IT Shields: Technology Adoption and Economic Resilience during the COVID-19 Pandemic

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Abstract

We study the economic effects of information technology (IT) during the onset of the COVID-19 pandemic, using data on IT adoption covering almost three million establishments in the US. We find that in areas where firms had adopted more IT before the pandemic, the unemployment rate rose less in response to social distancing. Our estimates imply that if the pandemic had hit the world 5 years ago, the resulting unemployment rate would have been 2 percentage points higher during Spring 2020 (16% vs. 14%), due to the lower availability of IT. IT shields all individuals, regardless of gender and race, except those with the lowest educational attainment. Instrumental variable estimates–leveraging historical routine employment share as a booster of IT adoption– confirm IT had a causal impact on fostering labor markets' resilience.

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1 Introduction

As COVID-19 spread across the world and the United States, people greatly reduced their mobility, stayed more at home, and spent less time producing and consuming products and services that require face-to-face interactions. These changes, caused by both voluntary behavior and various mitigation policies, have also severely damaged the economy. With the spread of Omicron across the world, people start once again reducing their mobility. What are the labor market consequences of lockdowns and mobility restrictions and can information technology (IT) mitigate these adverse effects? For everyone?

This paper analyzes the interplay between the sudden decline in mobility, its effect on the labor market, and firms' adoption of IT in the US. It relies on several data sources, and in particular on survey data covering software and hardware purchases of almost three million establishments in different industries.

Firm-level IT adoption can strengthen or dampen the effect of mobility on economic outcomes in several ways. On the one hand, IT adoption can cushion the impact of the pandemic by facilitating work-from-home or contact-less interactions [*Bloom*, 2020; *Brynjolfsson et al.*, 2020; *Papanikolaou and Schmidt*, 2020] and increase online sales. IT adoption can also increase firms' organizational flexibility, allowing them to change their business practices and operations more promptly. On the other hand, the pandemic may reinforce the substitution of labor with technology for ex-ante heavy IT adopters [*Chernoff and Warman*, 2020]. High-technology adopting firms may be more inclined to automate processes when the pandemic spreads as humans would be at risk of contracting the virus.

We show that IT adoption significantly shields workers from the economic consequences of the pandemic. Figure 1 illustrates the increase in the unemployment rate between February and April 2020 for each US state and the decline in mobility during the same period. In low-IT adoption states, there is a strong correlation between the drop in mobility and the rise in the unemployment rate. Conversely, mobility is not associated with rising unemployment rates in states with higher IT adoption. We confirm this suggestive evidence in individual-level regressions using within-state (MSA-level) variation in IT adoption and controlling for various other potential confounding factors.

Importantly, we provide causal estimates on the mitigating role of firms' IT adoption on local labor markets thanks to an instrumental variable approach. IT adoption can be correlated (and caused by) several local characteristics, such as availability of human capital. While we control for various potential confounding factors, such as the level of education, we cannot rule out that unobservable characteristics are driving the mitigating impact of IT. We thus follow *Autor et al.* [2003] by instrumenting regional-level IT adoption by its historical routine employment share. In regions where historically more routine workers were employed, IT adoption has been faster and stronger when the price of IT equipment fell and routine workers could be replaced by technology. Because of path-dependency, even today IT adoption is higher in areas where historically the routine employment share was higher than in other regions. Instrumental variable regressions confirm our OLS estimates: the impact of the mobility drop on unemployment probability is lower in areas where IT is adopted more intensely by firms. This points toward IT playing a causal role in mitigating adverse employment outcomes during a pandemic.

We quantify the effect of IT adoption relative to a counterfactual scenario in which the pandemic had hit the world five years earlier. The digital economy as a share of employment grew by around 10% relative to five years ago (See subsection 5.3 for details). Combining this number with our regression results, we find that the unemployment rate would have been around 2 percentage points higher during April and May 2020 if IT adoption would have been at the level of 2015. Instead of an unemployment rate of 14% the unemployment rate would have reached 16%.

We find that local IT adoption is strongly correlated with measures of the feasibility of working at home [*Dingel and Neiman*, 2020]. However, we shot that local IT adoption and the ability to work from home are both independently shielding the economy from a local mobility shock. This suggests that other channels, rather than just working from home abilities protect the economy from the consequences of the pandemic. For instance, firms that employ more technology may be better at absorbing a mobility decline as they are faster and more efficient in switching to online sales.

The recent literature (see section 2 for a brief review) has argued that the economic consequences of COVID-19–especially at its onset–are significantly more severe for more economically vulnerable individuals, such as women, racial minorities, immigrants, and individuals with lower educational attainment. IT adoption may also have a heterogeneous impact along those dimensions. For instance, information technology can be a complement for skilled labor, while it may substitute unskilled labor. If the COVID-19 shock promotes further automation of production processes, and more so for more IT intense companies, then it may differentially impact women or men according to which industry is subject to the greatest changes (e.g. manufacturing sector predominantly employs male workers). Minorities have been experiencing COVID deaths and infections at higher rates [*Kirby*, 2020]; an occupational distribution skewed towards occupations requiring in-person contacts is a main potential culprit. Therefore, IT adoption, by facilitating the delivery of contactless services and goods, may help individuals employed in these risky occupations.

The effect of IT adoption in shielding workers is consistent across most groups. We show that both males and females as well as individuals of different races benefit from IT adoption. However, the effect is weaker for males, suggesting that automation of tasks weakens the beneficial impact of technology. Minorities benefit slightly more from IT adoption. These findings are reassuring as women and minorities have suffered more from the economic consequences of the onset of COVID-19.

Most strikingly, we find a large difference in the way IT adoption shields individuals with heterogeneous levels of educational attainment. Individuals with high-and medium levels of education significantly benefit from IT adoption, while individuals with low educational attainment (those who did not complete high school) are not shielded by IT. These findings suggest that the COVID-19 pandemic increases inequality across educational groups through skill-biased technical change. This is consistent with evidence from past recessions when low-skilled individuals were disproportionately affected, which further reduced complementary IT skills and persistently widened inequality [*Heathcote et al.*, 2020].

The remainder of the paper is structured as follows. In section 2 we present a brief literature review. In section 3 we describe the data. In section 4 we illustrate state-level patterns. In section 5 we present evidence (including IV estimates) on the mitigating role of IT from from individual-level data. In section 6 we study the heterogeneity of the mitigating impact of IT. In section 7 we conclude.

2 Related Literature

The literature on the economic crisis triggered by the COVID-19 pandemic has been expanding very rapidly. For a review of this literature, see Chapter 2 of the 2020 October WEO (IMF) or *Brodeur et al.* [2020].

