***				
(ln) PY		0.316	0.390	0.434	0.005
		(0.076)***	(0.052)***	(0.085)***	(0.029)
Obs.	960	960	960	960	960
F Cragg-Donald		60.56	7,310.11	60.56	7,310.11

Robust standard errors clustered at industry level. * p < 0.1; ** p < 0.05; *** p < 0.01. $\Delta\%PY$, a Emp and $\Delta\%$ Wage are log change of output, employment and wage at PAC aggregation level (60 sectors). $\Delta\%IV^2$ is the output instrument at PAC aggregation level (60 sectors).All models include time trend and industry fixed-effects.

Employment and Wages, and the Shift-Share Product Demand Instrument

Figure 3: Employment, Output, Capital Deepening and Investment in ICT and Regular capital

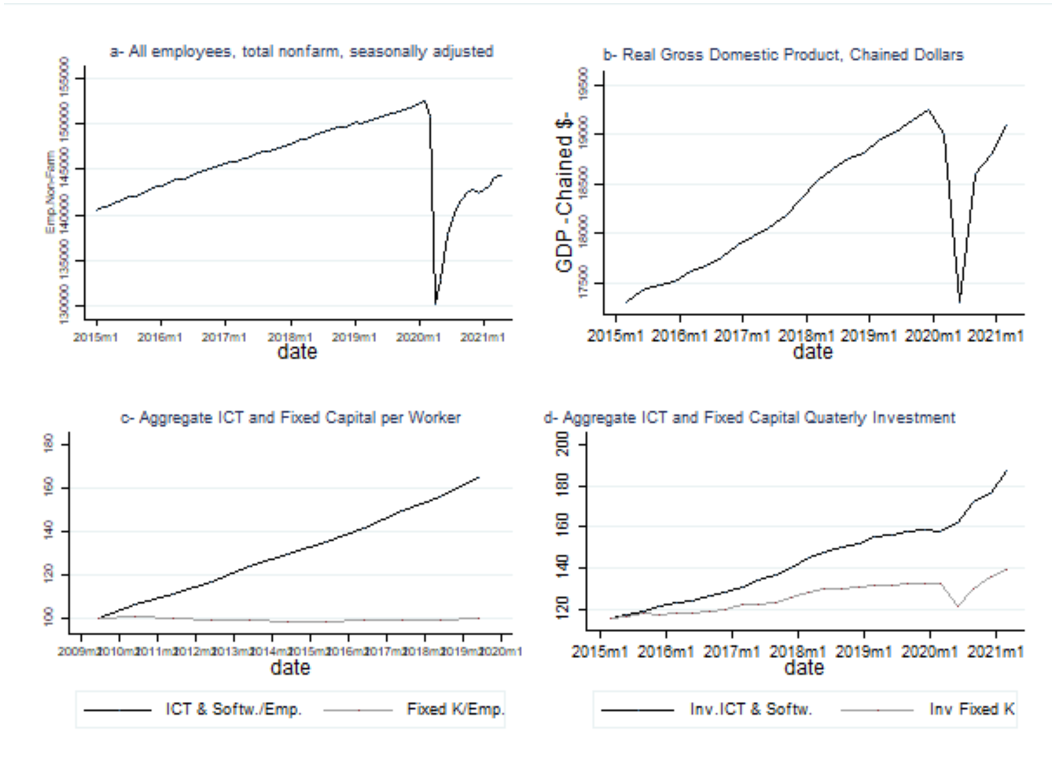

Figure 3a shows the evolution of total employment in the non-farm sector in the USA. Figure 3b shows the evolution of real quarterly aggregate GDP (ln). Figure 3c shows the evolution of capital deepening. ICT & Softw./EMP and IF & Softw./EMP are aggregate real capital in ICT and Software over total private employment (2012=100)(BEA and BLS). Figure 3d shows the evolution of real Private fixed investment in information processing equipment and software and Private fixed investment (2012==100). Source. Bureau of Labor Statistics and Bureau of Economics Analysis.

