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

Myrto Oikonomou[†] Nicola Pierri [‡] Yannick Timmer[§]

Abstract

We study the labor market 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. 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. Additional evidence suggests this shielding effect is due to the easiness of working-from-home and to stronger creation of digital jobs in high IT areas.

JEL Codes: E24, O33

Keywords: Unemployment Rate, Technology, IT Adoption, Inequality, Skill-Biased Technical Change

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1 Introduction

As COVID-19 spread across the world and the United States in 2020, 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. 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 in 2016 for 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 by increasing online sales. IT adoption can facilitate online job search, which may be particularly important when physical mobility is reduced. Availability of IT investments and capabilities may also spur the creation of new digital-intensive jobs. 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 find 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. An event study empirical design confirms this finding and illustrate that states hit more harshly by the pandemic and states with more IT adoption were *not* experience different pre-pandemic trend in unemployment. We present further evidence relying on individual-level data from the CPS (Current Population Survey) respondents and using within-state (MSA-level) variation in IT adoption while controlling for a rich set of various other potential confounding factors, such as the pre-pandemic industry and occupation of the respondent. We find that respondents living in MSAs with a larger drop in mobility are more likely to be unemployed during Spring 2020 (controlling for pre-pandemic unemployment), but the impact of mobility is less pronounced among MSAs where IT was adopted more intensely.

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 before (see subsection 5.2 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%.[1]

The recent literature (see section 2 for a brief review) has argued that the economic consequences of COVID-19–especially at its onset–were 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,

[1]This back-of-the-envelope calculation should be taken with a grain of salt, as computing the aggregate effects from cross-sectional heterogeneity is difficult. Our specification does not allow us to take potential general equilibrium effects into account that would affect the aggregate consequences of IT adoption and instead only captures the partial equilibrium effects coming through IT.

while it may substitute unskilled labor. If the COVID-19 shock promotes further automation of production processes, and more so for more IT intensive 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, we find a striking 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].

Finally, we investigate the role of different channels in explaining the shielding effect of IT. We find that local IT adoption is strongly correlated with measures of the feasibility of working from home [*Dingel and Neiman*, 2020]. We find that local IT adoption and the ability to work from home are both independently shielding the economy from a local mobility shock, but the role of local IT is significantly reduced when local working-from-home ability is controlled for. This suggests that part of the shielding impact of IT is due to high IT firms having facing lower disruption in the shift to work from home, but other forces are also at play. Conversely, we find no significant role for local firms' access to e-commerce technologies.

Local unemployment can be impacted by both job destruction and job creation. The pandemic depressed job creation both because of lower labor demand and because mobility restrictions limited firms and workers ability to meet in person, potentially worsening labor market search frictions. To shed more light on the importance of IT adoption for the job creation margin, we study how online job postings respond to the pandemic and to local IT adoption. We find that during Spring 2020, job postings declined more in MSAs that suffered a larger drop in mobility, but this decline was less pronounced in high-IT MSAs. This shielding impact of IT is present only for job postings that relate to digital-intensive occupations and not for other jobs. Thus, a further reason why IT shielded local labor markets from the impact of the pandemic was that it protected firms' ability to create vacancies for digital jobs. These results suggest that IT adoption improved firms' ability to adjust job creation in a flexible and dynamic manner and highlight the role that local IT played in facilitating the transition to a more digital economy during the early stages of the pandemic.

We finally test for the importance of local demand spillover–which can be a source of general equilibrium effects at the local level–by testing whether IT shields local-level employment in tradable or non-tradable industries [*Mian and Sufi*, 2014]. We find no mitigating role of local IT for non-tradable industries, suggesting a minor role for such spillovers.

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 using individual-level data. In section 6 we investigate the potential channels through which IT shields and in section 7 we conclude.

2 Related Literature

The literature on the economic crisis triggered by the COVID-19 pandemic has expanded very rapidly. For an early 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 in disrupting economic activities [*Allcott et al.*, 2020; *Bartik et al.*, 2020; *Kahn et al.*, 2020; *Maloney and Taskin*, 2020]. This literature documents 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 visits to nearby retail establishments by people that faced different regulatory restrictions because of being 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 slightly 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-19 shock. One exception is low-educated individuals for which we do not find shielding by IT adoption.

In areas where firms are heavy IT adopters, the increase in overall inequality can be dampened. However, in these areas only highly educated individuals benefit from the higher ex-ante IT adoption, not lowly educated ones. Therefore, in these areas, the COVID-induced mobility shock, raises this type of 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 (see for instance, *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] that 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].

Finally, there was been a growing body of literature that studies how COVID-19 impacted labor markets tapping on high-frequency data from online job boards (see for example *Hensvik et al.* [2021], *Bellatin and Galassi* [2022], *Soh et al.* [2022], *Adrjan et al.* [2021] and *Marinescu et al.* [2020]). The use of online job platform data predates the pandemic. We contribute to this literature by exploring the impact of the pandemic on online vacancies, and the role of local IT adoption for digital and non-digital job postings.

3 Data Sources

IT adoption We construct a set of measures of local-level IT adoption building on an establishment survey on IT budget per employee by CiTBDs Aberdeen (previously known as "Harte Hanks") for 2016. We access data on more than 2,800,000 establishments, e, in all states in the US.[2] 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.

[2] While the IT data are at the establishment level, we use *firms* and *establishments* interchangeably in the rest of paper.

Other 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. We rely on additional standard data sources for local-level characteristics. These include the American Community Survey for local socio-demographic characteristics, the County Business Patterns and Quarterly Workforce Indicators for local level industrial composition of the workforce, and Occupational Employment and Wage Statistics data for local level occupations.

We use high-frequency online job postings data from Indeed, a leading job postings platform. Using data from online job boards has become a common practice in a wide range of labor market studies as these data provide rich information on the characteristics of the jobs posted (including granular regional information, and detailed occupational information).[3] The use of online job postings data has become prevalent also in the recent literature that studies the labor market impact of the COVID-19 shock as these data are available at very high frequency.

[3]For example, *Hershbein and Kahn* [2018] use online vacancy postings to document how skill requirements changed in response to the Global Financial Crisis shock, *Marinescu and Wolthoff* [2020] employ data from an online job board to study what high-wage job postings imply for job search, while *Brown and Matsa* [2020] use similar data to analyze how housing market conditions impacted job search behaviour during the Great Recession.

From the Indeed database we obtain detailed job titles of the individual job postings as well as information on the region and date of each posting from January 2019 onwards. We aggregate job postings at the MSA level and at monthly frequency and we employ a series of matching algorithms to map Indeed job titles into 4-digit 2008 International Standard Classification of Occupations (ISCO-08) occupation codes. We obtain approximately 60 million vacancies for 2019 and 2020. To classify occupations into digital and non-digital, we follow closely *Muro et al.* [2017] and *Soh et al.* [2022] and compute a ranking of occupation codes by their digital content based on O*NET. Specifically, we create a digital score for each occupation based on two measures of the O*NET 2019 vintage: (i) a measure of the overall knowledge of computers and electronics required by a job and (ii) a measure of the importance of working with computers for a job. These two measures aim to capture the level and importance of digital skills per occupation. We classify occupations as digital if their score is above the 50^{th} percentile of the digital score distribution, with the remaining occupations classified as non-digital.[4]

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 is 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 shows 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 for the correlation between the stringency of lockdown policies and the increase in the unemployment rate over the period between February to April 2020.

