WP/20/208

IMF Working Paper

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

by Nicola Pierri and Yannick Timmer

INTERNATIONAL MONETARY FUND

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

Nicola Pierri [†] Yannick Timmer[‡]

Abstract

We study the economic effects 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 technology adoption can partly shield the economy from the impact of the pandemic. In areas where firms adopted more IT the unemployment rate rose less in response to social distancing. Our estimates imply that if the pandemic had hit the world 5 years ago, the resulting unemployment rate would have been 2 percentage points higher during April and May 2020 (16% vs. 14%), due to the lower availability of IT. Local IT adoption mitigates 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: G21, G14

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

[*]Most recent version: here. This paper was prepared as background material for the US Article IV 2020 and for the WEO October 2020 Chapter 2. We are grateful to Nigel Chalk, Damiano Sandri, Anke Weber, and presentation participants at the IMF for their insightful comments. The views expressed in the paper are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or its Management.

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

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

1 Introduction

As COVID-19 spread across the world and the United States, people have 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.

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 relies on several data sources, and in particular on survey data covering software and hardware purchases of almost three million establishments in different industries.

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

We show that IT adoption significantly shields workers from the economic consequences of the pandemic. Figure 1 illustrates the increase in the unemployment rate between February and April 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. This suggests that IT may significantly shield local economies during the COVID-19 pandemic. We confirm this suggestive evidence in individual-level regressions using within-state (MSA-level) variation in IT adoption and controlling for various other potential confounding factors.

We quantify the effect of IT adoption relative to a counterfactual scenario in which the pandemic had hit the world five years earlier. The digital economy as a share of employment grew by around 10% relative to five years ago.[1] Combining this number with our baseline estimates we find that the unemployment rate would have been around 2 percentage points higher during

[1] See subsection 5.3 for the details of the calculation.

April and May 2020 if IT adoption would have been at the level of 2015. Instead of an unemployment rate of 14% the unemployment rate would have reached 16%.

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

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

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

Most strikingly, we find a large difference in the way IT adoption shields individuals with heterogeneous levels of educational attainment. Individuals with high-and medium levels of education significantly benefit from IT adoption, while low-educated individuals (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].

We also investigate more broadly how the decline in mobility affected economic outcomes and COVID-19 infection rates in the US and how it links to lockdown measures. We show that mobility frontran the state-level lockdown tightenings and loosenings. Before lockdowns were implemented in states, mobility already declined strongly, suggesting that a large part of the mobility decline can be attributed to voluntary social distancing. On the reopening side, mobility already started to increase before states loosened restrictions. However, infection rates started to increase strongly after around 30 days of the lockdown loosening for the average state that reopened, but other states' infection rates remained almost unaffected after they reopened.

The decline in mobility is strongly correlated with the decline in consumer spending. This effect is mainly driven by high-income individuals and discretionary spending. High-income individuals spend more on sectors that are more affected by the lockdown, such as restaurants, bars, and travel. These individuals, therefore, cut their spending most when mobility falls. Low-income individuals' spending is more concentrated in essential goods, and thus less sensitive to mobility drops. Overall, besides spending on accommodation and food services, spending on health care and social assistance was highly sensitive to declines in mobility. This suggests that non-COVID related medical appointments decreased significantly due to the fear of contracting the virus. Over and above the economic consequences of the mobility drop, this can have negative long-term implications for non-COVID related health conditions.

The remainder of the paper is structured as follows. In section 2 we review the literature. In section 3 we describe the data. In section 4 we illustrate some descriptive patterns. In section 5 we show the main results. In section 6 we conclude.

2 Related Literature

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

Some authors have argued that voluntary social distancing has had a more important role than lockdowns [*Allcott et al.*, 2020; *Bartik et al.*, 2020; *Kahn et al.*, 2020; *Maloney and Taskin*, 2020] in disrupting economic activities. This literature notices that people's mobility and economic activity in the US contracted before lockdowns *Chetty et al.* [2020] and that lifting lockdowns led to a limited rebound in mobility [*Dave et al.*, 2020] and economic activity (*Cajner et al.* [2020] is an exception). *Goolsbee and Syverson* [2020] find small differences in people's visits to nearby retail establishments that faced different regulatory restrictions because located in different counties. Similar results are documented in *Chen et al.* [2020] that expand the analysis to Europe and find no robust evidence of the impact of lockdowns on several high-frequency indicators of economic activities. The importance of voluntary social distancing is also highlighted by the case of Sweden that—despite avoiding strict lockdown measures—has experienced similar (though a bit smaller) declines in mobility and economic activities with respect 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 to for the decline in mobility.

