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

Nicola Pierri [†]    Yannick Timmer[‡]

**Abstract**

We study the role of information technology (IT) adoption during the COVID-19 pandemic. Using data on IT adoption covering almost three million establishments in the US, we find that in areas where firms adopted more IT the unemployment rate rose less in response to social distancing. Our estimates suggest that if the pandemic had hit the world 5 years ago, the resulting unemployment rate would have been 2 percentage points higher during April and May 2020 (16% vs. 14%), due to the lower availability of IT. Local IT adoption appears to mitigate the labor market consequences of the pandemic for all individuals, regardless of gender and race, except those with the lowest level of educational attainment.

**JEL Codes**: E24, O33

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

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[†]International Monetary Fund. Email: npierri@imf.org

[‡]International Monetary Fund. Email: ytimmer@imf.org

# 1 Introduction

As COVID-19 spread across the United States, people greatly reduced their mobility, stayed more at home, and spent less time producing and consuming products requiring face-to-face interactions. These changes–caused by both voluntary behavior and various mitigation policies–led to a severe recession. It is therefore important to understand which factors determine the size of the economic losses coming from social distancing.

This paper analyzes the interplay between the sudden decline in mobility, its effect on the economy, and firms' adoption of information technology (IT) in the US. IT adoption may dampen the effect of mobility by facilitating work-from-home, contact-less interactions, and organizational flexibility; in fact, more high-tech banks have performed better during the pandemic at least partly due to better online services [*Dadoukis et al.*, 2021; *Kwan et al.*, 2021; *Branzoli et al.*, 2021]. On the other hand, IT may magnify employment losses by helping the process of substitution of labor with capital when face-to-face interactions are limited.

Using data on IT equipment covering almost three million establishments in the US, we find evidence pointing towards a mitigating role of IT on the labor market consequences of the pandemic. We document that a larger mobility drop during the Spring of 2020 is associated with higher increase in the probability of unemployment–but only in areas where companies have adopted IT less intensively before the pandemic. Similar results emerge focusing on correlations across States (Figure 1) or using individual-level regressions relying on within-state (MSA-level) variation in IT and controlling for various other potential confounding factors (including heterogeneity in location exposure to different industries). Our estimates imply that the unemployment rate would have been around 2 percentage points higher (16% instead of 14%) during April and May 2020 if IT adoption had been at the level of 2015.

Both male and female workers as well as individuals of different races appear to benefit from IT adoption, while low-educated workers do not. Finally, we find suggestive evidence that enhancing the feasibility of working at home [*Dingel and Neiman*, 2020] is one channel–but not the only one–behind the mitigating role of IT.

# 2 Data Sources

IT data comes from an establishment survey on IT budget per employee by CiTBDs Aberdeen [*Bloom et al.*, 2012] for 2016, covering more than 2,800,000 establishments across the US. We consider the log of the IT budget per employee $IT_e$ at establishment $e$ and estimate:

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

where $\alpha_g$ is a fixed effect for the geographical unit we are interested in, (state or MSA). The estimated coefficients (after being normalized to have mean zero and variance one) are used to measure local IT adoption. We control for (2-digit) industry to ensure that the measure is not driven by a location's exposure to different industries.

Other data sources are standard: Current Population Survey (CPS) for labor market data, Google mobility reports to capture the decline in mobility (individuals' visits of retail, recreation, and transport sites), and *Dingel and Neiman* [2020] for MSA-level share of workers that can work from home.

# 3 Results

Figure 1 shows that of job losses are correlated with the decline in mobility only in those states where firms utilize a relatively low level of IT (left panel). In states that are stronger adopters of IT, the increase in unemployment period between February to April 2020 showed relatively little relationship to the degree to which mobility fell. Regression analysis–unreported for brevity–confirms these results are statistically significant.

An analogous pattern emerges from the right panel of Figure 1, which illustrates the correlation between the increase in unemployment and the stringency of lockdown policies (collected from States' websites by Keystone research).