[4]Examples of ISCO-08 occupation codes at the bottom decile of the digital score distribution include home-based personal care workers, bricklayers and related workers, carpenters and joiners. Examples of occupations at the top decile include web technicians, systems administrators, information and communications technology service managers and software developers. Examples of occupations in the middle 10% include psychologists, employment agents and contractors and nursing associate professionals. Since our digital scores are based on a pre-pandemic vintage of O*NET, the occupational ranking does not reflect changes in digitalization within occupation codes that may have occurred during the pandemic. For more details on our methodology see *Soh et al.* [2022]).

There is a positive correlation between the severity of mitigation policies and the increase of unemployment only among low-IT adoption states (Figure A1).

These results suggest that more IT-oriented states appear better able to shift quickly to a socially distant environment and, in doing so, maintain their workforce.

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:

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

where ΔUR_s is the change in the unemployment rate in state s between April and February 2020. $\Delta Mobility_s$ 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_s 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 which 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 this 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. Because of the small sample size (N=51), it is difficult to include a much richer set of controls. Nonetheless, our results suggest that such key demographic factors are not the drivers of the mitigating impact of IT on the rising unemployment rate.

We also investigate how the results change when we vary the cutoff for labeling a state as high or low IT. As illustrated by Table A3 (column 3 in particular), states in the top quartile of the IT distribution are shielded from the impact of mobility changes, while states in the middle or the bottom of the IT adoption distribution are not.

4.1 Event Study Design

A complementary approach to analyze the data, is to rely on the panel dimension and estimate the following event study (two-way fixed effects) specification:

$$UR_{s,t} = \alpha_s + \alpha_t + \sum_{\tau \neq \tau*} 1(t=\tau) \cdot \Delta Mobility_s \cdot \left(\beta_\tau + \beta_{\tau,3} * IT_s\right) + \epsilon_{s,t} \tag{3}$$

where $UR_{s,t}$ is the unemployment rate in state s in month t, while IT_s is the continuous pre-pandemic IT adoption in the same state, and $\Delta Mobility_{s,t}$ is the mobility shock (the average change in mobility in April and May). Both IT_s and $\Delta Mobility_{s,t}$ are standardized for ease of interpretation. α_s and α_t are state and month fixed effects, which allow us to control for time-invariant local characteristics and national-level time-varying shocks. The coefficients β_τ capture the impact of the change in mobility on unemployment rate in the month τ, ($\tau*$ is the omitted month, February 2020) while the coefficients $\beta_{\tau,3}$ capture the shielding impact of local IT adoption.

The estimated coefficients are reported, together with 95% confidence intervals, in Figure 2.[5] Panel (a) illustrates that states which were hit more harshly by the pandemic were not on a different path before February 2020, but experienced a sharper increase in the unemployment rate. However, as illustrated by Panel (b), the impact of the shock is smaller for states where firms adopted more IT before the pandemic. To visualize such heterogeneity, To visualize the heterogeneity in the response of unemployment in high versus low IT states, Panel (c) reports the estimated impact over time of a one-standard deviation mobility drop in a state above and below the standardsized IT mean. This alternative specification, which allows us to control for local observable and unobservable (fixed over time) characteristics through fixed effects, confirms the findings of the previous subsection and highlights the absence of pre-pandemic differential trends.

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, in analyzing which workers are more protected by IT adoption.

We therefore use individual-level data from CPS to control for respondent- and local-level

[5] The model is estimated by OLS. Recent econometric literature has highlighted that OLS can provide biased estimates of two-way fixed effects when the time of the shock or treatment is different across units [*Goodman-Bacon*, 2021; *Callaway and Sant'Anna*, 2021]. This is likely to be a minor concern in our setting as all MSA are impacted at the same time, but the intensity of the shock is different.

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:

$$\begin{aligned} Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\ + Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t} \end{aligned} \tag{4}$$

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. X captures MSA-level controls and includes the level and interaction between mobility and GDP per capita, the share of minorities, the share of people with a three year Bachelor's degree and the unemployment rate in February 2020. Z_i are individual level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level and 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.[6]

Table 2 shows the results based on a pooled linear regression across individuals reporting their employment status in either April or/and May (Table A1 reports 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 MSAs which experienced larger mobility declines, but IT adoption of companies mitigates this impact. The increase in the probability of being unemployed asso-

[6]As the panel component of CPS is limited, and respondents are not necessarily reporting their employment status in consecutive months, we do not include individual fixed effects. In a robustness exercise, described below, we focus only on individuals who were employed before the pandemic.

ciated 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 increase in the probability by 0.7 percentage points to 1.7 percentage points. Column (3) shows that 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 holds when comparing individuals with also the same gender or 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 for explaining the employment status of the individual but even after controlling for these characteristics the level of IT adoption in the MSA remains 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 not interpretable (and therefore omitted in most of the following exercises).

Robustness We conduct several robustness tests, reported in Table A2, all of which confirm our main findings. Column (1) shows the baseline equation for reference (similar to column (3) of Table 2). 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 5% 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 baseline IT measure, log IT budget per employee, with another measure that has been used commonly in the literature, also from the Harte Aberdeed/Hanks dataset, namely the ratio of personal computers per employees [*Bloom et al.*, 2012]. Next, we substitute our left-hand-side variable, the dummy indicating whether the person is unemployed, to capture 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. This measure also includes anyone who has gone back to school, become disabled, and people who are underemployed or working part-time hours. Our results remain robust to using this broader unemployment measure.

To further control for differences in local economic structure across different MSAs, we add a set of controls for the share of employment in different occupations and different industries at the MSA-level (we focus on the largest 2-digit NAICS sectors and the largest 2-digit SOC 2018 occupations which accounted for more than one third of national employment in 2019). Both the level of the industry and occupation employment shares as well as their interaction with the mobility shock are added as controls. The inclusions of such controls has limited impact on the estimated shielding effect of local IT adoption, as reported by column (6).

We then focus on respondents that were in the CPS also in February 2020, to investigate the impact of mobility and local IT among individuals that were employed in that month. (In this way, the empirical specification investigates the impact of local mobility and IT on the probability that an individual *becomes* unemployed.) The estimating sample shrinks considerably both because of the rotating panel structure of the survey and because only about 60% of respondents were employed in February 2020. We find that the shielding impact of IT is present among the workers who were actually employed before the pandemic (column 7). Focusing on the respondents who worked in February 2020, we can also include two sets of fixed effects to control for the (4 digit) occupation and industry in that month. The inclusion of such controls does not change the estimated shielding effect of IT, mitigating the concern that the local IT effect is capturing differences in the local sectoral and occupational mix.