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

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

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

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

IT adoption has been considered an important skill-biased technological change [*Violante*, 2008]. While IT is often a complement for highly skilled workers, it can often substitute the work of less-skilled workers. In previous recessions, less-skilled workers have been also hard hit by economic conditions, which reinforced the trend of skill-biased technological change *Heathcote et al.* [2020].

3 Data Sources

We use the Current Population Survey (CPS) to assess the effect of the lockdown on the labor market. 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 use consumer spending data from *Chetty et al.* [2020]. They use aggregated and anonymized consumer purchase data collected by Affinity Solutions Inc, a company that aggregates consumer credit and debit card spending information to support a variety of financial service products. We use their data at the state level.

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

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

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

4 Descriptive Patterns

Figure 3 shows the lockdown intensity across states in the US at the beginning of April, May, June, and July. In April the US implemented strong lockdown policies, with some states having all of the 11 lockdown policies in place. These lockdown policies were already partially loosened in May and June, but even more so in July.

Figure 4 shows the inverse of the weighted average lockdown across states and the mobility to retail and transit stations on a daily level. Mobility across all states started declining in mid of April at the same time when lockdown policies were put in place.

Relative to the baseline period in January, mobility for retail and recreation has declined by 30 percent across the U.S. Since mid-April there has been a gradual increase in overall mobility, but also a large heterogeneity across states, with Washington D.C. at the lower end and Mississippi at the upper end of the mobility distribution. While the implementation of lockdown policies coincided with the decrease in mobility in mid-March and the gradual reopening went hand-in-hand with a slow increase in mobility, the time series is insufficient to disentangle whether de facto mobility responded to a de jure change in the lockdown.

The strong drop in mobility occurred heavily across all states, with mobility dropping by more than 60% relative to the pre-COVID baseline in the strongest responding states and by around 20% by the least responding states. Mobility remained at a similar level until mid-April when mobility started increasing at a gradual level. The gradual mobility increase seemed to have occurred already before the lockdown measures were lifted, but soon after mobility started increasing lockdown measures were also gradually lifted. The gradual recovery in mobility, in contrast to the sharp drop, did not occur consistently across states. Mobility in some states came back to pre-COVID levels as early as mid-May and are now at higher levels, e.g. South Dakota, while other (e.g. DC) had not seen a strong increase in mobility in July, despite many restrictions being lifted.

From the simple time-series graph, it is difficult to disentangle whether the lockdown policies were implemented before or after the mobility declined. Figure 5 plots the mobility of retail and transit places around a day when a lockdown in a given state was implemented. The lockdown implementation seems to have occurred after mobility already declined. This evidence suggests that voluntary social distancing, rather than the de jure implementation of the state-level lockdown may have led to the decline in mobility. Figure 6 repeats the exercise around a day when a lockdown in a given state has loosened. As seen in Figure 4 mobility already increased before de jure lockdowns were lifted.

Figure 7 plots the infection rate around the loosening of the state-level lockdown restrictions. While the infection rates remained relatively stable immediately after the lockdown measures were lifted, a spike in some states can be seen after around 40 days, while in other states infection rates remained at levels compared to before the reopening decision was implemented.

5 Results

5.1 Mobility and Economic Outcomes

As documented in section 4 visits to retail places and transit stations declined significantly in the middle of April when individuals socially distanced themselves. While this decline in mobility was not necessarily driven by the implementation of de jure lockdowns, such as closures of restaurants, the economic implications of the decline in mobility that seems to have been driven at least partly by voluntary social distancing may have impacted the economy through various channels. The decline in mobility to retail places or restaurants likely implies spending at these places has also declined.

To test this hypothesis we estimate the following cross-sectional regression:

$$\Delta Spending_s^k = \alpha + \beta_k \Delta Mobility_s + X'\gamma + \epsilon_s \tag{2}$$

where $\Delta Spending$ is defined as the percentage change in credit card spending by subgroup or in category k between April and the pre-COVID baseline in state s. $\Delta Mobility$ reflects the percentage change in mobility between April and the pre-COVID baseline in state s. The set of X are state-level controls, such as GDP per capita, the minority share, and population density. Figure 8 and Figure 9 display the β for each k. There is a strong positive correlation between the decline in mobility and the decline in spending at the aggregate level, but it masks significant heterogeneity across individuals and spending categories.