## 3.1 Individual Level Data

We perform a related analysis using individual-level data to include detailed controls and to compare areas within the same State. We estimate the linear probability model:

$$\begin{aligned} Unemployed_{i,t} = \alpha + \beta_1 \Delta Mobility_{msa(i),t} + \beta_2 IT_{msa(i)} + \beta_3 \Delta Mobility_{msa(i,t)} * IT_{msa(i)} \\ + Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t} \end{aligned} \tag{2}$$

where $Unemployed_{i,t}$ is a dummy that equals one if the individual (a CPS responder) is unemployed in a month $t$ (either April or May 2020, the peak of the unemployment spike), and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility (with respect to pre-COVID 19) while $IT_{msa(i)}$ is the IT adoption of firms in the MSA where the individual $i$ lives. $Z_i$ are fixed effects for $i$'s gender, education, and race. $X_{msa(i)}$ are and MSA-level controls (pre-pandemic GDP per capita, population density, unemployment rate, and the minority share) which are also interacted with mobility, as they might change the labor market response to social distancing. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. Observations are weighted by the assigned weight of the respondent.

Table 1 presents the results. Column (1) illustrates that a stronger decline in mobility in an MSA is associated on average with a larger probability of a person reporting to be unemployed. However, as reported by columns (2) and (3), the interaction between changes in mobility and IT is positive: the negative impact of social distancing (a mobility drop) is significantly muted in areas with more IT adoption, confirming State-level results.

**Heterogeneity** To analyze whether IT can shield workers with different characteristics, we estimate:

$$\begin{aligned} Unemployed_{i,t} = \alpha &+ \beta_1 \Delta Mobility_{msa(i),t} * A_i + \beta_2 \Delta Mobility_{msa(i),t} * B_i \\ &+ \beta_3 IT_{msa(i)} * A_i + \beta_4 IT_{msa(i)} * B_i \\ &+ \beta_5 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * A_i \\ &+ \beta_6 \Delta Mobility_{msa(i),t} * IT_{msa(i)} * B_i \\ &+ Z_i' \delta + X_{msa(i)}' \sigma + (X_{msa(i)} * Mobility_{msa(i),t})' \gamma + \alpha_{s(i)} + \epsilon_{i,t} \end{aligned} \tag{3}$$

where $A_i$ and $B_i$ are dummy variables for individual demographic characteristics or education.

Figure 2 reports estimates for $\beta_5$ and $\beta_6$. The coefficient is positive for males, females, whites, non-whites, and high/medium education, indicating the probability of unemployment is less sensitive to social distancing in areas where firms adopted more IT. We do not find evidence in favor of a mitigating impact of IT on unemployment of workers with low educational attainment (less than high school).

**Working from home** An explanation for the role of IT is that it facilitates the transition to working-from-home (WFH), avoiding output and employment losses. Indeed, Figure 3 reveals a high correlation between IT and the share of jobs that can be done from home in an MSA (local WFH hereafter).

We then reestimate Equation 2 substituting local IT adoption with local WFH. As reported in column (4), the probability of unemployment of individuals living in MSAs with higher local WFH is less impacted by the decline in mobility–consistent with firm-level findings of *Alipour et al.* [2021] and *Bai et al.* [2021]. We then add both local WFH and IT adoption, and focus on their interaction with mobility. The coefficient are statistically significant but of smaller magnitude than when only one of the two factors is included in the model. This suggests that WFH is one channel, but not the only one, through which IT can shield workers from the economic consequences of the pandemic.

## 3.2 Counterfactual

The cross-sectional estimates can be used to compute the counterfactual labor market consequence that would have occurred in a world with a lower level of IT adoption. According to *Bureau of Economic Analysis* [2019] *"since 2010, digital economy real gross output growth averaged 2.5 percent per year."*, while labor force grew at about 0.5 percent per year. Thus–ignoring heterogeneity across locations–IT expenditures over employees grew at 2 percentage points per year, and was, therefore, approximately 10% smaller 5 years ago. We thus compute the counterfactual probability that an individual $i$ is unemployed as:

$$Unemployed_{i,t} = \alpha + \widehat{\beta_1}\Delta Mobility_{msa(i),t} + \widehat{\beta_2} * 0.9 * \widehat{IT_{msa(i)}} + \widehat{\beta_3}\Delta Mobility_{msa(i,t)} * 0.9 * \widehat{IT_{msa(i)}} \\ + Z_i'\delta + X'_{msa(i)}\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)} \tag{4}$$

where the "hat" signs highlight that the IT adoption measure and the coefficients are not normalized, and are therefore expressed in terms of IT expenses per employee.