Some authors have argued that voluntary social distancing has had a more important role than lockdowns [*Allcott et al.*, 2020; *Bartik et al.*, 2020; *Kahn et al.*, 2020; *Maloney and Taskin*, 2020] in disrupting economic activities. This literature notices that people's mobility and economic activity in the US contracted before lockdowns *Chetty et al.* [2020] and that lifting lockdowns led to a limited rebound in mobility [*Dave et al.*, 2020] and economic activity (*Cajner et al.* [2020] is an exception). *Goolsbee and Syverson* [2020] find small differences in people's visits to nearby retail establishments that faced different regulatory restrictions because located in different counties. Similar results are documented in *Chen et al.* [2020] that expand the analysis to Europe and find no robust evidence of the impact of lockdowns on several high-frequency indicators of economic activities. The importance of voluntary social distancing is also highlighted by the case of Sweden that—despite avoiding strict lockdown measures—has experienced similar (though a bit smaller) declines in mobility and economic activities to comparable countries [*Anderson et al.*, 2020; *Chen et al.*, 2020]. While not the focus of this paper, our results also suggest that voluntary social distancing rather than de jure restrictions are mostly responsible for the decline in mobility.

Some papers have documented that more economically vulnerable individuals—such as those with lower income and educational attainment [*Cajner et al.*, 2020; *Chetty et al.*, 2020; *Shibata*, 2020], minorities [*Fairlie et al.*, 2020], immigrants *Borjas and Cassidy* [2020], and women [*Alon et al.*, 2020; *Del Boca et al.*, 2020; *Papanikolaou and Schmidt*, 2020]—have been impacted more harshly during the early phases of the COVID-19 pandemic, both in the US and other countries [*Alstadsæter et al.*, 2020; *Béland et al.*, 2020]. One reason is that lower-paid workers are often unable to perform their jobs while working from home [*Dingel and Neiman*, 2020; *Gottlieb et al.*, 2020]. This points to a potential widening of inequality [*Mongey and Weinberg*, 2020; *Palomino et al.*, 2020]. We also show that the decline in mobility has raised the unemployment rate for ethnic minorities as well as low-educated individuals most strongly, thereby widening inequality. However, we add an additional element to the debate. We show that IT adoption can shield various members of society, regardless of their gender or race, from the mobility-induced COVID-shock. We however do not find that low-educated individuals can be shielded by IT adoption.

In areas where firms are heavy IT adopters, the overall increase in inequality can be dampened. However, in these areas only highly educated individuals benefit from the higher ex-ante IT adoption, but not lowly educated ones. In these areas, the COVID induced mobility shock, therefore, rises inequality even more than in low IT adopting areas.

The closest paper to ours is *Chiou and Tucker* [2020], which study the impact of the diffusion of high-speed Internet on an individual's ability to self-isolate during the pandemic. They also focus on the US and find that, while income is correlated with the ability of social distancing, the diffusion of high-speed internet explains most of this income effect.

A large literature has also studied the implications of IT adoption for various outcomes, such as productivity and local wages. For instance, see *Akerman et al.* [2015]; *Autor et al.* [2003]; *Brynjolfsson and Hitt* [2003]; *Bloom et al.* [2012]; *Beaudry et al.* [2010]; *Bresnahan et al.* [2002]; *Bloom and Pierri* [2018]; *Forman et al.* [2012]; *McElheran and Forman* [2019]; *Bessen and Righi* [2019]. We study the role of IT as a mitigating factor for the COVID-19 shock. Closer to us is therefore *Pierri and Timmer* [2020] which show that IT adoption in finance was a mitigating factor during the Global Financial Crisis.

IT adoption has been considered an important skill-biased technological change [*Acemoglu and Autor*, 2011]. While IT is often a complement for highly skilled workers, it can often substitute the work of less-skilled workers. In previous recessions, less-skilled workers have been also hard hit by economic conditions, which reinforced the trend of skill-biased technological change *Heathcote et al.* [2020].

3 Data Sources

We use the Current Population Survey (CPS) to assess the effect of the lockdown on the labor market [*Flood et al.*, 2021]. The CPS is a survey that is the primary source of monthly labor force statistics in the US. We construct the unemployment rate at different levels of aggregation, i.e. MSA, state, and national levels.

The mobility data are coming from Google mobility reports. Google Community Mobility Reports data use the location history of users on different types of activities, such as retail and recreation, to document how the number of visits and the length of stay at various locations changed compared to a pre-COVID baseline. The data capture the GPS location of individuals at various places, such as retail and recreation, workplaces, transit station, parks, etc.. The data are made available as disaggregated as the county level for the US and are reported as an index compared to the pre-COVID 19 period (January-February).

Lockdown data are obtained through Keystone and their original source are the state webpages. Lockdown data are based on 11 non-pharmaceutical intervention (NPI) dummy variables, i.e. (i) the closing of public venues, (ii) ban of gathering size 500-101, (iii) ban of gathering size 100-26, (iv) ban of gathering size 25-11, (v) ban of gathering size 10-0, (vi) full lockdown, (vii) non-essential services closure, (viii) ban of religious gatherings (ix) school closure, (x) shelter in place, and (xi) social distancing. The dummy variables take the value one if the specific NPI is in place and zero if not. For each state on a given day, we take the average across the 11 lockdown dummies so that a lockdown of 100% refers to having all 11 NPIs in place at a given time.

The IT data come from an establishment survey on IT budget per employee by CiTBDs Aberdeen (previously known as "Harte Hanks") for 2016. We have data on more than 2,800,000 establishments, e, in all states in the US. We take the log of the IT budget per employee IT_e and estimate the following regressions:

$$IT_e = \delta + \alpha_{g(e)} + \theta_{ind(e)} + \epsilon_i \tag{1}$$

where α_g is a fixed effect for the geographical unit we are interested in, i.e. state or MSA. θ_{ind} is an industry (2-digit) fixed effect. α_g is used as our measure of IT adoption for the respective geographical unit. The fixed effect can be interpreted as the average log of the IT budget per employee in an establishment in a given geographic unit, conditional on its industry. We control for industry fixed effects to ensure that our measure of IT adoption is not solely driven by the fact that some industries are heavier IT adopters and located in regions where unemployment behaved differently during the COVID-19 pandemic than in others due to reasons other than IT adoption of the establishments.

4 Mobility, IT and Unemployment across US States

In this section, we ask whether the impact of the onset of the COVID pandemic on US states' labor markets is affected by local firm IT adoption.

Figure 1 shows that the extent of job losses are correlated with the decline in mobility only in those states where their firms utilize a relatively low level of IT. In states where firms are relatively strong adopters of information technology, the increase in unemployment showed little relationship to the degree to which mobility fell. For instance, both Colorado and Nevada experienced a decline in mobility of (a bit more than) 40%. However, the increase of the unemployment rate was twice as large in Nevada, which is a low-IT adoption state than in Colorado, which is a high-IT adoption state.

An analogous pattern emerges from Figure 2, which illustrates the correlation between the stringency of lockdown policies and the increase in the unemployment rate over the period between February to April 2020. There is a positive correlation between the severity of mitigation policies and the increase of unemployment only among low-IT adoption states.

These results suggest that more IT-oriented states appear able to shift quickly to working-from-home modalities and, in doing so, maintain their workforce and output.