We finally investigate whether the results are also robust to MSA-level aggregation. We construct MSA-level unemployment rate and we aggregate all individual-level controls of Equation 4. We then estimate an MSA-level version of Equation 4 where we regress the change in unemployment rate between February and April or May 2020 on the change in mobility, MSA-level IT, and the interaction between the two variables while controlling for the other covariates. Results, presented in Table A4, are in line with the respondent-level estimates: MSAs where mobility dropped more experienced a stronger increase in unemployment rate, but less so if they have firms that adopted more IT before the pandemic.

5.1 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 is adopted more intensely [*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 predate 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 shares 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 predicts IT adoption 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 3 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. Under 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:

$$Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i),t} * IT_{msa(i)} + \alpha_{s(i)} + \epsilon_{i,t} \tag{5}$$

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 MSAs where firms adopted more IT were also more resilient to the pandemic is not mainly driven by the presence of unobserved confounding factors.

5.2 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 scale the use of working-from-home, contactless delivery, and other remedies needed to respond to 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 consequences that would have occurred given a lower level of IT adoption. To perform such an exercise, we re-estimate Equation 4 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.[7] 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, we can estimate the counterfactual probability that an individual i is unemployed as:

$$\begin{aligned} Unemployed_{i,t} = \alpha + \widehat{\beta_1}\Delta Mobility_{msa(i),t} + \widehat{\beta_2} * 0.9 * \widehat{IT_{msa(i)}} + \widehat{\beta_3}\Delta Mobility_{msa(i,t)} * 0.9 * \widehat{IT_{msa(i)}} \\ + Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} \end{aligned} \tag{6}$$

[7] 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 measures of "digital economy".

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.

This back-of-the-envelope calculation should be treated with caution. Although our IV estimate and our coefficients after controlling for various observable characteristics are relatively stable, we cannot completely rule out potential exclusion restriction violations or that other unobservable or omitted characteristics which are correlated with IT spending partially bias our coefficient of interest. Moreover, this type of calculation assumes that there are no spillover effects from the adoption of IT. If, for example, IT spending in one region makes not only the region itself more resilient, but also other regions that do not adopt IT as strongly more resilient – for instance via a smaller decline in aggregate demand– our estimate would provide a lower bound for the total effect of how much IT shields unemployment losses. See also *Nakamura and Steinsson* [2018] for an in-depth discussion of the caveats of extrapolating aggregate effects from cross-sectional regressions.

5.3 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:

$$
\begin{aligned}
Unemployed_{i,t} = \alpha &+ \beta_1 \Delta Mobility_{msa(i),t} * A_i + \beta_2 \Delta Mobility_{msa(i),t} * (1 - A_i) \\
&+ \beta_3 IT_{msa(i)} * A_i + \beta_4 IT_{msa(i)} * (1 - A_i) \\
&+ \beta_5 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * A_i \\
&+ \beta_6 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * (1 - A_i) \\
&+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t}
\end{aligned}
\tag{7}
$$

which is similar to Equation 4 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 7 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. (Observation where 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 3 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 4. 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.

6 Channels

In this section we analyze various channels through which IT adoption could have mitigated the adverse consequences of social distancing. In particular, we test whether IT adoption is associated with better ability to work from home, higher e-commerce activity, greater resilience of job creation, as well as a reallocation of labor demand from non-digital to digital jobs during Spring 2020.

6.1 IT, Working-From-Home, and E-commerce

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 5 shows there is a high correlation between the share of jobs that can be done from home in an MSA and IT adoption.

We re-estimate Equation 4 substituting the IT measure with the share of jobs that can be done from home 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 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, the coefficient on the interaction remains statistically significant, suggesting that teleworking does not seem to be the only channel through which IT has a mitigating effect and other channels through which IT adoption mitigates the consequences of social distancing are at work.

Another potential channel for the shielding effect of local IT adoption could be that IT-savvy firms have better e-commerce capabilities and thus can more promptly expand online sales. The Aberdeen survey contains more detailed information on the presence of specific e-commerce technology for about 1% of the sample establishments. For these establishments, we know whether or not they have adopted a e-commerce related technology in 2016. We construct an MSA-level measure of e-commerce presence by estimating the same regression used to estimate the baseline measure of IT (Equation 1).[8]

We then augment the baseline individual-level specification with the MSA-level measure of e-commerce prevalence and its interaction with the change in mobility. Results are reported in Table 5. We do not find evidence in favor of a significant shielding impact of pre-COVID e-commerce technologies on local labor markets. The empirical irrelevance of this channel may be surprising given the rise of online sales during the onset of the pandemic. We conjecture two reasons that could justify this finding. First, it may be easier for IT-savvy firms to start selling online once the pandemic hit, even if they did not do so before. Second, as we show below, the shielding impact of IT is particularly important in tradable industries, but not in non-tradable ones. Firms in tradable industries, like many manufacturing or mining industries, tend to sell to other business rather than consumers, thus limiting the importance of e-commerce.

6.2 IT, Online Vacancies, and Digital Jobs

The abrupt skyrocketing of the unemployment rate at the onset of the pandemic indicates a severe increase in (temporary) layoffs. While job destruction was a key driver of the unemployment rate, depressed job creation was another important margin of adjustment. Labor demand collapsed in the Spring of 2020 as firms responded to mobility restrictions and the extraordinary degree of uncertainty by severely restricting vacancies. Mobility restrictions may

[8] That is, we estimate the MSA-level fixed effect $\alpha_{g(e)}$ from the linear probability model

$$Ecommerce_e = \delta + \alpha_{g(e)} + \theta_{ind(e)} + \epsilon_i \tag{8}$$

where $Ecommerce_e$ is an indicator variable flagging the presence of e-commerce technology.

have affected firms' ability to create new posting not only due to the contraction in aggregate demand that they entailed but also by exacerbating search frictions as in-person interactions were rarer. However, the impact of the COVID-19 shock on job creation may have been asymmetric across regions with different degrees of IT adoption. IT-adopters may have benefited from higher quality and more readily available digital infrastructure and greater degree of digital preparedness which could allow firms to flexibly adapt their working practices and shield job creation. In contrast, lagging regions may have suffered from lower digital infrastructure and may have struggled to digitalize their business models and work practices with stronger negative effects for job creation.