Figure 8 shows that the correlation between mobility and spending is stronger for high- and medium-income individuals than for low-income individuals. This can be explained by the relatively larger absolute amount of spending of high household incomes and their relatively higher disposition to spend on discretionary goods and services, which were more likely to be reduced during the pandemic. This is confirmed in Figure 9, where the different categories are plotted. Spending on health care and social assistance is most strongly correlated with mobility, indicating that individuals avoided physical medical appointments, potentially due to a higher perceived risk to interact with a COVID-19 infected person. The estimated elasticity of 0.4 implies that a 10 percentage points strong reduction in mobility was associated with a 5 percentage points stronger reduction in spending on health care and social assistance.

This strong correlation does not only point toward negative consequences for the economy but also suggests that individuals postponed necessary doctor's appointments with negative health consequences in the medium-run. The second most responsive category is spending on accommodation and food services, followed by general merchandise stores, transportation and warehousing, and entertainment and recreation. Spending on grocery and food stores has a negative elasticity with respect to mobility. This negative correlation suggests that individuals that socially distanced themselves by avoiding visiting restaurants and bars instead increased spending on groceries, either physically or online for delivery.

The large decline in spending in areas where mobility dropped more may have induced firms to reduce the number of workers, leading to a stronger increase in the unemployment rate where mobility declined more. To test this hypothesis we estimate the following regression:

$$\Delta UR_s^k = \alpha + \beta_k \Delta Mobility_s + X_s' \gamma + \epsilon_s \tag{3}$$

where UR_s^k is the difference in the unemployment rate in state s for each category k between April and February. Figure 10 shows the results across categories. Across all individuals, there is a strong negative correlation between mobility and the unemployment rate. A 10 percentage points stronger decline in mobility was on average associated with a 3 percentage points stronger increase in the unemployment rate. The effect is larger for low education individuals and non-whites. For low-education individuals, those without a high-school degree, in a state where mobility declined by 10 percentage points more, the unemployment rate increased by 7.5 percentage points more. For non-Whites, the elasticity is slightly smaller at around 0.6. In contrast, high-educated individuals only saw a very small significantly larger increase in unemployment rates in areas where mobility dropped more. This collection of results indicates that the drop in mobility caused by the COVID-19 pandemic widens inequality across races and individuals with different levels of educational attainment further.

5.2 Technology, Mobility, and Unemployment

In this section, we address the question of whether IT mitigates or worsens the problem of the drop in mobility on economic outcomes and inequality.

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

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

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

To test formally for the difference in the response of unemployment rate to the mobility decline across regions with different levels of IT adoption we estimate the following regression:

$$\Delta UR_s^k = \alpha + \beta_1 \Delta Mobility_s + \beta_2 IT_s + \beta_3 \Delta Mobility_s * IT_s + X_s'\sigma + (X_s * Mobility_s)'\gamma + \epsilon_s \quad (4)$$

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

Table 1 shows the results. However, first, we show a simplified version of Equation 4 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) 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) shows 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 in a different way. We then focus our attention to the coefficient of the interaction between IT adoption and mobility. If such coefficient were to decline substantially and losing its statistically significance, we would infer that the estimated impact of IT adoption as a mitigating factor is probably driven by spurious correlation. However, the coefficient on the interaction in column (4) remains almost identical. This suggests that these factors are not the drivers of the the mitigating impact of IT on the rise unemployment rate.

5.2. 1 Individual Level Data

In this section, we analyze individual-level data to test whether the results shown in the previous section are robust and shed more light on the heterogeneous impact of mobility and IT on the unemployment rate. As discussed in the previous section, other state-level characteristics can be correlated with IT adoption, which could drive the mitigating effect of IT on the unemployment rate in response to a decline in mobility.

Using individual-level data we can use more disaggregated data on mobility and IT adoption patterns. We use both the decline in mobility and the IT adoption on the MSA level to shed light on whether the patterns hold in a more disaggregated form. The more disaggregated data has the advantage that we can compare different cities within a state with each other, which are similar in various characteristics but not in terms of IT adoption and the decline in mobility. Moreover, in the cross-sectional regression estimated in Table 1 we only have 51 observations to identify different patterns between high-IT and low-IT states. Using more disaggregated data gives us more "power" to estimate the relationship.

We estimate the following linear probability model:

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

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

Table 2 shows the results based on pooled linear regression across individuals reporting their employment status in either April or/and May. Table 3 shows the results of the same equation using a probit model. However, the individuals are not necessarily reporting their employment status in both months, which is why we cannot include individual fixed effects in the regression equation.