Background and Related Literature

Historical data suggests that pandemics take a toll on economic development (Bell et al., 2006; Acemoglu et al., 2003; Well, 2007; Ashraf et al., 2008; Lorentzen et al., 2008; Goenka and Liu, 2012; Voigtlander and Voth, 2013; Bloom et al., 2014; Barro et al., 2020), and the Covid-19 pandemic has not been an exception. Between January and May 2020, the US labor market lost 21.9 million jobs in the non-farm sector due to the Covid-19 pandemic (See Figure 3a). Just a few months later, in August, almost 10.8

million jobs had already been recovered.[21] By March 2021, US output, measured by the quarter gross domestic products, almost reached its pre-pandemic level (See Figure 3b), but employment is still 5.4% below its December 2020 level, with almost 6.9 million fewer jobs. While this is clearly a rapid recovery, the future of these lost jobs still raises concerns. Several factors have contributed to job destruction during the Covid-19 pandemic. These factors involve a variety of restrictions imposed by governments (quarantine, confinements, curfews, social distancing policies, etc.) to control the spread of Covid-19 and subsequent workers' behavioral responses (Atkeson, 2020; Barrero et al., 2020; Beland et al., 2020; Coibion et al., 2020; Beirne et al., 2020; Kahn et al., 2020; Forsythe et al., 2020; Mongey et al., 2020; Agrawal et al., 2021).[22] Studies show that the impacts are modulated by the physical proximity of coworkers, the exposure to infectious diseases in the workplace, the capacity to perform the work remotely, and lockdown policies taken by governments (Beland et al., 2020; Dingel and Neiman, 2020; Alipour et al., 2020; Fadinger et al., 2020; Gottlieb et al., 2020; Hensvik et al., 2020; Irlacher and Koch, 2020). Women have experienced sharper employment losses because they work in sectors that suffered the largest demand shocks and because they are more affected by school and daycare closures (Alon et al., 2020).[23] Our results show that the policy stringency index affects employment negatively. In addition, we also find that women are more affected by school restrictions than men, which is also consistent with recent evidence of this asymmetric effect (Alon et al., 2020). Interestingly, these effects are contrary to the findings of Elsby et al. (2010) relative to the Great Recession, in which men were more affected. This difference is likely due to the original supply shock in the education and care sector (e.g. school closures) and the uneven role that women do in parenting or caring compared to men.

[21] "All employees, thousands, Total Non-Farm, seasonally adjusted" from the Current Employment Statistics (CES) National- Bureau of Labor Statistics (BLS).

[22] There is also a broader and growing literature on the economic consequences of Covid-19 (Alon et al., 2020; Atkeson, 2020; Briscese et al., 2020; Fang et al., 2020; Fetzer et al., 2020; Jordà et al., 2020; Guerrieri et al., 2022; Ramelli and Wagner, 2020).

[23] There is a large literature that provides evidence of the effect of childcare availability on women's labor market outcomes (Blau and Currie, 2004; Simonsen, 2004).

The degree of substitution between labor and technology-capital investment highlights as a critical driver of the labor demand. In recent decades, there has been an upward trend in technology-capital investment—e.g. Information processing equipment and software (ICT). Autor et al. (2003), Jaimovich and Siu (2020), among others, argue that there has been a reduction in occupations at risk of automation (OaRA) during the last decades because they have been substituted by technology-capital, mainly during recessions.[24] After the Great Recession, the price of technology-capital has continued to fall,[25] and investment has continued to grow faster in this type of capital than in total fixed capital. Although Jaimovich and Siu (2020) reports that employment contraction in OaRA has slowed down post 2009, the presence of adjustment costs may explain this evolution of OaRA employment in stable periods after the Great Recession.[26] After the Great Recession, the initial employment recovery was lower in OaRAs because firms knew that in the near future they would have to fire newly hired employees because of the downward trend of technology-capital prices. Evidence consistent with the latter is depicted in Figure 3c and 3d. This small recovery, which already takes into account the secular downward trend of OaRA, helps to explain the low rate of employment contraction in OaRAs during the 2010s.