The estimated counterfactual unemployment rate (average between April and May 2020) under the 2015 IT adoption is 16% versus the observed 14%: 2 percentage points (or 14.3%) higher. A Probit model delivers very similar results.

## 4 Conclusion

We find evidence in favor of IT adoption lowering the economic cost of the social distancing for most workers, except the less educated ones. This suggests, IT can—in the aggregate—significantly shield labor markets from the effects of a pandemics. However, it may also increase disparities between individuals with different education.

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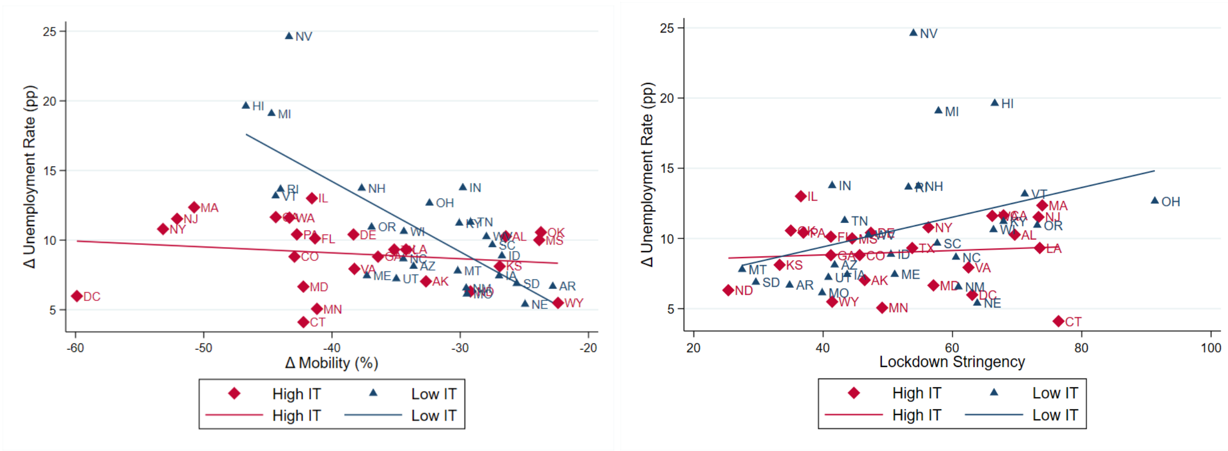
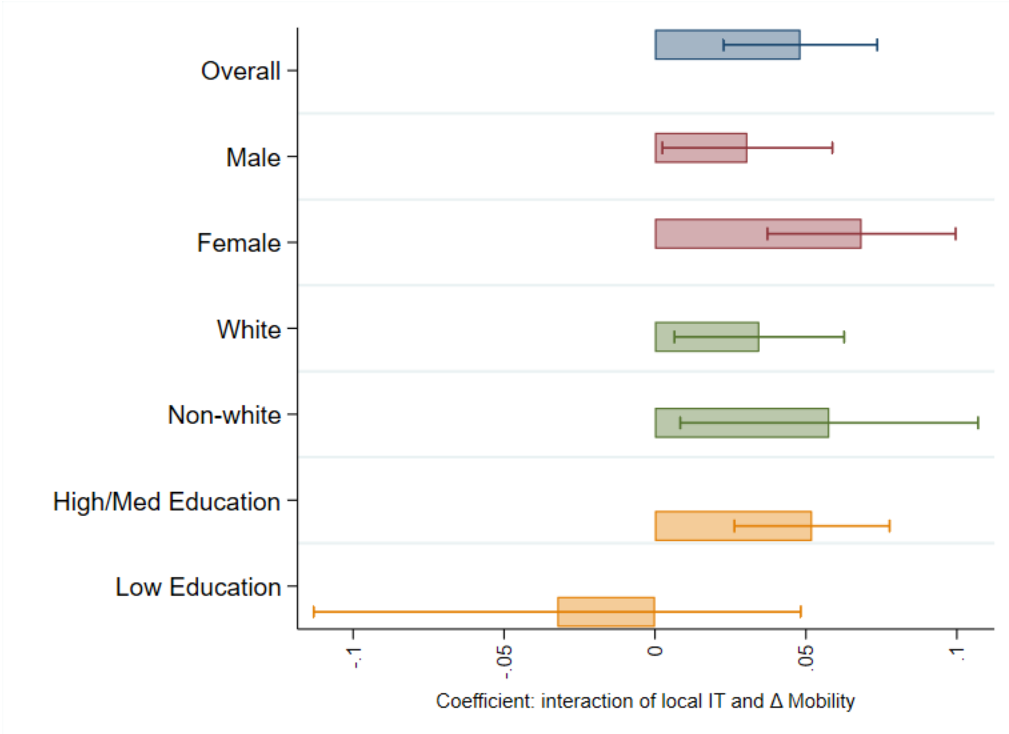
Figure 1: Unemployment and Mobility, and Lockdowns in the US