This pattern in Figure 1 and Table 1 is confirmed using individual-level data from the Current Population Survey. Column (1) shows that a stronger decline in mobility in an MSA is associated on average with a larger probability of a person reporting to be unemployed. A higher level of IT adoption is associated with a lower probability of being unemployed in April and

May of 2020. Column (2) shows that the probability of being unemployed in April and May is higher for respondents living in MSA which experienced larger mobility declines, but IT adoption of companies mitigates this impact. The increase in the probability of being unemployed associated with a large drop in mobility (one standard deviation, equal to 10 pp) is 2.4 percentage points in a low-IT MSA. A one standard deviation larger level of IT adoption in an MSA reduces the increase in the probability by 0.7 percentage points to 1.7 percentage points. Column (3) shows the coefficient remains stable and statistically significant after controlling for the interaction of the mobility in the MSA and various MSA-level characteristics such as per capita income, the share of people with a three year Bachelor's degree, the share of minorities and the unemployment rate in February.

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

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

While the effect does hold within groups, this does not imply the effect is homogenous across these categories. To test for whether IT shields all genders, races or individuals with different education level in the same way we estimate the following equation:

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

where A_i and B_i are dummy variables for individual characteristics. In particular, we estimate Equation 6 for three different types. First, we estimate the regression equation for gender, where $A_i = 1$ is one if the individual is a male and $B_i = 1$ if the individual is a female and zero otherwise. Second, we estimate the equation for ethnicity where $A_i = 1$ if the individual is white and $B_i = 1$ if the person is non-white. Third, $A_i = 1$ if the individual has a high- or medium level of education (high school or more) and $B_i = 1$ if the individual has no high school degree. The remaining variables are defined as above, where the vector Z includes the various categories as dummies. Note that the coefficient on the triple interactions (β_5 and β_6) would not be both identified if we included the interaction between mobility and IT, as in Equation 5, as A and B are perfectly collinear. In that case, we could not identify whether the mitigating effect of IT holds across groups, but only whether the groups are significantly different from each other.

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

The coefficient β_5 and β_6 are also plotted in Figure 11. Interestingly, the effect is largest for females and non-white individuals. These are the individuals which are besides low educated most hit during 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 hardly hit, as shown in Figure 10 are not shielded by IT adoption.

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.

One potential reason why low educated individuals are not shielded by IT adoption is due to the 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 12 shows there is a high correlation between the share of jobs that can be done from home in an MSA and IT.

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

Table 5 shows the results. The results for WFH mirror those of IT. 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.

This 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, importantly teleworking does not seem to be the only channel through which IT has a mitigating effect. Other potential channels that could be at work are that companies are better able to switch to online sales or that more sophisticated IT systems facilitate contactless sales.

In Table 6 we conduct several robustness test, all of which confirm our main findings. Column (1) shows the baseline equation for comparison. In column (2) we replace our measure of IT adoption with the share of high-speed internet that is available in the MSA. The interaction is, as for our IT measure, positive and statistically significant, but only at the 10% level. In column (3) we replace our continuous measure of IT with a dummy that takes the value one if firms in the MSA are above-median IT adopters and zero if firms in the MSA are below median IT adopters. Again, the coefficient is positive and statistically significant. Column (4) replaces the IT measures, log IT budget per employee, with another measure that has been used commonly in the literature, also from the Harte Hanks dataset, namely the ratio of personal computers per employees.[2] Lastly, we substitute our left-hand-side variable, the dummy whether the person is unemployed with a broader measure of unemployment. Our baseline unemployment rate is the U-3 unemployment rate, which is the official one. It takes into account people who are jobless but actively seek employment. In column (5) instead, we use the U-6 unemployment rate definition that accounts for anyone who has been seeking employment for at least 12 months

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

but left discouraged without being able to secure a job. It also includes anyone who has gone back to school, become disabled, and people who are underemployed or working part-time hours.

5.3 Counterfactual

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

Our estimates allow, under certain assumptions (in particular, see *Nakamura and Steinsson* [2018] for a discussion of the caveats of extrapolating aggregate effects from cross-sectional regressions), to compute the counterfactual labor market consequence that would have occurred given a lower level of IT adoption.

To perform such an exercise, we re-estimate Equation 5 without normalizing the measure of IT adoption; non-normalized coefficients are expressed in terms of IT expenses per employee. *Bureau of Economic Analysis* [2019] reveals that *"since 2010, digital economy real gross output growth averaged 2.5 percent per year."*, while the growth rate of the labor force is about 0.5 percent per year.[3] Thus, we assume that IT adoption grows at 2 percentage points per year, and was, therefore, approximately 10% smaller 5 years ago. We also assume that the growth rate of IT is homogeneous across all MSAs.