Our paper is related to the growing literature regarding the labor-market consequences of the deployment of industry 4.0's technologies [27]—e.g., automation, digitization, cognitive computing, and chatbots, among others (e.g. Autor et al. (2003); Goldin and Katz (2009); Autor and Dorn (2013); Brynjolfsson and McAfee (2014); Frey and Osborne (2017); Arntz et al. (2017); Pedemonte et al. (2018); Graetz and Michaels (2018); Acemoglu and Restrepo (2018, 2019); Egana-delSol and Joyce (2020); Egana-

[24]We defined OaRA using Autor et al. (2003)'s routine tax index and/or Frey and Osborne (2017)'s risk of automation.

[25]Post the Great Recession technology-capital prices have been falling at a rate of -2% year, whereas the price of total equipment has been rising at 4% per year. See BEA.

[26]See Caballero and Engel (1993) and Cooper et al. (2015) for a discussion of labor adjustment costs in the US.

[27]Industry 4.0 accounts for the recent developments in cognitive computing, artificial intelligence, the internet of things, and big data analysis that is changing the whole process used to produce and deliver products and services (Schwab, 2017).

delSol et al. (2022,?)). These technologies can automate tasks previously performed by labor (the substitution effect) or complement human tasks and create new ones (the complementary effect). Thus, automation may increase demand for some occupations and decrease demand for others. In this paper, we use the methodologies in Autor et al. (2003) and Frey and Osborne (2017) to define and investigate the occupations at risk of automation during the massive collapse in sector demand due to Covid-19. Because of investment irreversibility, this is a unique opportunity to study the level of substitution or complementarity between different occupations and technology-capital.

Our study is also related to the literature documenting the impact of economic crises on the labor market and technology adoption (e.g. Caballero and Hammour (1996)). For instance, Kopytov et al. (2018) studied the Great Recession, arguing that the adoption of new technologies by firms and the acquisition of new skills by workers are concentrated during downturns due to low opportunity costs, which in turn speeds up adoption of the new technology. Jaimovich and Siu (2020) shows that loss of routine tasks employments, which can be a proxy of OaRA, has happened almost entirely during the 1991, 2001 and 2009 recessions. Almost all of the contraction in per capita aggregate employment during these recessions can be attributed to recessions in middle-skill-routine occupations. Micco (2020) shows that this "cleansing effect" during the Great Recession happens across and within several economic sectors in the United States. We complement this literature showing that sectors with a large share of employment in OaRA and high investment in technology-capital also fall more during the drastic initial contraction of output during the Covid-19 pandemic. However, we also show that they recovered faster after the output rebound during the second half of 2020, although to a lower level relative to riskless employment.

Employment in Occupations at Risk of Automation During the Pandemic

OES data allows us to study the evolution of employment across occupations during the first phase of the pandemic. We can compute the employment rate of growth for different occupations between May 2019 and May 2020 and correlate them with their routine task component, the initial share of women in each occupation, the perception of risk of contagion proxy by coworker proximity, and the possibility of work from home. During this period, employment in occupations at risk of automation should fall more because it features a high elasticity of substitution with ICT capital and because ICT capital cannot adjust. Hence, the excess level of ICT capital should imply a large contraction in OaRA. We cannot study the rebound phase in output using OES data. In this phase, the excess of ICT investment should imply a large rebound of OaRA.

Figure 4a describes a strong relationship between the Routine Task Index (OaRA), Ã la Autor et al. (2003), and occupation employment growth. We group occupations into 40 equal-sized bins and report the average of employment rate of growth. Occupations in the first bin (first 5 percent of occupations with the lowest levels of routine tasks) present a negative employment rate of growth of 2%, whereas occupations in the last bin present a negative employment growth of 10%. This first evidence suggests that employment in occupations with a high risk of automation fall more during the initial phase of the pandemic. Figure 4b reports the bin scatter plot between the share of women across occupations, measured in 2019, and the rate of employment growth between May 2019 and May 2020. OES data does not provide employment by gender, and therefore we compute the women's share by occupations from the Current Employment Survey. We do not find any correlation. This result suggests that within occupation, the initial impact of Covid-19 pandemic is similar between women and men. Figure 4c reports the correlation between occupation employment growth and the Beland et al. (2020) coworker proximity index. For the initial phase of the pandemic, data shows a high negative correlation. Employment growth for occupations divided into 40 equal-sized