To test for the difference between high- and low-IT states in the response of unemployment rate to the mobility decline, we estimate the following equation:

$$\Delta UR_s^k = \alpha + \beta_1 \Delta Mobility_s + \beta_2 IT_s + \beta_3 \Delta Mobility_s * IT_s + X_s' \sigma + (X_s * Mobility_s)' \gamma + \epsilon_s \quad (2)$$

where ΔUR_s is the change in the unemployment rate in state s between April and February in state s for category k. $\Delta Mobility_s$ is the average decline in mobility in state s in April and IT_s is a dummy that indicates whether a state is above the median in terms of IT adoption and zero if it is below the median. X includes the level and the interaction between mobility and GDP per capita, the population density and the manufacturing share of the state as control variables in the regressions. β_3 is our main coefficient of interest is equivalent to testing the difference in the slope between high and low IT adopting states in Figure 1.

Table 1 reports the results. We first estimate a simplified version of Equation 2 that regresses the change in the unemployment rate on the IT adoption dummy. A higher level of IT adoption is associated with a lower increase in the unemployment rate: a state in which firms adopt IT more strongly saw a 1.8 percentage points weaker increase in the unemployment rate relative to states where firms are not adopting IT as heavily.

Column (2) then shows that on average, a larger drop in mobility is associated with a stronger increase in the unemployment rate. A 10 percentage points stronger drop in mobility is associated with a 1.5 percentage points stronger increase in the unemployment rate.

Column (3) reports estimates of our full specification, which includes the interaction between the IT dummy and the change in mobility. The coefficient on the interaction is positive and statistically significant. The coefficient on $\Delta Mobility$ indicates the correlation between the change in mobility and the increase in the unemployment rate for low IT states. The coefficient is now much larger than in column (2) which reflected the average effect across both high and low IT adopters. For low IT adopters, a 10 percentage points larger decline in mobility was associated with a 5 percentage points larger increase in the unemployment rate. For instance, in the case of Michigan mobility declined by around 40% while in Ohio mobility declined by 30%; both are low IT states. Ohio saw its unemployment rate rising by around 13 percentage points while Michigan's unemployment rate rose by approximately 18 percentage points, a 5 percentage points difference with respect to a 10 percentage points difference in the decline in mobility, see Figure 1.

The coefficient on the interaction is positive, which indicates that in high IT states the impact of mobility on unemployment is more muted. The point estimate of the interaction is 0.463, close in absolute value to the coefficient on the mobility coefficient. This indicates a small or negligible impact of mobility in high IT states; the sum of the coefficient (-0.505+0.463=-0.042) reflects the slope of high IT adopters in Figure 1.

A potential explanation for why high IT states exhibit a weaker correlation between mobility and the unemployment could be that these states are different from low IT ones for some other reasons. This problem is known as omitted variable bias. For instance, states in which firms adopt more technology may just be more economically developed and thus more resilient to economic shocks. Hence, in column (4) we include the GDP per capita, the population density, and the manufacturing share of the state as control variables in the regressions. We also include the interaction of each control with the mobility drop: in this way we allow states which are richer, more educated, or less dense to be affected by the pandemic differently. We then focus our attention to the coefficient of the interaction between IT adoption and mobility. If such coefficient were to decline substantially and lose its statistical significance, we would infer that the estimated impact of IT adoption as a mitigating factor is probably driven by spurious correlation. However, the coefficient on the interaction in column (4) remains almost identical. This suggests that these factors are not the drivers of the mitigating impact of IT on the rising unemployment rate.

5 Evidence from Individual-Level Data

The state-level analysis suggests firm IT adoption can partially shield the local economy from the impact of the pandemic. While insightful, this analysis has important drawbacks: the small sample size limits our ability to control for other potential confounding factors, to understand which workers are more protected by IT adoption.

We therefore use individual-level data from CPS to control for respondent- and local-level characteristics. We also compute local IT adoption at a finer geographical level (MSA), in order to measure more precisely technology adoption for the individual's relevant labor market.

This analysis relies on the following linear probability model:

$$\begin{aligned} Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\ + Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed, but in the labor force, in a month t, where t is either April or May 2020, the height of the unemployment rate during the pandemic. The variable $Unemployed_{i,t}$ is zero if the individual is employed in month t. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives, and $IT_{msa(i)}$ is the level of IT adoption in the MSA where the individual i lives. Z_i are individual level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent.

This specification thus compares workers' with the same socio-demographic characteristics, living in different cities which are similar in various characteristics–and are within the same state–but have different degrees of pre-pandemic firm IT adoption.[1]

Table 2 shows the results based on pooled linear regression across individuals reporting their employment status in either April or/and May. Table 3 shows the results of the same equation using a probit model. These results illustrate the same pattern documented by the state-level analysis. Column (1) shows that a stronger decline in mobility in an MSA is associated on average with a larger probability of a person reporting to be unemployed. A higher level of IT adoption is associated with a lower probability of being unemployed in April and May of 2020. Column (2) shows that the probability of being unemployed in April and May is higher for respondents living in MSA which experienced larger mobility declines, but IT adoption of companies mitigates this impact. The increase in the probability of being unemployed associated with a large drop in mobility (one standard deviation, equal to 10 pp) is 2.4 percentage points in a low-IT MSA. A one standard deviation larger level of IT adoption in an MSA reduces the

[1]As respondents are not necessarily reporting their employment status in consecutive months, we cannot include individual fixed effects.

increase in the probability by 0.7 percentage points to 1.7 percentage points. Column (3) shows the coefficient remains stable and statistically significant after controlling for the interaction of the mobility in the MSA and various MSA-level characteristics such as per capita income, the share of people with a three year Bachelor's degree, the share of minorities, and the unemployment rate in February.

In column (4) we saturate the specification with additional fixed effects. The fixed effects include individual fixed effects based on gender, race, and education level, as well as state fixed effects. The inclusion of state fixed effects implies that comparing two individuals living within the same state but in different MSAs are differentially affected by a mobility decline due to different levels of IT adoption in the MSA. The result also holds comparing the same gender, race, or within the same education level.

Moreover, the coefficient on the interaction between mobility and IT remains stable after including these additional sets of fixed effects, but the R-squared increases from 0.418% to 3.8%. The increase in the R-squared confirms that the additional control variables are highly important explaining the employment status of the individual but even after controlling for these characteristics the level of IT adoption in the MSA is a significant predictor of whether the person was unemployed.

The coefficient on IT turns from negative to positive as soon as we include the interaction term. This flip in the coefficient is purely mechanical. The coefficient on IT can be interpreted as the hypothetical effect of IT on the probability of being unemployed in an MSA where mobility has not changed. As mobility declined strongly in all MSAs, the effect of IT on the probability of being unemployed is difficult to interpret in practice (and it therefore omitted hereafter).

In Table 6 we conduct several robustness tests, all of which confirm our main findings. Column (1) shows the baseline equation for comparison. In column (2) we replace our measure of IT adoption with the share of high-speed internet that is available in the MSA. The interaction is, as for our IT measure, positive and statistically significant, but only at the 10% level. In column (3) we replace our continuous measure of IT with a dummy that takes the value one if firms in the MSA are above-median IT adopters and zero if firms in the MSA are below median IT adopters. Again, the coefficient is positive and statistically significant. Column (4) replaces the IT measures, log IT budget per employee, with another measure that has been used commonly in the literature, also from the Harte Hanks dataset, namely the ratio of personal computers per employees.[2] Lastly, we substitute our left-hand-side variable, the dummy whether the person is unemployed with a broader measure of unemployment. Our baseline unemployment rate is the U-3 unemployment rate, which is the official one. It takes into account people who are jobless but actively seek employment. In column (5) instead, we use the U-6 unemployment rate definition that accounts for anyone who has been seeking employment for at least 12 months but left discouraged without being able to secure a job. It also includes anyone who has gone back to school, become disabled, and people who are underemployed or working part-time hours.