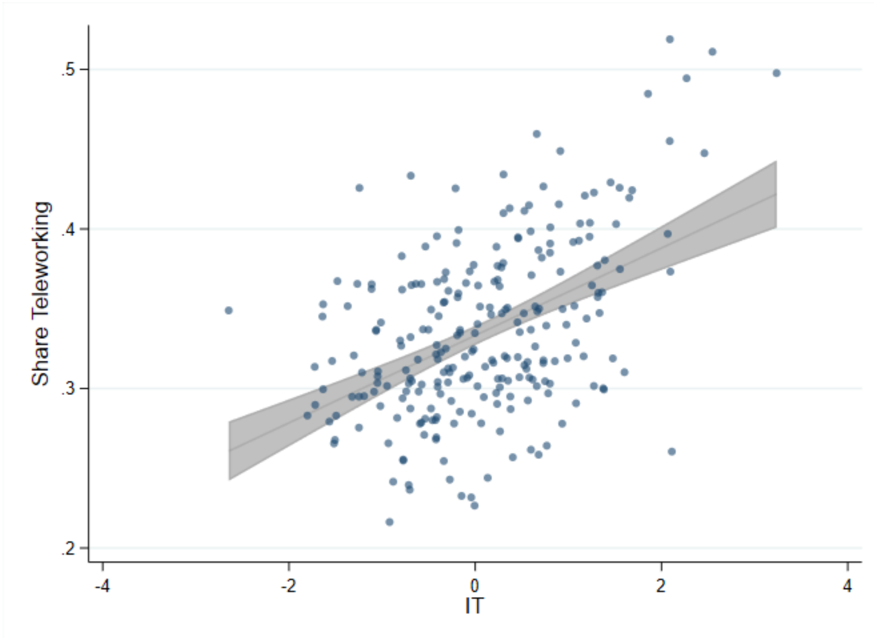

The change in the unemployment rate between February and April by state is on the vertical axis. The average change in mobility in retail, recreation and transit station in April (left panel) or the average Lockdown stringency index over the same period (right panel) is on the horizontal axis. The red diamonds represent states where IT adoption is above the median and the blue triangles represent states where IT adoption is below the median.

Figure 2: Mitigating Impact of IT across Individuals




The coefficient and the 90% confidence interval of $\beta_5$ and $\beta_6$ from Equation 3.

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




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.

Table 1: Unemployment, Mobility and IT (Individual-level)

| | Dependent variable: Unemployed | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Δ Mobility | -0.186*** | -0.246*** | 0.0614 | -0.553 | 0.774 | -1.264 | -0.690 |
| | (0.033) | (0.039) | (1.399) | (1.357) | (1.605) | (1.180) | (1.203) |
| IT | -0.00719 | -0.00683* | 0.00499 | | 0.0110 | -0.0101 | -0.00362 |
| | (0.005) | (0.004) | (0.007) | | (0.008) | (0.010) | (0.005) |
| Δ Mobility * IT | | 0.0710*** | 0.0752*** | | 0.0601** | 0.0982* | 0.0564** |
| | | (0.024) | (0.026) | | (0.027) | (0.052) | (0.024) |
| Δ Mobility * WFH | | | | 1.173** | 1.049* | | |
| | | | | (0.559) | (0.557) | | |
| R-squared | 0.00347 | 0.00418 | 0.0384 | 0.0384 | 0.0386 | 0.0383 | 0.0383 |
| N | 71812 | 71812 | 71812 | 71812 | 71812 | 71812 | 71812 |
| Controls | No | No | Yes | Yes | Yes | No | No |
| FEs | No | No | Yes | Yes | Yes | Yes | Yes |
| Specification | | | | | | High IT | PCs/Emp |

Results of estimating Equation 2