Figure 4: Emp.Growth across OaRAs, Women Share, Co-woker Proximity and Work-from-Home Index

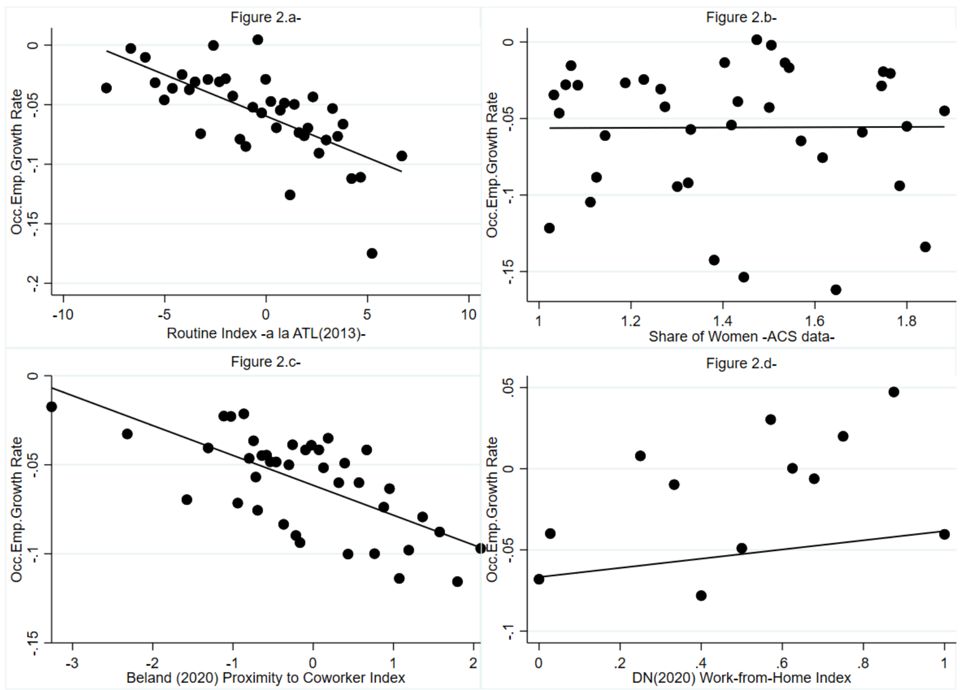

Figure a shows the correlation between Routine Task Index Ã la Autor et al. (2003) and employment growth at the level of 734 detailed occupations between May 2019 and May 2020 (6 digits SOC classification). Figure b shows the correlation between the share of women and employment growth at the level of 93 detailed occupations. To compute the share of women, we use information from the 2019 American Community Survey (93 occupations defined at 3digit SOC classification). Figure c presents the correlation between Coworker Proximity and employment growth at the level of 705 detailed occupations. Figure d shows the correlation between Teleworking Index and employment growth at the level of 745 detailed occupation. In all figures, we present the Stata binscatter plot with 40 groups. Source. Bureau of Labor Statistics, Autor et al. (2003), Dingel and Neiman (2020), and Beland et al. (2020).

bins of coworker proximity ranges from minus 2% to minus 11%. Finally, there is a weak correlation between employment growth and the Dingel and Neiman (2020) index for the possibility to work from home.[28]

To study the second phase of the Covid-19 pandemic, we use monthly sector employment defined at the 4 digit NAICS code from the Current Population Survey, as explained in the previous section. We follow the evolution of (ln) employment for sectors

[28]The Dingel and Neiman (2020) index takes 10 values.

classified by their weighted average of Routine Task Index (OaRA), coworker-proximity and Work-from-Home, and the evolution of women's and men's employment at the sector level. A sector with a high RISK of automation index—e.g. High routine task index or FO risk of automation— should cut more its employment during the first phase of Covid-19 and then rebound more during the economic activity recovery.