5.1 IT and Working-From-Home

One potential reason why low-educated individuals are not shielded by IT adoption is due to skill-biased technological change. More skilled workers have larger complementarities with information technologies compared to lower-educated workers for which IT may even substitute their work. High-skilled individuals have been able to switch to work from home with little adjustment necessary. *Dingel and Neiman* [2020] show that around 1/3 of all workers can do jobs from home, of which most of them are higher-educated workers.

One potential explanation for our results is therefore that IT adoption and work-from-home abilities are highly correlated and the reason why individuals living in areas where firms adopt IT more heavily are also areas where more people can work from home. Indeed, Figure 3 shows there is a high correlation between the share of jobs that can be done from home in an MSA and IT.

We re-estimate our regression with the share of jobs that can be done from home instead of the IT measure to test whether the work from home abilities can also shield workers from the decline in mobility.

Table 5 shows the results. The results for WFH mirror those of IT, in line with the results by *Bai et al.* [2021]. Individuals living in MSAs where WFH is more feasible are less likely to be unemployed for a given decline in mobility than individuals who live in areas where WFH is not as widely possible. Column (3) shows the results with both interactions, between IT and mobility and between WFH and mobility. Both coefficients remain statistically significant, but the coefficient declines in both cases.

The fact that the coefficient on the interaction between IT and mobility declines once the

[2] See for example *Pierri and Timmer* [2020].

interaction between WFH and mobility is included in the regression suggests that WFH is one channel through which IT shields workers from the economic consequences of the pandemic. However, importantly teleworking does not seem to be the only channel through which IT has a mitigating effect. Other potential channels that could be at work are that companies are better able to switch to online sales or that more sophisticated IT systems facilitate contactless sales.

5.2 Instrumental Variable Approach

IT adoption can be correlated with many other local characteristics. For instance, in areas where the complementarities between workers' human capital and IT adoption are higher, more IT adoption is adopted [*Beaudry et al.*, 2010]. In our regression analysis, we control for various characteristics that are likely correlated with IT adoption–such as the share of the population with a bachelor's degree or the industry composition– and our results are insensitive to the inclusion of these controls. However, it is difficult to completely rule out the presence of unobserved confounding factors which are correlated with IT and also limit the economic harm of the pandemic. Such factors could bias our estimates.

We therefore adopt an instrumental variable approach, relying on characteristics of the local labor market that predates the origins of the digital revolution, i.e. when computers became widely available for the local adoption of IT. When computer equipment prices started falling strongly, it became more and more attractive to replace routine workers with IT equipment. During the end of the 20th century, US regions that were historically specialized in routine intensive occupations (e.g. butchers or payroll and timekeeping clerks) indeed experienced a larger workplace computer use after 1980 [*Autor and Dorn*, 2013].

We closely follow *Autor and Dorn* [2013] who argue that the measure of historical routine employment share can be seen as an exogenous shifter of IT adoption, as they are unlikely to affect employment outcomes today through other channels other than technology. We test whether historical variation in routine task shares at the regional level predict IT adoption even just before the Covid-19 pandemic. To measure routine tasks the job task requirements from the fourth edition of the US Department of Labor's Dictionary of Occupational Titles (DOT) (US Department of Labor 1977) are merged to their corresponding Census occupation classifications *Autor et al.* [2003]. Then for each commuting zone, a routine employment share is created. We directly take the data from *Autor et al.* [2015] on the commuting zone level and apply the share of routine work to each county within that commuting zone and then average across MSAs.

Figure 4 shows that there is a strong positive correlation between the employment share in routine tasks in 1980 and the level of IT adoption just before the pandemic. If the exclusion restriction that the occupational structure in 1980 affects the employment outcomes during the pandemic only through higher IT adoption and not through other channels, we can use the share of routine employment in a region as an instrument for IT adoption before the pandemic, which allows us to estimate the causal effect of IT adoption on employment outcomes.

We re-estimate the linear probability model:

$$Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} + \alpha_{s(i)} + \epsilon_{i,t} \tag{4}$$

while instrumenting the endogenous variables $IT_{msa(i)}$ and $Mobility_{msa(i,t)} * IT_{msa(i)}$ with the excluded instruments $Routine_{msa(i)}$ and $\Delta Mobility_{msa(i,t)} * Routine_{msa(i)}$.

We perform estimation via two-stages least square. The estimates for the coefficient of interests (β_3, which refers to the interaction term between IT and the change in mobility) are reported in Table 7. In column (1) we report the OLS estimate. In columns (2)-(5) we estimate the 2SLS specification with two endogenous variables and varying saturation of the models with controls and fixed effects.

The coefficient on the interaction term between IT and mobility is positive in all specifications, confirming our previous result that IT adoption can mitigate the adverse economic consequences in response to a mobility decline. However, the coefficient is smaller in the OLS specification than in the IV estimates, although not statistically different, as shown in the row $P - value = OLS$.

As we have two endogenous variables, the conventional first-stage F-stage statistic is not appropriate to test for the strength of the instrument [*Angrist and Pischke*, 2008]. Instead, we report the *Sanderson and Windmeijer* [2016] F-statistics for models with multiple endogenous variables to test for weak instruments. The two F-statistics for the first stage for IT itself and the interaction range between 7 and 30. In columns (3) and (4) the F-stats for both first stages are all above 15, above the rule-of-thumb threshold of 10.

In conclusion, the IV estimates confirm that IT adoption has a causal impact on mitigating the adverse employment outcomes in response to restrictions in mobility. Therefore, the finding that labor markets in states or MSA where firms adopted more IT were also more resilient to the pandemic is not mainly driven by the presence of unobserved confounding factors.

5.3 Counterfactual

In an interview with *The Economist*, Bill Gates argued that "if [the pandemic] would have come 5 years earlier that would have been a disaster", referring to the economic damage due to a "crappy online experience". Other commentators have also highlighted that if the pandemic had happened in the past–even in the recent past–the ability of companies and worker to quickly boost the use of working-from-home, contactless delivery, and other remedies to the need for social distancing would have been significantly less developed. The improvements in IT, internet infrastructure, the widespread use of smartphones and delivery apps, have been of great help.

We can use our estimates to compute the counterfactual labor market consequence that would have occurred given a lower level of IT adoption. To perform such an exercise, we re-estimate Equation 3 without normalizing the measure of IT adoption; non-normalized coefficients are expressed in terms of IT expenses per employee (rather than in terms of cross-sectional standard deviation as in section 4 and section 5). *Bureau of Economic Analysis* [2019] reveals that *"since 2010, digital economy real gross output growth averaged 2.5 percent per year."*, while the growth rate of the labor force is about 0.5 percent per year.[3] Thus, we assume that IT adoption grows at 2 percentage points per year, and was, therefore, approximately 10% smaller 5 years ago. We also assume that the growth rate of IT is homogeneous across all MSAs.