We test whether part of the shielding impact of IT comes from enhancing the resilience of job creation. We focus on online job posting as online job search became an increasingly important way through which firms posted vacancies in the presence of mobility restrictions.[9] We estimate the following linear regression:

$$\begin{aligned}\Delta JobPosting_{msa} = \alpha + \beta_1 \Delta Mobility_{msa} + \beta_2 IT_{msa} + \beta_3 \Delta Mobility_{msa} * IT_{msa} \\ + X'_{msa}\sigma + (X_{msa} * Mobility_{msa})'\gamma + \epsilon_{msa}\end{aligned} \tag{9}$$

where $\Delta JobPosting_{msa}$ is the average change in the log level of vacancies between February 2020 and May or April 2020 at the MSA level. $\Delta Mobility_{msa}$ is the average decline in mobility between February 2020 and April or May 2020 in each MSA and IT_{msa} measures local IT adoption. The coefficient β_1 captures the impact of the mobility drop on vacancy postings while β_3 captures the shielding impact of local IT adoption.

Results are reported in Table 6. Aggregate online job postings dropped more in areas that suffered a larger decline in mobility during Spring 2020, as reported in column (1). However, consistently with the results presented in section 5, the negative impact of the mobility drop on job postings is mitigated in areas with stronger pre-COVID IT adoption (as shown in column (2)). These results lend support to the hypothesis that the shielding impact of firm IT adoption on local labor markets is driven also by increasing the resilience of job creation, rather than only because of less severe job destruction.

To shed further light on this mechanism, we test whether shielding took place for occupations characterized by skills that are complimentary to IT, or whether IT adoption benefited less

[9] Unfortunately our data do not provide information on whether the job listing resulted in a final hiring.

digitally-savvy occupations as well. We re-estimate Equation 9 separately for two categories of vacancies: on digital and on non-digital occupations (see section 3). We find that local IT adoption shielded the impact of the pandemic only on digital jobs, as illustrated by comparing the coefficient on the interaction between IT and mobility in columns (4) of Table 6, which refers to vacancies for digital jobs, to the one in column (6), which refers to non-digital vacancies. While both types of job posting are impacted by local mobility (as suggested by the positive coefficient on the change in mobility in columns (3) and (5)), the interaction coefficient is statistically different than zero only for digital job postings. In fact, columns (7) and (8) illustrate that the share of digital vacancies over total job postings increased in areas more hit by the pandemic, and even more so in areas that also had a higher degree of pre-pandemic IT adoption.

These findings suggest that an important reason why IT shielded local labor markets from the impact of the pandemic is because it facilitated and amplified the expansion of the digital economy, helping firms to create more digital jobs. In areas hit more harshly from the pandemic, the transition to a more digital-intense economy was stronger. Importantly, in places where pre-pandemic IT adoption was higher, there was an even stronger shift in the demand towards more digitally-intensive jobs which absorbed in part the negative impact of mobility restrictions on job creation during Spring 2020.

Event-study design A complementary approach to analyze the data, is to rely on the panel dimension and estimate the following event study (two-way fixed effects) specification:

$$JobPosting_{msa,t} = \alpha_{msa} + \alpha_t + \sum_{\tau \neq \tau*} 1(t = \tau) \cdot \Delta Mobility_{msa} \cdot \left(\beta_\tau + \beta_{\tau,3} * IT_{msa}\right) + \epsilon_{msa,t} \quad (10)$$

which differs from Equation 3 only in that the unit of observation is an MSA rather than a state, and the dependent variable is the log level of online vacancies in that MSA in month t. Results, illustrated in graphical form by Figure 6, confirm the results of the cross-sectional regression (Equation 9). MSAs in which mobility dropped more severely experienced a larger decline in online job postings, however the impact of mobility was reduced in areas where firms had adopted IT more intensively pre-pandemic. The figure also shows that the dynamics of job postings before the pandemic were similar for areas more or less hit by the drop in mobility. This absence of a pre-trend mitigates the concern that other confounding shocks are driving the results and suggests the parallel-trend assumption is not violated. In particular, we would expect that regions with differential levels of IT adoption would have performed similarly during the spring of 2020 if the pandemic would not have hit the world.

6.3 Demand Spillovers

Our empirical investigation relies on variables measured at the local level. Therefore, part of the shielding impact of IT could come from general equilibrium effects impacting local markets. Demand spillovers are a channel of particular importance when analyzing local impact of shocks [*Mian and Sufi*, 2014]. For instance, if some firms are shielded because of IT and thus can maintain their workforce, other nearby firms that sell products or services to the employees of the latter may also benefit. To gauge the importance of such demand spillovers, we study the dynamics of employment in tradable versus non-tradable industries in Spring 2020. We compute MSA monthly employment by industry collapsing CPS data, and use tradable vs non-tradable industry classification from *Mian and Sufi* [2014]. In line with the results of our baseline specification, we find that the change of total employment from February 2020 to April and May 2020 was more negative for MSAs which experienced a more severe drop in mobility, but less so when IT was adopted pre-pandemic. However, the shielding role of IT is present only for tradable industries, and not for non-tradable ones.[10] These results (reported by Table A5) suggest that demand spillovers play a minor role in explaining the shielding impact of IT during the onset of the pandemic.

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

[10]Note that tradable and non-tradable is not a partition of all industries according to *Mian and Sufi* [2014]'s classification. So total employment is larger than the sum of tradable and non-tradable employment.