Figure 5 reports the evolution of employment for different subgroups. At the end of every trend line, we can see the contraction and rebound of employment for each of these groups occurring during the first cycle of the Covid-19 pandemic.

Figure 5a reports the evolution of employment in sectors with a share of employees in OaRAs below the 2019 sector median (black line) and above (grey line). This is in keeping with our previous results. The thick black line illustrates the share of employment in sectors with a large share of OaRA. In line with Jaimovich and Siu (2020), the loss of employment in OaRA is concentrated in the Great Recession and during the first phase of the pandemic. Employment in all sectors fell during the first quarter of 2020, although this fall is two times larger for sectors with a large share of jobs in OaRA (-22% versus -11%). Since May, the same is true for the recovery. The raw evolution of employment in sectors with high and lower shares of jobs in OaRA is in line with the hypothesis that occupations characterized by routine tasks, and therefore prone to automation, have large elasticity of substitution with technology-capital.

Figure 5b reports the evolution of men's (black line) and women's employment (grey line) in the economy. Women's employment presents an upward trend during the whole period. During the Great Recession, women's employment increased relative to men's (thick black line). However, during the initial phase of Covid-19 pandemic, the share of women's employment fell by 1.2 percentage points. It rebounded after May 2020, but it is still 0.3 percentage points down by February 2021.

Figure 5c reports the evolution of sector with coworker proximity below (black line) and above (grey line) the median sector. In line with the hypothesis that workers are afraid to work in places were the risk of contagion is high, employment falls more in the

Figure 5: Employment in OaRAs, by gender, by co-woker proximity and ICT capital deepening

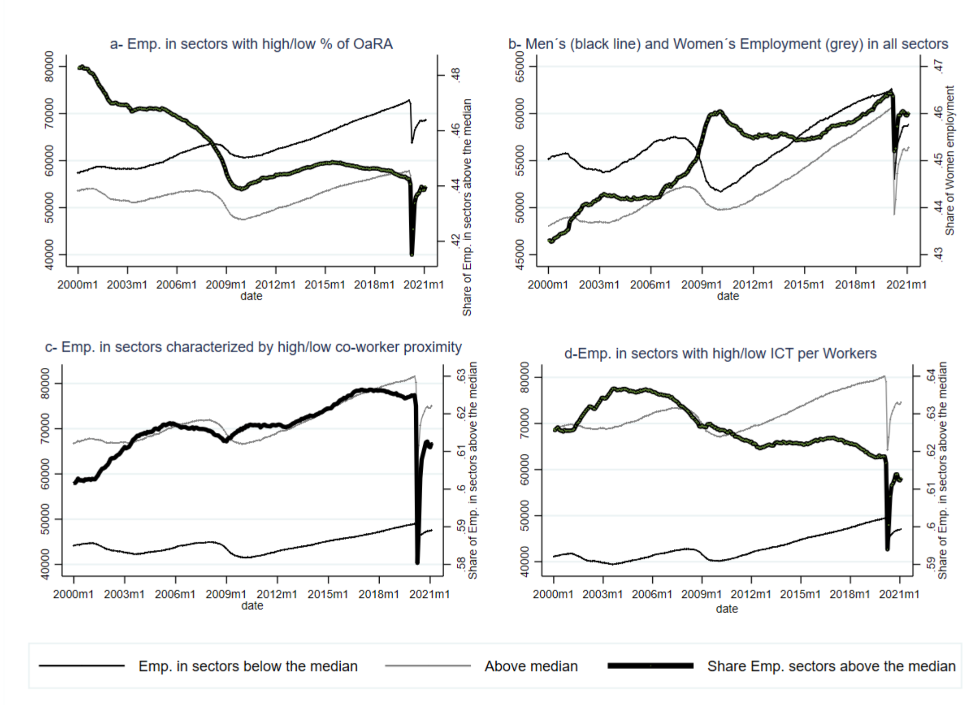

Figure a shows the evolution of employment in sectors with weighted average of Routine Task Index Ã la Autor et al. (2003) above and below the median sector. Figure b shows the evolution of men's and women's employment in the whole private sector. Figure c shows the evolution of employment in sectors with a weighted average of Beland (2019) Coworker Proximity Index above and below the median sector. Figure d shows the evolution of employment in sectors with ICT capital per worker above and below the median sector (information for ICT capital is at 3dig. NAICS sectotrs). Source. Bureau of Labor Statistics, Bureau of Economics Analysis,Autor et al. (2003), Dingel and Neiman (2020), and Beland et al. (2020).