Under the assumptions described above,[4] we can estimate the counterfactual probability that an individual i is unemployed as:

$$\begin{aligned} Unemployed_{i,t} = \alpha + \widehat{\beta_1}\Delta Mobility_{msa(i),t} + \widehat{\beta_2} * 0.9 * \widehat{IT_{msa(i)}} + \widehat{\beta_3}\Delta Mobility_{msa(i,t)} * 0.9 * \widehat{IT_{msa(i)}} \\ + Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} \end{aligned} \tag{5}$$

[3] Expenses in information technology are the main but not the only component of the digital economy, as defined by the BEA. *Bureau of Economic Analysis* [2019] specifies that *"BEA includes in the digital economy the entire information and communications technologies (ICT) sector as well as the digital-enabling infrastructure needed for a computer network to exist and operate, the digital transactions that take place using that system ("e-commerce"), and the content that digital economy users create and access ("digital media")"*. However, as long as either the other parts of the digital economy grow at the same rate as IT adoption, or they are similarly correlated to unemployment, we can still equate the growth rate of IT expenses to one of the more broadly defined "digital economy".

[4] See also *Nakamura and Steinsson* [2018] for a discussion of the caveats of extrapolating aggregate effects from cross-sectional regressions.

where the "hat" signs highlight that the IT adoption measure and the coefficients are not normalized.

The estimated counterfactual unemployment rate (average between April and May 2020) under the 2015 IT adoption is 16% versus the observed 14%. It is therefore 2 percentage points (or 14.3%) higher than what was observed in the data. The estimates from a linear model may overestimate the counterfactual impact of a large change in IT adoption if non-linearities are important. It is therefore reassuring that using a probit model (instead of a linear probability model) provides the same results. This finding illustrates the importance of investments in IT adoption to build an economy that is not only faster-growing but also more resilient to shocks.

6 IT and Inequality

Does IT shield all workers from the impact of the pandemic? We test whether the mitigating effect of local firms' IT adoption on workers' labor market outcomes depends on their characteristics, such as gender, race, and educational attainment. To this aim, we estimate the following linear probability model:

$$\begin{aligned}
Unemployed_{i,t} = \alpha &+ \beta_1 \Delta Mobility_{msa(i),t} * A_i + \beta_2 \Delta Mobility_{msa(i),t} * (1 - A_i) \\
&+ \beta_3 IT_{msa(i)} * A_i + \beta_4 IT_{msa(i)} * (1 - A_i) \\
&+ \beta_5 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * A_i \\
&+ \beta_6 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * (1 - A_i) \\
&+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned} \tag{6}$$

which is similar to Equation 3 except for the addition of the interaction terms disciplined by A_i, which is a dummy variable equal to one if respondent i belongs to a certain category. In particular, we estimate Equation 6 for three different characteristics: gender, race, and educational attainment. First, we estimate the regression equation for gender, where $A_i = 1$ is one if the respondent is male and $A_i = 0$ if the respondent is female. Second, we estimate the equation for ethnicity where $A_i = 1$ if the respondent is white and $A_i = 0$ if the respondent is non-white. Third, $A_i = 1$ if the individual has a high- or medium level of education (high school or more) and $A_i = 0$ if the individual has no high school degree. (Observationwhere the relevant categorical variable is missing are dropped.) The remaining variables are defined as above, where the vector Z includes the various categories as dummies.

Table 4 presents the results for β_5 and β_6. The coefficient is positive for males, females, whites, non-whites, and high/medium education. Only in the case of low-education individuals, we do not find a mitigating impact of IT on the effect of mobility on the probability of being unemployed.

The coefficient β_5 and β_6 are also plotted in Figure 5. Interestingly, the effect is largest for females and non-white individuals. These are among the individuals which are most hit during the first phase of the pandemic and IT adoption has more room to mitigate the shock for these individuals rather than for example highly-educated ones whose unemployment rates have not responded as strongly to the decline in mobility. Low educated individuals, however, although hit very harshly from the pandemic are not shielded by firm IT.

Overall, even though IT adoption may—in the aggregate—significantly shield labor markers against the effects of the COVID-19 pandemic, it may also contribute to widening inequality by increasing economic disparities between high- and low-educated individuals.

7 Conclusion

In this paper, we show that technology adoption can act as an important mitigating factor when the economy is hit by a shock, and therefore our results contribute to the question of how to build a more resilient society [*Brunnermeier*, 2021].

The dampening effect of IT adoption has important implications for the implementation of lockdown policies. Our results imply that the cost of the social distancing is lower in places where firms adopt IT more heavily, reducing a potential trade-off between health and the economy. This implication is relevant independently of whether individuals willingly reduce their mobility or are compelled to do so by more restrictive policies.

However, even in high-IT areas, not everyone is shielded from the economic consequences of lockdowns. While IT protects people of different races and both women and men, IT does not shield low-skilled workers from the economic consequences of the COVID-19 shock.

Over the last decades, low-skilled individuals have already suffered from the consequences of skill-biased technological change, which seems to be reinforced by the COVID-19 pandemic. The large burden of the COVID-19 pandemic, which falls hardest on the less-skilled, may not only have negative economic, but also indirect health consequences over and above the direct impact of the pandemic [*Case and Deaton*, 2020]. Our findings speak to the importance of policies targeted to improve digital skills for the less-educated population, in order to promote inclusive growth and well-being.