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

[3]Expenses in information technology are the main but not the only component of the digital economy, as defined by the BEA. In fact, *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 the one of the more broadly defined "digital economy".

$$
\begin{aligned}
Unemployed_{i,t} = \alpha + \widehat{\beta_1}\Delta Mobility_{msa(i),t} + \widehat{\beta_2} * 0.9 * \widehat{IT_{msa(i)}} + \widehat{\beta_3}\Delta Mobility_{msa(i,t)} * 0.9 * \widehat{IT_{msa(i)}} \\
+ Z_i'\delta + X_{msa(i)}'\sigma + (X_{msa(i)} * Mobility_{msa(i),t})'\gamma + \alpha_{s(i)}
\end{aligned} \tag{7}
$$

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 observe in the data. The estimates from a linear model may overestimate the counterfactual impact of a large change in IT adoption if non-linearities are important. It is therefore reassuring that using a probit model (instead of a linear probability model) provides the same results. This finding illustrates the importance of investments in IT adoption to build an economy that is not only faster-growing but also more resilient to shocks.

6 Conclusion

In this paper, we show that technology adoption can act as an important mitigating factor when the economy is hit by a pandemic.

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

For obvious reasons, this analysis focuses only the short-term economic impact of the pandemic; several factors may play a role in the future. For instance, firms may substitute labor with technology in the medium- or long-run, thus increasing job losses. On the other hand, the production of information technology and related products may be an even more important engine of growth, increasing the advantages of IT-intense areas.

References

Akerman, A., I. Gaarder, and M. Mogstad, The skill complementarity of broadband internet, *The Quarterly Journal of Economics*, *130*(4), 1781–1824, 2015.

Allcott, H., L. Boxell, J. Conway, M. Gentzkow, M. Thaler, and D. Y. Yang, Polarization and public health: Partisan differences in social distancing during the coronavirus pandemic, *NBER Working Paper*, (w26946), 2020.

Alon, T., M. Doepke, J. Olmstead-Rumsey, M. Tertilt, et al., This time it's different: The role of women's employment in a pandemic recession, *Tech. rep.*, University of Bonn and University of Mannheim, Germany, 2020.

Alstadsæter, A., J. B. Bjørkheim, W. Kopczuk, and A. Økland, Norwegian and us policies alleviate business vulnerability due to the covid-19 shock equally well, *Unpublished Working Paper*, 2020.

Anderson, R. M., H. Heesterbeek, D. Klinkenberg, and T. D. Hollingsworth, How will country-based mitigation measures influence the course of the covid-19 epidemic?, *The Lancet*, *395*(10228), 931–934, 2020.

Autor, D. H., F. Levy, and R. J. Murnane, The skill content of recent technological change: An empirical exploration, *The Quarterly Journal of Economics*, *118*(4), 1279–1333, 2003.

Bartik, A. W., M. Bertrand, Z. B. Cullen, E. L. Glaeser, M. Luca, and C. T. Stanton, How are small businesses adjusting to covid-19? early evidence from a survey, *Tech. rep.*, National Bureau of Economic Research, 2020.

Beaudry, P., M. Doms, and E. Lewis, Should the personal computer be considered a technological revolution? evidence from us metropolitan areas, *Journal of Political Economy*, *118*(5), 988–1036, 2010.

Béland, L.-P., A. Brodeur, and T. Wright, The short-term economic consequences of covid-19: exposure to disease, remote work and government response, 2020.

Bessen, J. E., and C. Righi, Shocking technology: What happens when firms make large it investments?, *Boston Univ. School of Law, Law and Economics Research Paper*, (19-6), 2019.

Bloom, N., The bright future of working from home, *SIEPR blog*, 2020.

Bloom, N., and N. Pierri, Cloud computing is helping smaller, newer firms compete, *Harvard Business Review*, 2018.

Bloom, N., R. Sadun, and J. Van Reenen, Americans do it better: Us multinationals and the productivity miracle, *American Economic Review*, *102*(1), 167–201, 2012.

Borjas, G. J., and H. Cassidy, The adverse effect of the covid-19 labor market shock on immigrant employment, *Tech. rep.*, National Bureau of Economic Research, 2020.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt, Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence, *The Quarterly Journal of Economics*, *117*(1), 339–376, 2002.

Brodeur, A., D. M. Gray, A. Islam, and S. Bhuiyan, A literature review of the economics of covid-19, 2020.

Brynjolfsson, E., and L. M. Hitt, Computing productivity: Firm-level evidence, *Review of Economics and Statistics*, *85*(4), 793–808, 2003.