first part of the pandemic in sector above the median and also rebounds more after that. The evolution of employment is in line with research that shows that the single cue of daily new cases can drive risk perception.[29] The total number of deaths per million was 0.003 in February 2020, then jumps to 16.102 in March and 185.95 in April. These are exactly the two months we observe a large fall in the number of employees in sectors above the coworker proximity median. In May, when the number of deaths per month started to fall, employment in these sectors also reverted to their negative trend. The

[29]Harman (2021) studies the risk perception and the evolution of time-series Covid-19 data (in particular the cumulative number of deaths).

share of sectors above the median continues to recover faster until October 2021 and then their share stops growing. Between May and mid-October, cases were falling; however, they started to increase again after this month.[30] Figure 5d presents employment in sectors with ICT capital per worker above the median sector (grey line) and below (black line).[31] Due to investment irreversibility, we should expect that employment in OaRA (with routine tasks) should fall more in these sectors. The data is in line with this hypothesis. Reassuring results from Figure 3d show that sectors with more ICT capital in 2009 report a large fall in employment at the beginning of the pandemic and subsequently a large rebound.

The evolution of employment in sectors both with a higher share of workers in OaRAs and higher initial ICT per worker had a higher amplitude over the output cycle of the Covid-19 pandemic. This evidence reinforces the idea that it is crucial to study employment in OaRAs to understand the evolution of employment during crises in general and the Covid-19 pandemic in particular.

Conceptual Framework: A Simple Model

We present a brief conceptual framework to guide our empirical work.

Firms

We assume a continuous distribution of mass 1 identical firms in the economy. Firms combine service S and regular capital using a Cobb-Douglas aggregation function with a constant return to scale (CRE).[32] The output elasticity for regular capital is α. To produce service S, firms mix the labor (L) and ICT capital using a CES aggregation function with CRE and elasticity of substitution $\rho > 1$. Firms rent regular (K) and

[30] Data for the number of deaths per month are from Our World in Data.

[31] We use the BEA-BLS productivity data set to construct ICT capital per worker in their 63 sectors defined using NAICS classification. We assign this ICT per worker index for sectors defined at a des-aggregate sector.

[32] We follow Card and DiNardo (2002)

technology-capital (K^{ICT}) at R and R^{ICT} rental prices. Each period firms maximize:

$$Max_{L,K^{ICT},K} \qquad P_tY_t - W_tL_t - R_t^{ICT}K_t^{ICT} - R_tK_t$$
$$sa$$
$$Y_t = \left(\lambda^{1/\rho}(A_tL_{,t})^{\frac{\rho-1}{\rho}} + \lambda_K^{1/\rho}K_t^{\frac{\rho-1}{\rho}}\right)^{(1-\alpha)\frac{\rho}{\rho-1}} K_t^{\alpha}$$

Without lost of generality we normalize $\lambda_K = 1$.

Households

There is a continuous distribution of mass 1 identical households. Households consume, supply labor L, and regular and ICT capital. For simplicity, we assume that households save a fixed share s of their income and maximize one-period utility.[33] To produce one unit of regular capital you need one unit of the final good (Y), and to produce one unit of ICT capital you require one over A^{ICT} unit of final goods. Both capitals depreciate at rate δ. In the short run, there is a fixed stock of regular and ICT capital K^{ICT} and K. Households maximize each period the following problem:

$$Max_L \qquad \frac{C_t^{1-\sigma}}{1-\sigma} - \frac{\Phi}{1+\epsilon}L_t^{1+\epsilon}$$
$$sa$$
$$PC_t(1-s) = WL_t + R_t^{ICT}K_t^{ICT} + R_tK_t$$
$$PI_t^R + P^{ICT}I_t^{ICT} = sPY_t$$

where I^R and I^{ICT} are investment levels in regular and ICT capital, respectively. And

$$\begin{aligned} P &= (\lambda A^{\rho-1}W^{1-\rho} + \lambda_K R_{ICT}^{1-\rho})^{(1-\alpha)/(1-\rho)}R^{\alpha}/(A\alpha^{\alpha}(1-\alpha)^{1-\alpha}) \\ P^{ICT} &= \frac{P}{A^{ICT}} \end{aligned} \tag{4}$$