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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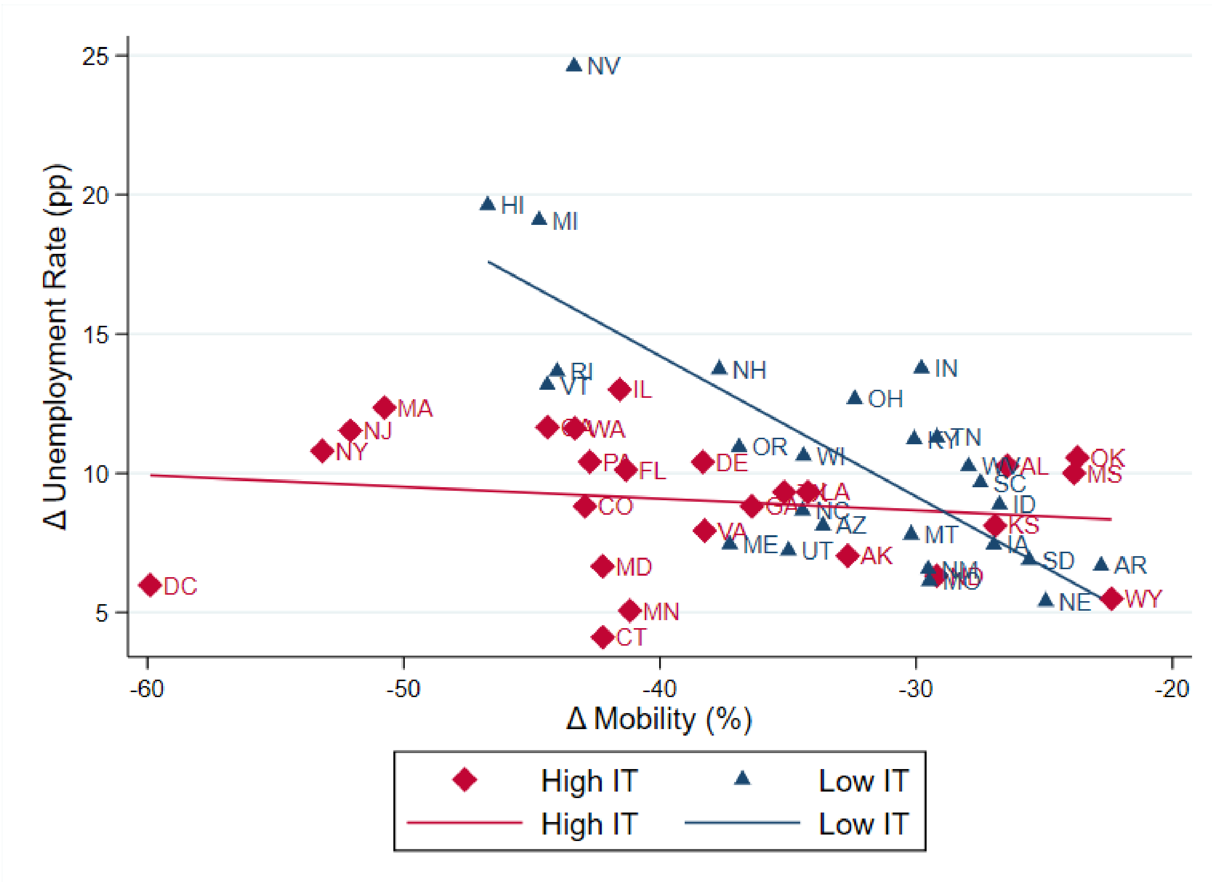
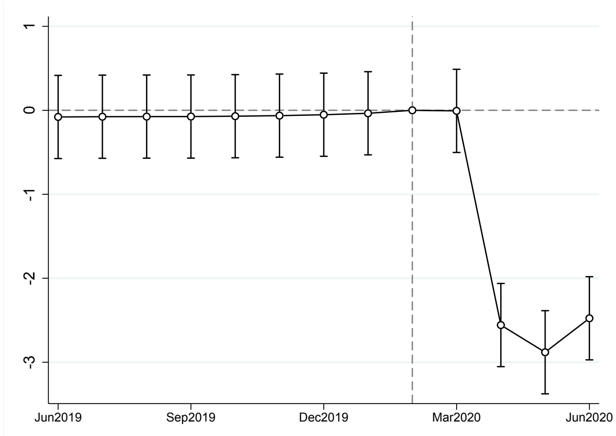
Figure 1: Unemployment and Mobility in the US



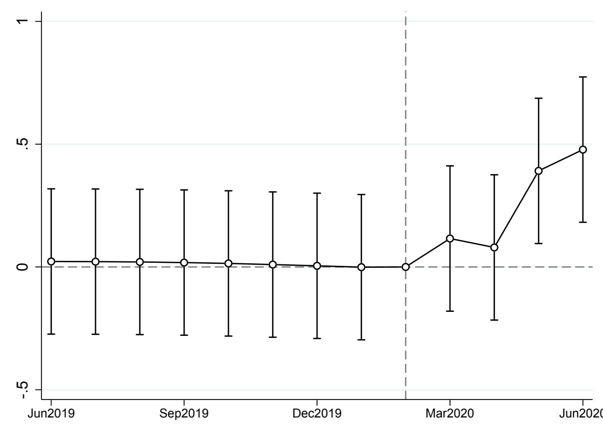
This figure plots the change in the unemployment rate between February and April by state on the average change in mobility in retail, recreation and transit station in April. The red diamonds represent states where IT adoption is above the median and the blue triangles represent states where IT adoption 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 section 4 for more details.