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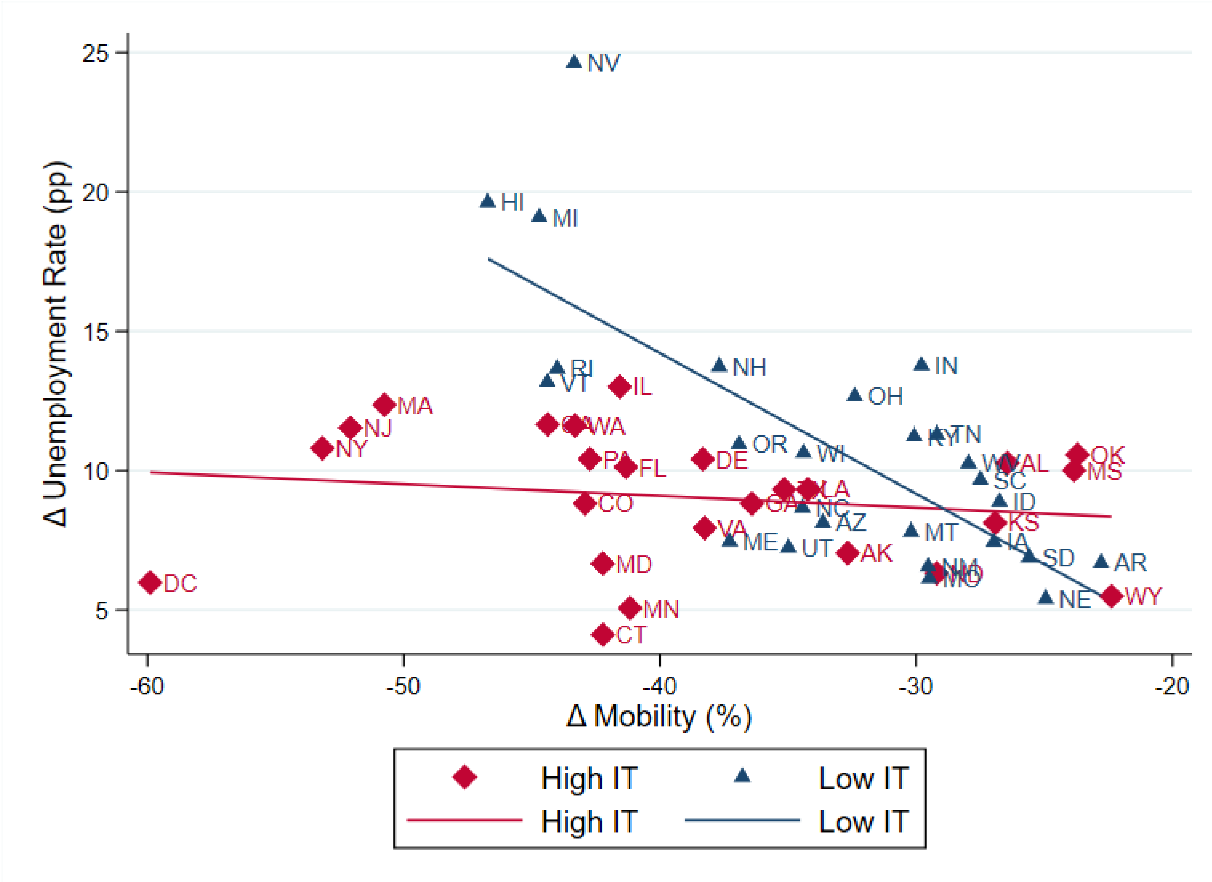
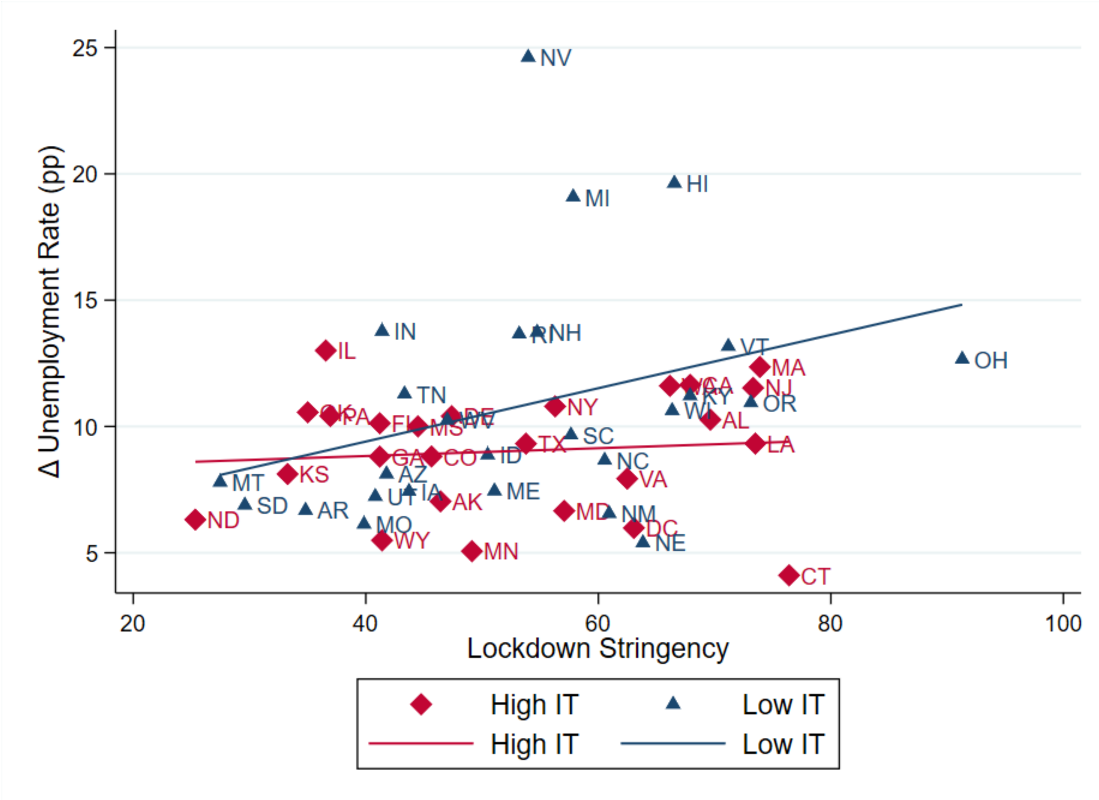
Figure 1: Unemployment and Mobility in the US



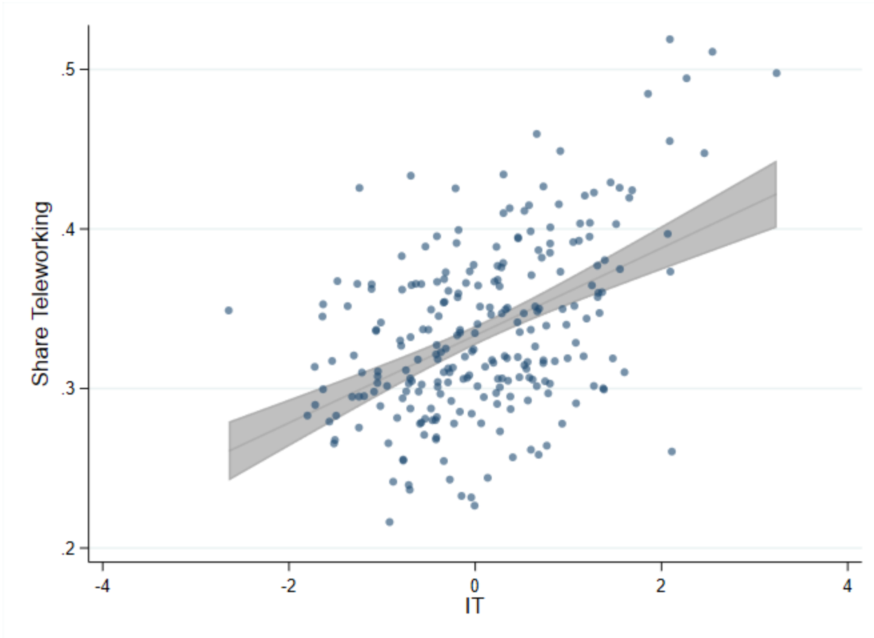
This figure plots the change in the unemployment rate between February and April by state on the average change in mobility in retail, recreation and transit station in April. The red diamonds represent states where IT adoption is above the median and the blue triangles represent states where IT adoption is below the median. The red line shows the linear fit for high-IT state and the blue line shows the linear fit for low IT states. See section 3 and **??** for more details.