[33]A multiperiod maximization problem does not provide any additional inside to the problem.

In steady state investment is equal to capital depreciation, therefore:

$$
\begin{aligned}
K &= \frac{s_R}{\delta} Y \\
K^{ICT} &= A^{ICT} \frac{s_{ICT}}{\delta} Y
\end{aligned}
\tag{5}
$$

where s_R and s_{ICT} are the share of household income invested in regular and ICT capital ($s_R + s_{ICT} = s$). In the steady state, by arbitrage, $R = R^{ICT}$.

Equilibrium

Firms' FOCs are:

$$
\begin{aligned}
L_t &= (1-\alpha) ShL_t \frac{PY_t}{W_t} \\
K_t^{ICT} &= (1-\alpha)(1 - ShL_t) \frac{PY_t}{R_t^{ICT}} \\
K_t &= \alpha \frac{PY_t}{R_t}
\end{aligned}
\tag{6}
$$

where

$$
ShL = \frac{\lambda^{1/\rho} A^{(\rho-1)/\rho} L^{(\rho-1)/\rho}}{\lambda^{1/\rho} A^{(\rho-1)/\rho} L^{(\rho-1)/\rho} + \lambda_K^{1/\rho} K_{ICT}^{(\rho-1)/\rho}} = \left(1 + \frac{\lambda_K^{1/\rho}}{\lambda^{1/\rho}} \left(\frac{K^{ICT}}{AL}\right)^{(\rho-1)/\rho}\right)^{-1} \tag{7}
$$

, which is decreasing in K^{ICT}/L if $\rho > 1$.

In the short run, households' FOCs are:

$$
\begin{aligned}
\Phi L^{\epsilon} &= C^{-\sigma} \frac{W}{P} \\
&= (Y(1-s))^{-\sigma} \frac{W}{P}
\end{aligned}
\tag{8}
$$

Labor to output elasticity

We are interested in the employment to output elasticity $dln(L)/dln(Y)$ in the short run (K and K^{ICT} are fixed) after a shock in A . From FOCs we have:

$$L = \left(ShL \frac{(1-\alpha)(1-s)^{\sigma}}{\Phi_A} \right)^{1/(1+\epsilon)} Y^{(1-\sigma)/(1+\epsilon)} \tag{9}$$

Therefore the employment to output elasticity is:[34].

$$\begin{aligned} \frac{dln(L)}{dlnY} &= \frac{1}{1+\epsilon} \frac{dln(ShL)}{dlnAL} \left(\frac{dlnY}{dlnAL} \right)^{-1} + \frac{1-\sigma}{1+\epsilon} \\ &= \frac{1-\sigma}{1+\epsilon} + \frac{1}{1+\epsilon} \frac{\rho-1}{\rho} \left(\frac{1}{(1-\alpha)ShL} - \frac{1}{(1-\alpha)} \right) \end{aligned} \tag{10}$$

Labor to output elasticity is monotonically increasing in ρ for a given level of ShL. Also, for any ρ the labor to output elasticity is increasing in the stock of ICT capital,[35] but for $\rho = 1$, in which case the labor to output elasticity is constant and equals to $(1-\sigma)/(1+\epsilon)$.

[34]Note: $\frac{dln(ShL)}{dlnAL} = \frac{\rho-1}{\rho}(1-ShL)$ and $fracdlYdlnAL = (1-\alpha)ShL$

[35]If $\rho > 1$ and increase in ICT decreases ShL, and if $\rho < 1$ an increase in ICT capital increase ShL.