Figure 2: Unemployment, Mobility, and IT in the US: Event-Study design

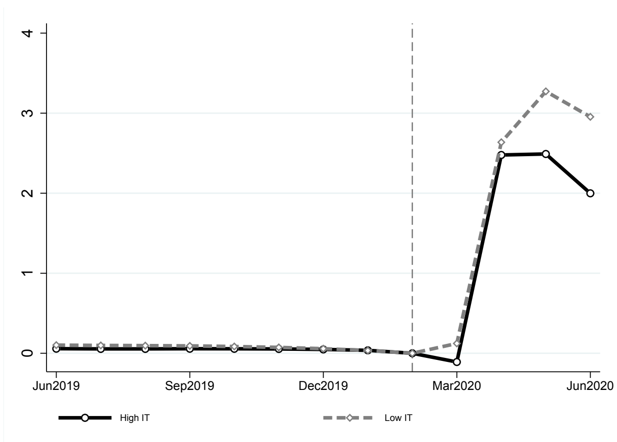
(a) Coefficients on ΔMobility



(b) Coefficients on ΔMobility × IT

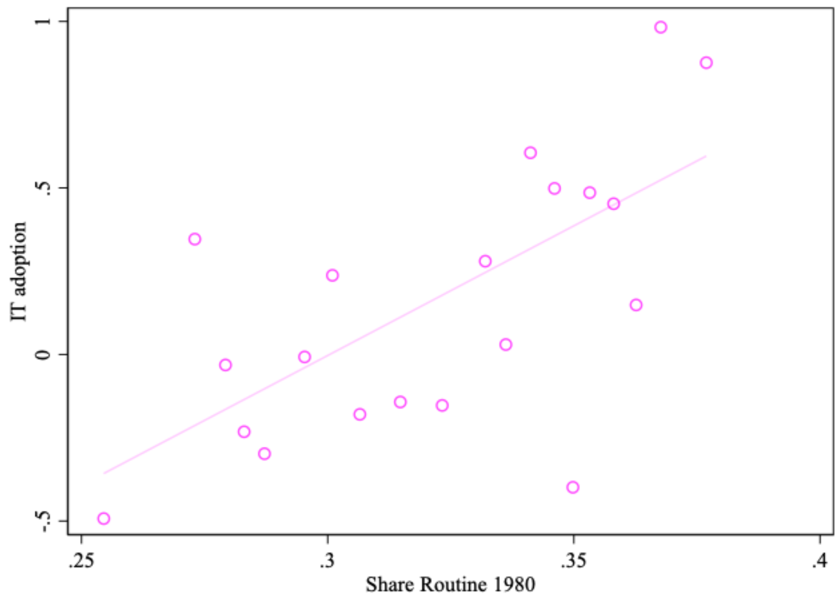


(c) Impact of a Mobility Drop for High vs Low IT States



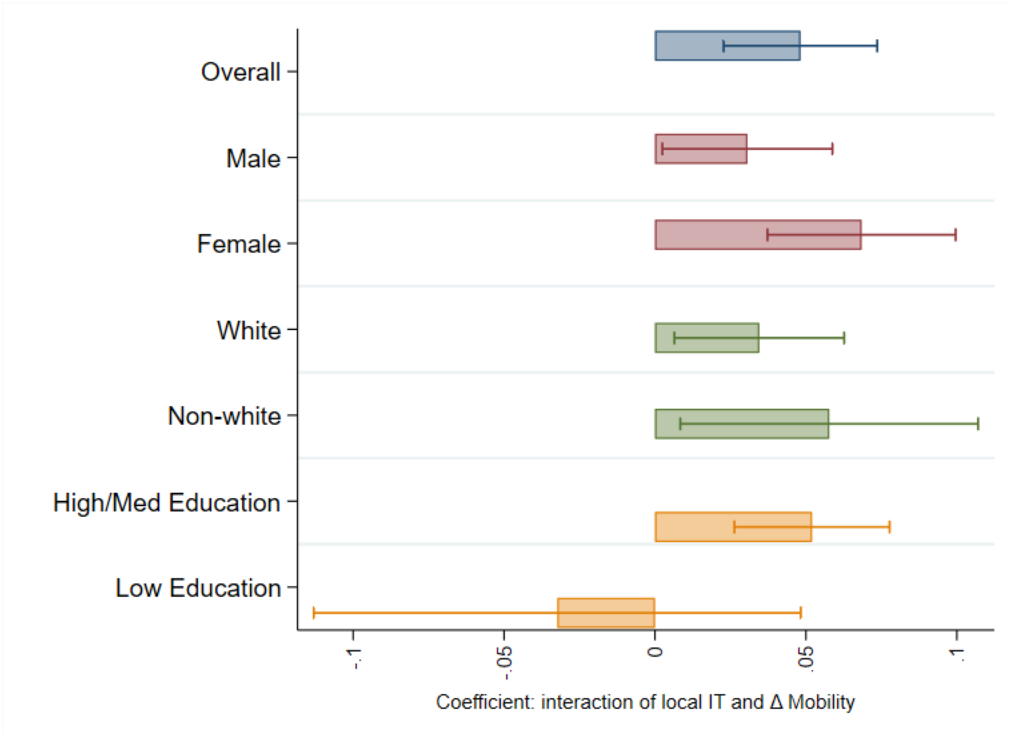
The Figure shows estimates of Equation 3. Panel (a) reports estimates of β_τ and 95% confidence intervals; Panel (b) reports estimates of $\beta_{3,\tau}$ and 95% confidence intervals; Panel (c) reports $-\sigma(\Delta Mobility_s)\cdot(\beta_\tau + / - \beta_{3,\tau}\sigma(IT_s))$ where $\sigma(\Delta Mobility_s)$ and $\sigma(IT_s)$ are the standard deviation of the mobility change and of the State-level IT adoption.

Figure 3: 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 5.1 for more details.

Figure 4: Mitigating Impact of IT across Individuals

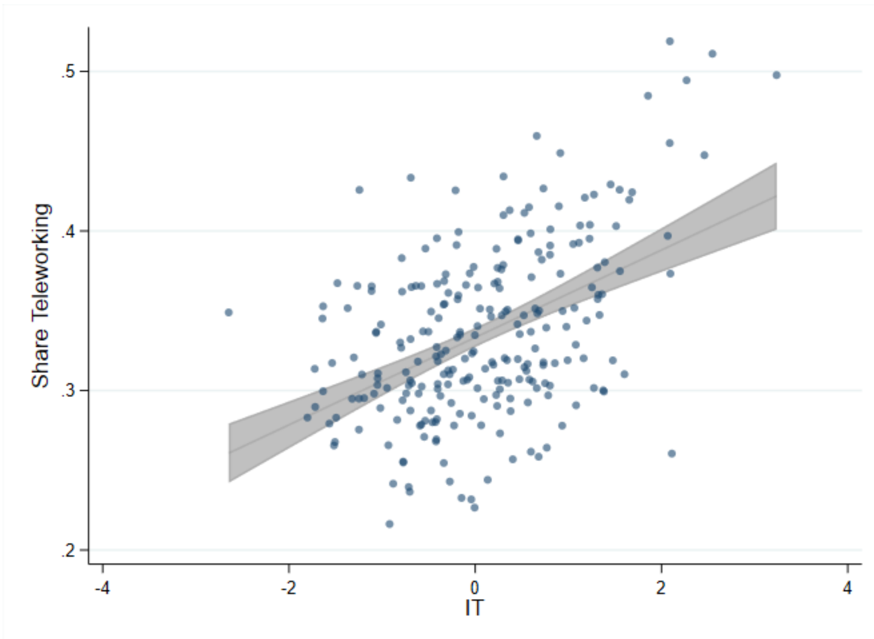


This figure plots the coefficient and the 90% confidence interval of β_5 and β_6 from Equation 7:

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

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.

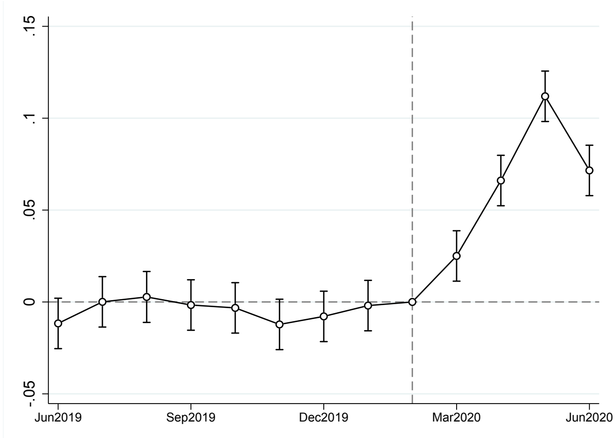
Figure 5: IT Adoption and Work-from-Home ability



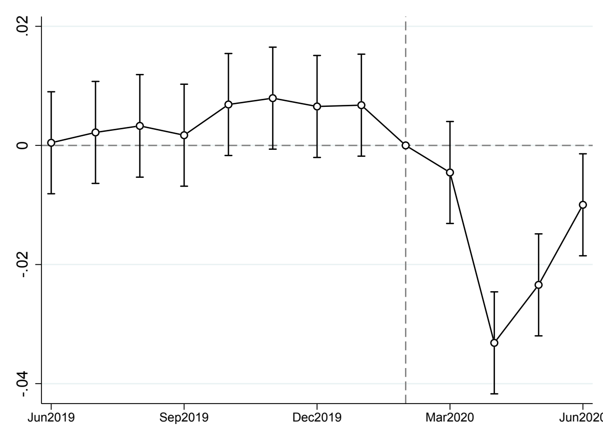
This figure plots the level of IT adoption in an MSA on the horizontal axis against the share of jobs that can be done from home on the vertical axis. The share of jobs that can be done from home are taken from *Dingel and Neiman* [2020]. See section 3 and section 5 for more details.