Figure 2: Unemployment and Lockdown Stringency in the US



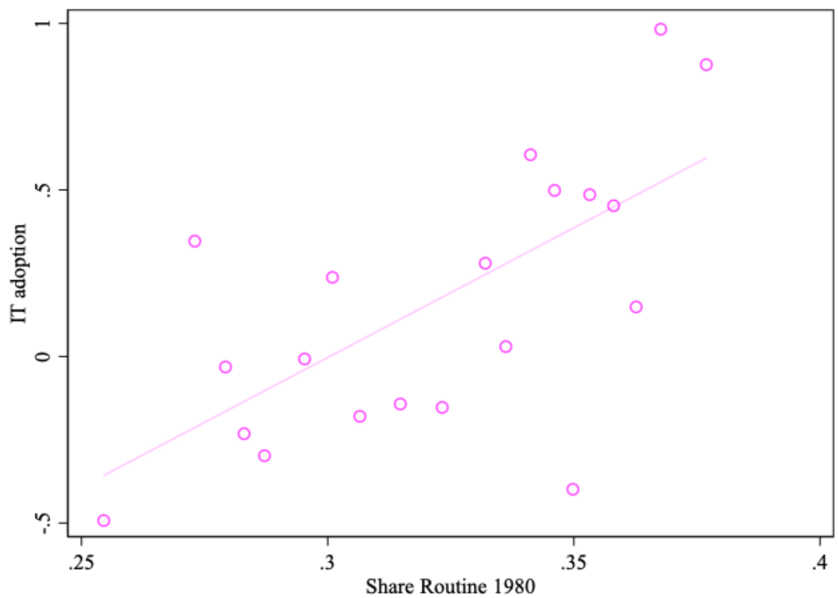
This figure plots the change in the unemployment rate between February and April by state on the average Lockdown stringency index (according to Keystone) over the same period. The red diamonds are states where IT adoption is above the median and the blue diamonds are states where IT adoption is below the median. The red line shows the linear fit for high-IT state and the blue line shows the linear fit for low IT states. See section 3 and **??** for more details.

Figure 3: IT Adoption and Work-from-Home ability



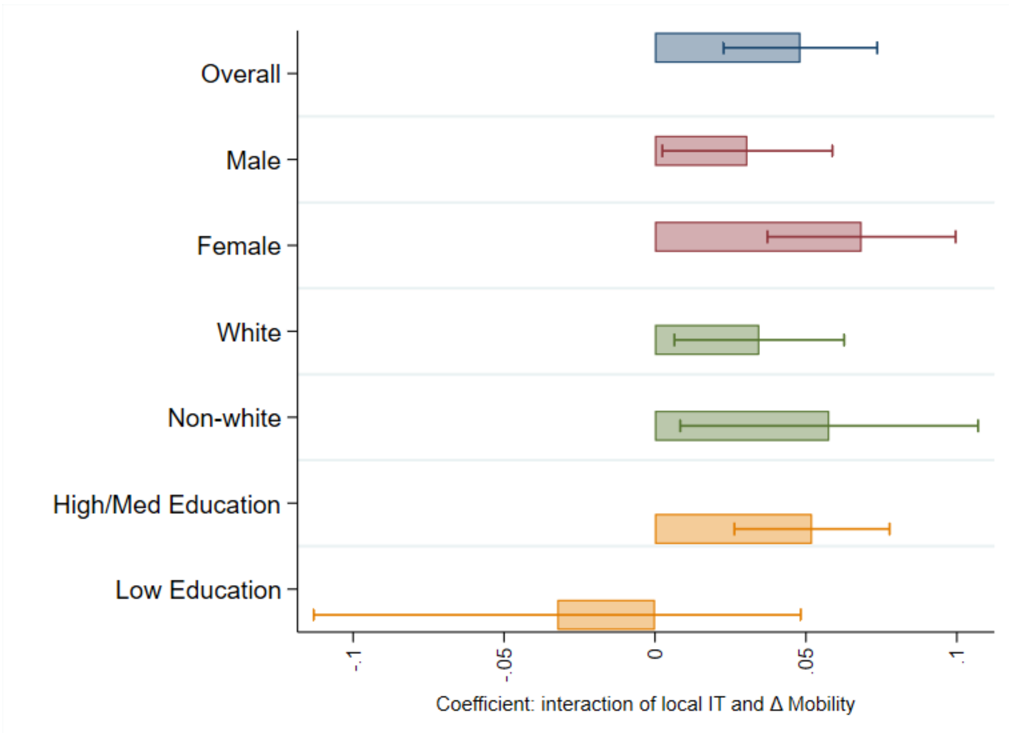
This figure plots the level of IT adoption in an MSA on the horizontal axis against the share of jobs that can be done from home on the vertical axis. The share of jobs that can be done from home are taken from *Dingel and Neiman* [2020]. See section 3 and section 5 for more details.

Figure 4: IT Adoption and Routine Work



This figure is a binscatter that plots the level of IT adoption in an MSA on the vertical axis against the routine employment share in an MSA on the horizontal axis. See section 3 and subsection 5.2 for more details.

Figure 5: Mitigating Impact of IT across Individuals



This figure plots the coefficient and the 90% confidence interval of β_5 and β_6 from Equation 6:

$$
\begin{aligned}
Unemployed_{i,t} = \alpha &+ \beta_1 \Delta Mobility_{msa(i),t} * A_i + \beta_2 \Delta Mobility_{msa(i),t} * (1 - A_i) \\
&+ \beta_3 IT_{msa(i)} * A_i + \beta_4 IT_{msa(i)} * (1 - A_i) \\
&+ \beta_5 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * A_i \\
&+ \beta_6 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * (1 - A_i) \\
&+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned}
$$

where $Unemployed_{i,t}$ is a dummy variable that takes the value one if the individual i is unemployment in month t (April/May 2020) and zero if the individual is employed. $\Delta Mobility_{msa(i),t}$ is the change in mobility in month t relative to the pre-COVID baseline. $IT_{msa(i)}$ is the average level of IT adoption in the MSA. A_i are dummy variables categorizing the respondent according to gender, race, and education subgroups. X includes GDP per capita, population density and the minority share. See section 3 and section 5 for more details.

Table 1: Unemployment, Mobility and IT

	Dependent variable: Δ Unemployment Rate			
	(1)	(2)	(3)	(4)
IT	-0.0180*		0.134***	0.142***
	(0.010)		(0.037)	(0.033)
Δ Mobility		-0.148**	-0.505***	-0.622
		(0.070)	(0.102)	(0.377)
Δ Mobility × IT			0.463***	0.476***
			(0.116)	(0.105)
R-squared	0.0575	0.116	0.478	0.598
N	51	51	51	51
Controls	No	No	No	Yes

Results of estimating Equation 2 :

$$\Delta UR_s^k = \alpha + \beta_1 \Delta Mobility_s + \beta_2 IT_s + \beta_3 \Delta Mobility_s * IT_s + X_s'\sigma + (X_s * Mobility_s)'\gamma + \epsilon_s$$

where ΔUR_s is the change in the unemployment rate in state s between April and February in state s for category k. $\Delta Mobility_s$ is the average decline in mobility in state s in April. IT_s is a dummy that indicates whether a state is above the median in terms of IT adoption and zero if it is below the median. X includes the level and the interaction between mobility and GDP per capita, the population density and the manufacturing share of the state as control variables in the regressions. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 for more details.