Brynjolfsson, E., J. J. Horton, A. Ozimek, D. Rock, G. Sharma, and H.-Y. TuYe, Covid-19 and remote work: An early look at us data, *Tech. rep.*, National Bureau of Economic Research, 2020.

Bureau of Economic Analysis, ., Measuring the digital economy: An update incorporating data from the 2018 comprehensive update of the industry economic accounts, 2019.

Cajner, T., L. D. Crane, R. A. Decker, J. Grigsby, A. Hamins-Puertolas, E. Hurst, C. Kurz, and A. Yildirmaz, The us labor market during the beginning of the pandemic recession, *Tech. rep.*, National Bureau of Economic Research, 2020.

Case, A., and A. Deaton, *Deaths of Despair and the Future of Capitalism*, Princeton University Press, 2020.

Chen, S., D. Igan, N. Pierri, and A. F. Presbitero, Tracking the economic impact of covid-19 and mitigation policies in europe and the united states, *Tech. rep.*, Working Paper, 2020.

Chernoff, A. W., and C. Warman, Covid-19 and implications for automation, *Tech. rep.*, National Bureau of Economic Research, 2020.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, et al., How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data, *Tech. rep.*, National Bureau of Economic Research, 2020.

Chiou, L., and C. Tucker, Social distancing, internet access and inequality, *Tech. rep.*, National Bureau of Economic Research, 2020.

Dave, D., A. I. Friedson, K. Matsuzawa, and J. J. Sabia, When do shelter-in-place orders fight covid-19 best? policy heterogeneity across states and adoption time, *Economic Inquiry*, 2020.

Del Boca, D., N. Oggero, P. Profeta, and M. Rossi, Women's work, housework and childcare, before and during covid-19, 2020.

Dingel, J. I., and B. Neiman, How many jobs can be done at home?, *Tech. rep.*, National Bureau of Economic Research, 2020.

Fairlie, R. W., K. Couch, and H. Xu, The impacts of covid-19 on minority unemployment: First evidence from april 2020 cps microdata, *Tech. rep.*, National Bureau of Economic Research, 2020.

Forman, C., A. Goldfarb, and S. Greenstein, The internet and local wages: A puzzle, *American Economic Review*, *102*(1), 556–75, 2012.

Goolsbee, A., and C. Syverson, Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020, *Tech. rep.*, National Bureau of Economic Research, 2020.

Gottlieb, C., J. Grobovšek, and M. Poschke, Working from home across countries, *Covid Economics*, *1*(8), 71–91, 2020.

Heathcote, J., F. Perri, G. L. Violante, et al., The rise of us earnings inequality: Does the cycle drive the trend?, *Tech. rep.*, Federal Reserve Bank of Minneapolis, 2020.

Kahn, L. B., F. Lange, and D. G. Wiczer, Labor demand in the time of covid-19: Evidence from vacancy postings and ui claims, *Tech. rep.*, National Bureau of Economic Research, 2020.

Kirby, T., Evidence mounts on the disproportionate effect of covid-19 on ethnic minorities, *The Lancet Respiratory Medicine*, *8*(6), 547–548, 2020.

Maloney, W., and T. Taskin, Determinants of social distancing and economic activity during covid-19: A global view, 2020.

McElheran, K., and C. Forman, Firm organization in the digital age: It use and vertical transactions in us manufacturing, *Available at SSRN 3396116*, 2019.

Mongey, S., and A. Weinberg, Characteristics of workers in low work-from-home and high personal-proximity occupations, *Becker Friedman Institute for Economic White Paper*, 2020.

Nakamura, E., and J. Steinsson, Identification in macroeconomics, *Journal of Economic Perspectives*, *32*(3), 59–86, 2018.

Palomino, J. C., J. G. Rodriguez, and R. Sebastian, Wage inequality and poverty effects of lockdown and social distancing in europe, *Available at SSRN 3615615*, 2020.