Figure 6: Vacancy Postings, Mobility, and IT in the US: Event-Study design

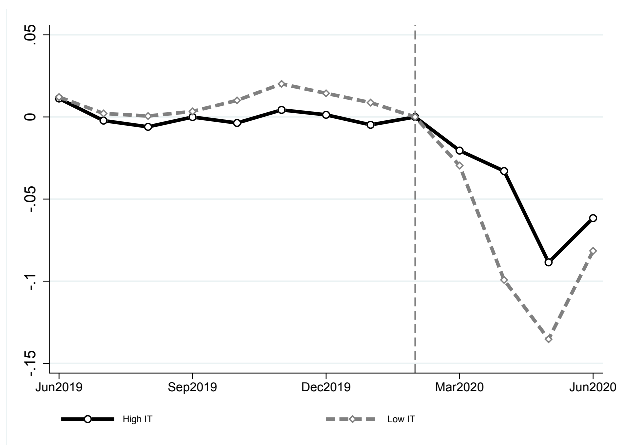
(a) Coefficients on ΔMobility



(b) Coefficients on Δ Mobility × IT



(c) Impact of a Mobility Drop for High vs Low IT MSAs



The Figure shows estimates of Equation 10. Panel (a) reports estimates of β_τ, Panel (b) reports estimates of $\beta_{3,\tau}$ and Panel (c) reports $-\sigma(\Delta Mobility_{msa}) \cdot (\beta_\tau + / - \beta_{3,\tau}\sigma(IT_{msa}))$ where $\sigma(\Delta Mobility_{msa})$ and $\sigma(IT_{msa})$ are the standard deviations of the mobility change and of the MSA-level IT adoption.

Table 1: Unemployment, Mobility and IT: State-level Regressions

	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 :

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

where ΔUR_s is the change in the unemployment rate in state s between April and February. $\Delta Mobility_s$ 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 4 for more details.

Table 2: Unemployment, Mobility and IT: Individual-level Regressions

	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 4:

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

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, including the level and the interaction between mobility and GDP per capita, the share of minorities, the share of people with a three year Bachelor's degree, and the unemployment rate in February 2020. $\alpha_{s(i)}$ 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: 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 7 :

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

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 captures MSA-level controls, including the level and the interaction between mobility and GDP per capita, the share of minorities, the share of people with a three year Bachelor's degree, and the unemployment rate in February 2020. 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: 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 $IT_{msa(i)} * \Delta Mobility_{msa(i),t}$ 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 5.1 for more details.

Table 5: Unemployment, Mobility, Teleworking abilities, E-commerce and IT

	Dependent variable: Unemployed				
	(1)	(2)	(3)	(4)	(5)
Δ Mobility × IT	0.0677***		0.0539**		0.0929***
	(0.025)		(0.025)		(0.030)
Δ Mobility × Teleworking		1.100**	1.002**		
		(0.517)	(0.506)		
Δ Mobility × E-commerce				0.0113	0.0196
				(0.021)	(0.020)
R-squared	0.0384	0.0385	0.0387	0.0373	0.0376
N	71812	71812	71812	62276	62276
Controls	Yes	Yes	Yes	Yes	Yes
State FEs	Yes	Yes	Yes	Yes	Yes

Results of estimating the following equation:

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

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. $W_{msa(i)}$ is either the share of jobs that can be done from home in the MSA where individual i lives, taken from *Dingel and Neiman* [2020] (columns 2 and 3) or the share of establishments that use e-commerce technologies according to 2016 Aberdeen survey, after controlling for establishment's industry, (columns 4 and 5). 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: Vacancies, Mobility and IT

	Δ Total Vacancies		Δ Digital Vacancies		Δ Non-Digital Vacancies		Δ Share of Digital Vacancies	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Mobility	0.553***	5.227	0.284**	8.148	0.825***	9.182	-0.541***	-1.033
	(0.132)	(8.992)	(0.130)	(9.658)	(0.087)	(10.126)	(0.141)	(9.060)
IT	-0.0259*	-0.125***	-0.0213	-0.128***	-0.0395***	-0.0633*	0.0182*	-0.0647*
	(0.014)	(0.038)	(0.016)	(0.044)	(0.009)	(0.035)	(0.011)	(0.035)
Δ Mobility × IT		-0.410***		-0.420**		-0.171		-0.248*
		(0.154)		(0.171)		(0.137)		(0.137)
R-squared	0.400	0.580	0.184	0.402	0.576	0.667	0.339	0.422
N	250	250	250	250	250	250	250	250
Controls	No	Yes	No	Yes	No	Yes	No	Yes

Results of estimating Equation 9:

$$\Delta JobPosting_{msa} = \alpha + \beta_1 \Delta Mobility_{msa} + \beta_2 IT_{msa} + \beta_3 \Delta Mobility_{msa} * IT_{msa} \\ + X'_{msa}\sigma + (X_{msa} * Mobility_{msa})'\gamma + \epsilon_{msa}$$

where $\Delta JobPosting_{msa}$ is the average change in the log level of vacancies between February 2020 and May or April 2020 in each MSA. $\Delta Mobility_{msa}$ is the average decline in mobility between February 2020 and April or May 2020 and IT_{msa} measures IT adoption at the MSA level. X includes the level and the interaction between mobility and various MSA-level characteristics such as GDP per capita, the share of people with a three year Bachelor's degree, the share of minorities and the unemployment rate in February 2020. Columns (1) and (2) report estimation results for the change in the log level of total vacancies, columns (3) and (4) report results for the same specification but focusing on digital vacancies, columns (5) and (6) report results on non-digital vacancies and columns (7) and (8) report results for the change in the share of digital vacancies. Regressions are weighted by the MSA pre-COVID-19 employment shares. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 for more details.

ONLINE APPENDIX—NOT FOR PUBLICATION

Table A1: Unemployment, Mobility and IT: Probit

	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 4 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 A2: Unemployment, Mobility and IT: Robustness

	Dependent variable: Unemployed							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ Mobility × IT	0.0655***	0.00497**	0.129***	0.0518***	0.0572**	0.0776***	0.0794***	0.0733***
	(0.016)	(0.002)	(0.043)	(0.019)	(0.022)	(0.025)	(0.026)	(0.024)
R-squared	0.0198	0.0195	0.0198	0.0198	0.0245	0.0211	0.0221	0.186
N	68923	68923	68923	68923	68923	68923	24680	24653
Controls	No	No	No	No	No	No	No	No
FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	High-Speed Internet	High IT	PCs/Emp	U6 Unemployment	Ind & Occ controls	Employed Feb 2020	Occ/Ind Feb 2020

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. Column (6) includes the level and the interaction between mobility and the employment shares of the largest pre-COVID-19 industry and occupation categories as additional control variables in the regression. The industry and occupation employment shares account for more than 1/3 of total employment in 2019. Column (7) includes only respondents that were in the survey also in February 2020 and were employed. Column (8) includes only respondents that were in the survey also in February 2020 and were employed and also adds fixed effects for the industry and the occupation of the respondent in that month. 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 A3: Unemployment, Mobility and IT: State-level Regressions with different cutoffs