Table 2: Unemployment, Mobility and IT

	Dependent variable: Unemployed			
	(1)	(2)	(3)	(4)
Δ Mobility	-0.181***	-0.239***	-0.742	0.0236
	(0.031)	(0.037)	(1.559)	(1.358)
IT	-0.00697	0.0187***	0.0193**	0.0292***
	(0.005)	(0.007)	(0.009)	(0.011)
Δ Mobility × IT		0.0699***	0.0656**	0.0677***
		(0.023)	(0.032)	(0.025)
R-squared	0.00346	0.00418	0.0293	0.0384
N	71812	71812	71812	71812
Controls	No	No	Yes	Yes
State FEs	No	No	No	Yes

Results of estimating Equation 3:

$$
\begin{aligned}
Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\
+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned}
$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives and $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. Z_i are individual level controls. $X_{msa(i)}$ are MSA level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table 3: Probit: Unemployment, Mobility and IT

	Dependent variable: Unemployed			
	(1)	(2)	(3)	(4)
Δ Mobility	-0.840***	-1.115***	-4.285	-0.555
	(0.147)	(0.165)	(7.616)	(6.912)
IT	-0.0324	0.0937**	0.0893*	0.154***
	(0.022)	(0.037)	(0.046)	(0.056)
Δ Mobility × IT		0.328***	0.292**	0.350***
		(0.105)	(0.147)	(0.128)
N	71812	71812	71812	71812
Controls	No	No	Yes	Yes
State FEs	No	No	No	Yes

Results of estimating Equation 3 with Probit:

$$Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} + Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} + \epsilon_{i,t}$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives and $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. Z_i are individual level controls. $X_{msa(i)}$ are MSA level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table 4: Unemployment, Mobility and IT

	Dependent variable: Unemployed					
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Mobility × IT × Male	0.0306*	0.0494*				
	(0.017)	(0.025)				
Δ Mobility × IT × Female	0.0684***	0.0894***				
	(0.019)	(0.028)				
Δ Mobility × IT × White			0.0346**	0.0610**		
			(0.017)	(0.027)		
Δ Mobility × IT × Non-White			0.0577*	0.0909***		
			(0.030)	(0.035)		
Δ Mobility × IT × High/Med Educ					0.0520***	0.0712***
					(0.016)	(0.025)
Δ Mobility × IT × Low Educ					-0.0324	0.0122
					(0.049)	(0.054)
R-squared	0.0204	0.0386	0.0206	0.0388	0.0208	0.0386
N	71812	71812	71812	71812	71812	71812
Controls	No	Yes	No	Yes	No	Yes
FEs	Yes	Yes	Yes	Yes	Yes	Yes

Results of estimating Equation 6 :

$$
\begin{aligned}
Unemployed_{i,t} = \alpha + \\
&+ \beta_1 \Delta Mobility_{msa(i),t} * A_i + \beta_2 \Delta Mobility_{msa(i),t} * (1 - A_i) \\
&+ \beta_3 IT_{msa(i)} * A_i + \beta_4 IT_{msa(i)} * A_i \\
&+ \beta_5 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * (1 - A_i) \\
&+ \beta_6 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * (1 - A_i) \\
&+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned}
$$

where $Unemployed_{i,t}$ is a dummy variable that takes the value one if the individual i is unemployment in month t (April/May 2020) and zero if the individual is employed. $\Delta Mobility_{msa(i),t}$ is the change in mobility in month t relative to the pre-COVID baseline. $IT_{msa(i)}$ is the average level of IT adoption in the MSA. A_i and B_i are dummy variables for gender, race, and education subgroups. X includes GDP per capita, population density and the minority share. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table 5: Unemployment, Mobility, Teleworking abilities and IT

	Dependent variable: Unemployed		
	(1)	(2)	(3)
Δ Mobility × IT	0.0677***		0.0539**
	(0.025)		(0.025)
Δ Mobility × Teleworking		1.100**	1.002**
		(0.517)	(0.506)
R-squared	0.0384	0.0385	0.0387
N	71812	71812	71812
Controls	Yes	Yes	Yes
State FEs	Yes	Yes	Yes

Results of estimating the following equation:

$$
\begin{aligned}
Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\
+ \beta_4 Teleworking_{msa(i)} + \beta_5 \Delta Mobility_{msa(i,t)} * Teleworking_{msa(i)} \\
+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned}
$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives. $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. $Teleworking_{msa(i)}$ is the share of jobs that can be done from home in the MSA where individual i lives, taken from *Dingel and Neiman* [2020]. Z_i are individual level controls. $X_{msa(i)}$ are MSA level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table 6: Unemployment, Mobility and IT: Robustness

	Dependent variable: Unemployed				
	(1)	(2)	(3)	(4)	(5)
Δ Mobility × IT	0.0488***	0.00391*	0.0880**	0.0388**	0.0457**
	(0.016)	(0.002)	(0.037)	(0.017)	(0.021)
R-squared	0.0202	0.0201	0.0202	0.0202	0.0246
N	71812	71812	71812	71812	71812
Controls	No	No	No	No	No
State FEs	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	High-Speed Internet	High IT	PCs/Emp	U6 Unemployment

Results of estimating the following equation:

$$Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\ + Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} + \epsilon_{i,t}$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. Column (1) is the baseline specification. Column (2) replaces our baseline IT measure with the share of people who have access to high-speed internet in the given MSA. Column (3) defines the IT variable as a dummy that equals one if the MSA has an above-median IT adoption and zero otherwise. Column (4) replaces the IT measure with a measure of the share of personal computers per employee. Column (5) classifies individuals as unemployed according to the U6 unemployment rate. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table 7: Instrumental Variable Approach

	Dependent variable: Unemployed				
	(1)	(2)	(3)	(4)	(5)
Δ Mobility	-0.246***	-0.230**	-0.237**	-0.168***	-0.165***
	(0.039)	(0.098)	(0.101)	(0.048)	(0.047)
IT	-0.0192***	-0.00590	-0.00404	-0.00596	-0.00524
	(0.007)	(0.018)	(0.019)	(0.010)	(0.010)
IT * Δ Mobility	0.0710***	0.188	0.223*	0.102*	0.0981*
	(0.024)	(0.117)	(0.134)	(0.059)	(0.058)
R-squared	0.00418	-0.00469	-0.00830	0.0111	0.0217
N	71812	51111	51111	51111	51111
F-stat IT		29.59	28.13	15.63	15.69
F-stat Int.		9.189	7.468	24.62	24.58
P-value = OLS		0.317	0.255	0.600	0.641
Instrument		Routine 1980	Routine 1980	Routine 1980	Routine 1980
Controls			Pre UR	Pre UR	+Demographics
State FE				✓	✓

Results of a 2SLS estimation of

$$Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} + \epsilon_{i,t}$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives and $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. The endogenous regressor $IT_{msa(i)}$ is instrumented with the routine employment share in 1980, and the endogenous regressor $IT_{msa(i)} * DeltaMobility_{msa(i),t}$ is instrumented with the product of the routine employment share in 1980 and the decline in mobility. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsection 5.2 for more details.