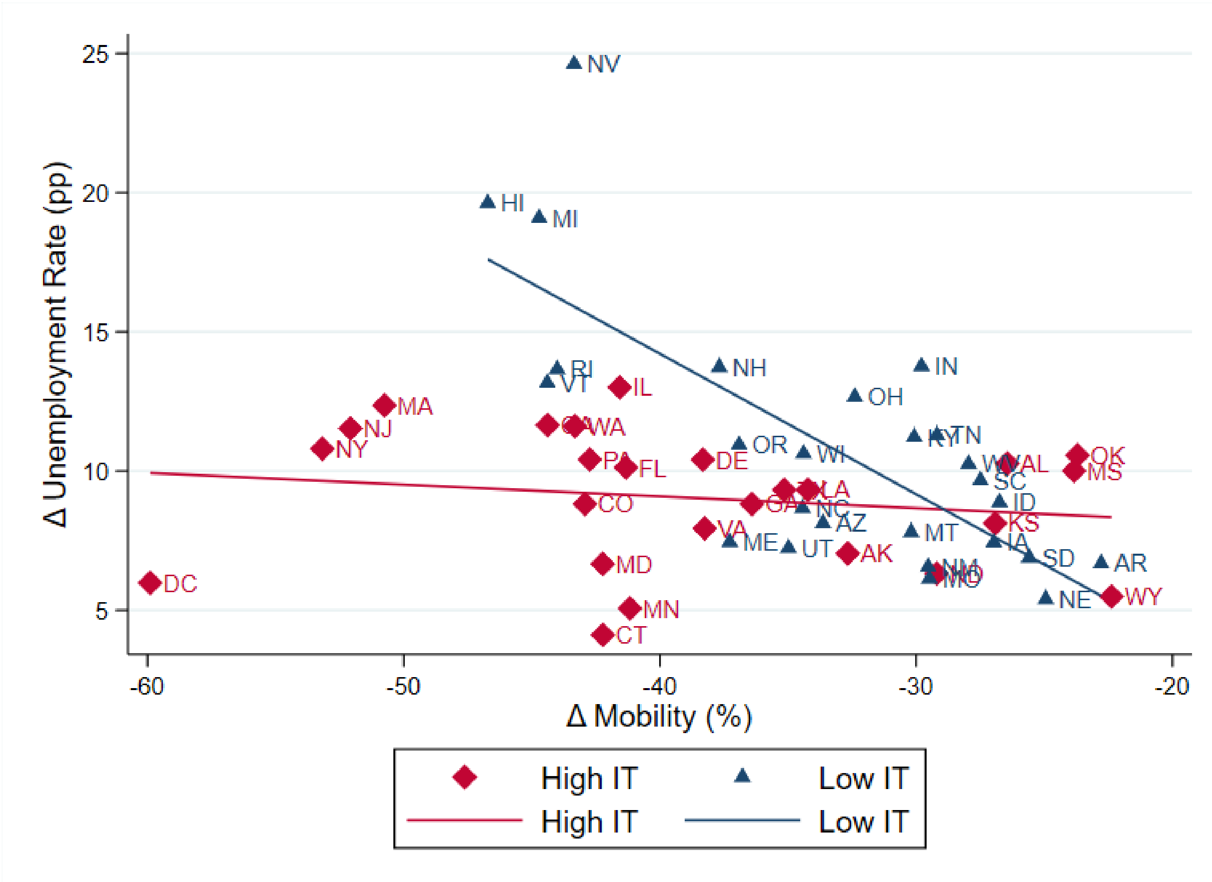
Papanikolaou, D., and L. D. Schmidt, Working remotely and the supply-side impact of covid-19, *Tech. rep.*, National Bureau of Economic Research, 2020.

Pierri, N., and Y. Timmer, Tech in fin before fintech: Blessing or curse for financial stability?, *Tech. rep.*, CESifo Group Munich, 2020.

Shibata, I., Unemployment in today's recession compared to the global financial crisis, 2020.