	Dependent variable: Δ Unemployment Rate		
	(1)	(2)	(3)
Δ Mobility × Above Median IT	-0.0423		
	(0.056)		
Δ Mobility × Below Median IT	-0.505***		
	(0.102)		
Δ Mobility × Top 33% IT		-0.0560	
		(0.077)	
Δ Mobility × Bottom 66% IT		-0.350***	
		(0.100)	
Δ Mobility × Top 25% IT			-0.0340
			(0.105)
Δ Mobility × 75% to 25% IT			-0.353**
			(0.133)
Δ Mobility × Bottom 25% IT			-0.291***
			(0.105)
R-squared	0.478	0.330	0.348
N	51	51	51

Results of estimating the equation:

$$\Delta UR_s = \alpha + \gamma IT_s + \beta_{high} \Delta Mobility_s * IT_s + \beta_{low} \Delta Mobility_s * (1 - IT_s) + \epsilon_s$$

where ΔUR_s is the change in the unemployment rate in state s between April and February in state s. $\Delta Mobility_s$ is the average decline in mobility in state s in April. In column (1) 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. In column (2) is a dummy that indicates whether a state is in the top tercile in terms of IT adoption and zero otherwise. In column (3), instead, a set of three dummies are interacted with the change in mobility: a dummy for states in the top quartile of IT adoption, a dummy for states in the bottom quartile of IT adoption, and a dummy for all state above the bottom quartile and below the top quartile. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 4 for more details.

Table A4: Unemployment, Mobility and IT: MSA-level

	Dependent variable: Δ Unemployment Rate		
	(1)	(2)	(3)
Δ Mobility	-0.191***	-0.251***	-2.930
	(0.031)	(0.041)	(2.263)
IT	-0.00928**	0.0166**	0.0266**
	(0.004)	(0.008)	(0.011)
Δ Mobility × IT		0.0687***	0.103***
		(0.024)	(0.035)
R-squared	0.140	0.164	0.210
N	508	508	508
Controls	No	No	Yes

Results of estimating Equation 4 at the MSA level

$$\Delta UR_{msa,t} = \alpha + \beta_1 \Delta Mobility_{msa,t} + \beta_2 IT_{msa} + \beta_3 \Delta Mobility_{msa,t} * IT_{msa} + X'_{msa}\sigma + (X_{msa} * Mobility_{msa,t})'\gamma + \epsilon_{msa,t}$$

where $\Delta UR_{msa,t}$ is the MSA's change in the unemployment rate between February 2020 and month t, where t is April or May 2020. $\Delta Mobility_{msa,t}$ is the change in MSA-level mobility over the same period. IT_{msa} is the level of IT adoption. X includes the level and the interaction between mobility and various MSA-level characteristics including GDP capita income, the share of people with a three year Bachelor's degree and the share of minorities pre-pandemic. Regressions are weighted by the MSA's pre-COVID-19 employment share. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and section 5 for more details.

Table A5: Employment, Mobility and IT: MSA-level

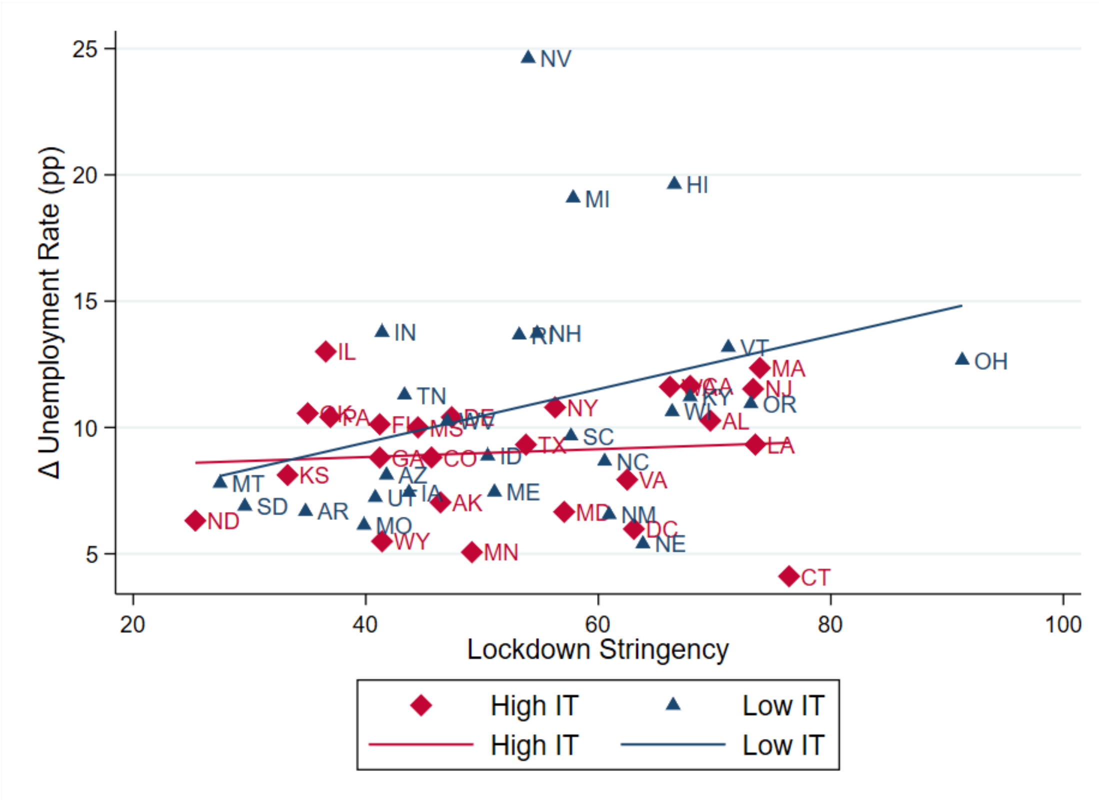
	Dependent variable: Δ Employment		
	Total	Tradable Industries	Non-Tradable Industries
	(1)	(2)	(3)
Δ Mobility	0.516***	0.235	0.613***
	(0.127)	(0.281)	(0.218)
IT	-0.0713***	-0.163*	-0.0423
	(0.025)	(0.086)	(0.050)
Δ Mobility × IT	-0.212***	-0.326*	-0.0606
	(0.065)	(0.195)	(0.133)
R-squared	0.0693	0.0240	0.0461
N	513	463	506

Results of estimating the following equation :

$$\Delta Employment_{msa,t} = \alpha + \beta_1 \Delta Mobility_{msa} + \beta_2 IT_{msa} + \beta_3 \Delta Mobility_{msa} * IT_{msa} + \epsilon_{msa,t}$$

where $\Delta Employment_{msa,t}$ is the change in (log) employment in each MSA between February 2020 and April or May 2020. $\Delta Mobility_{msa}$ is the change in mobility over the same period and IT_{msa} is the level of IT adoption at the MSA. Regressions are weighted by the MSA's pre-covid employment share. Robust standard errors are reported in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 6 for more details.

Figure A1: 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 section 4 for more details.