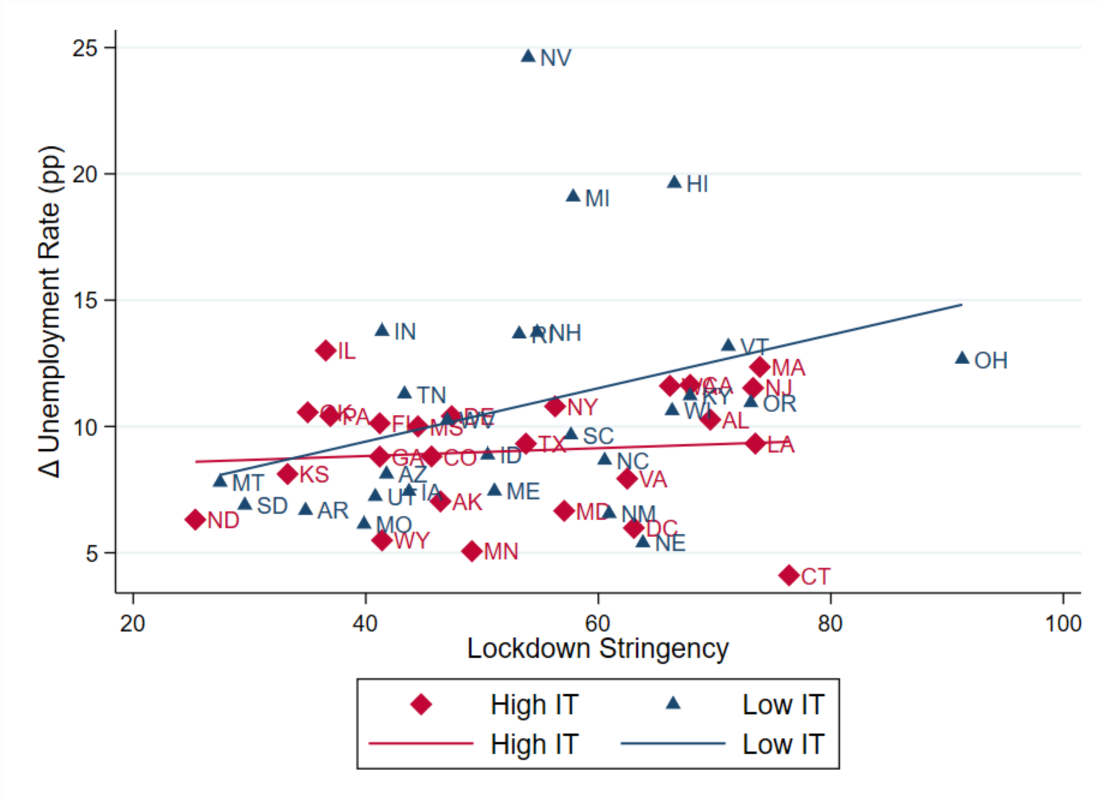
Violante, G. L., Skill-biased technical change, *The new Palgrave dictionary of economics*, *2*, 2008.

Figure 1: Unemployment and Mobility in the US



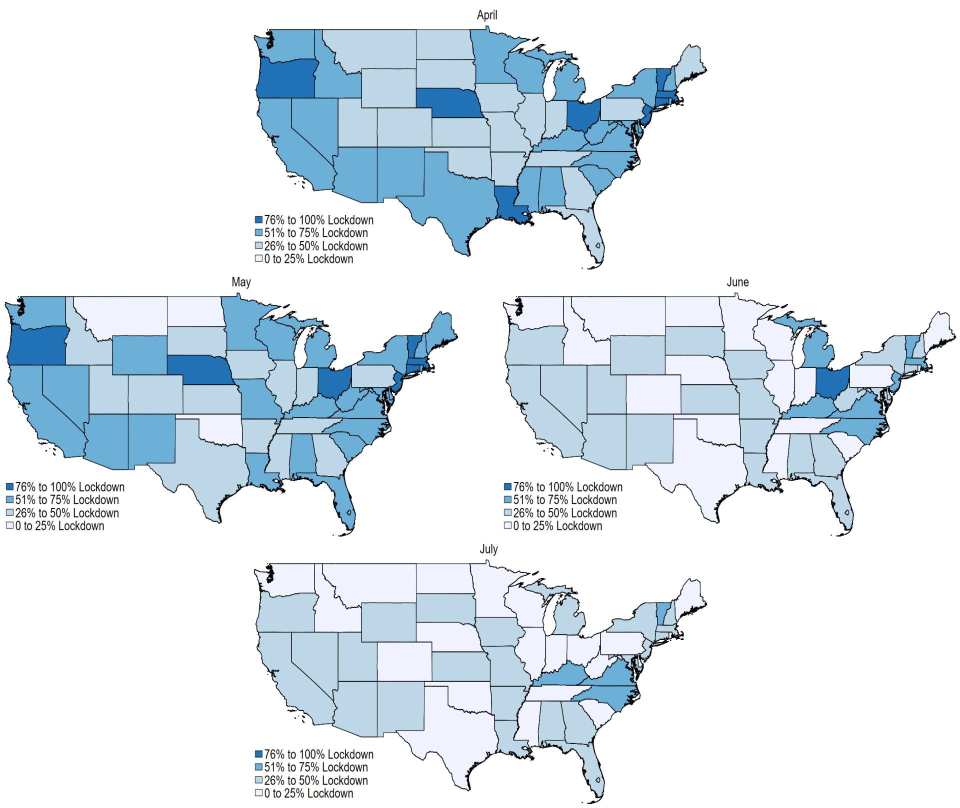
This figure plots the change in the unemployment rate between February and April by state on the average change in mobility in retail, recreation and transit station in April. The red diamonds represent states where IT adoption is above the median and the blue triangles represent states where IT adoption 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 subsection 5.2 for more details.

Figure 2: Unemployment and Lockdown Stringency in the US



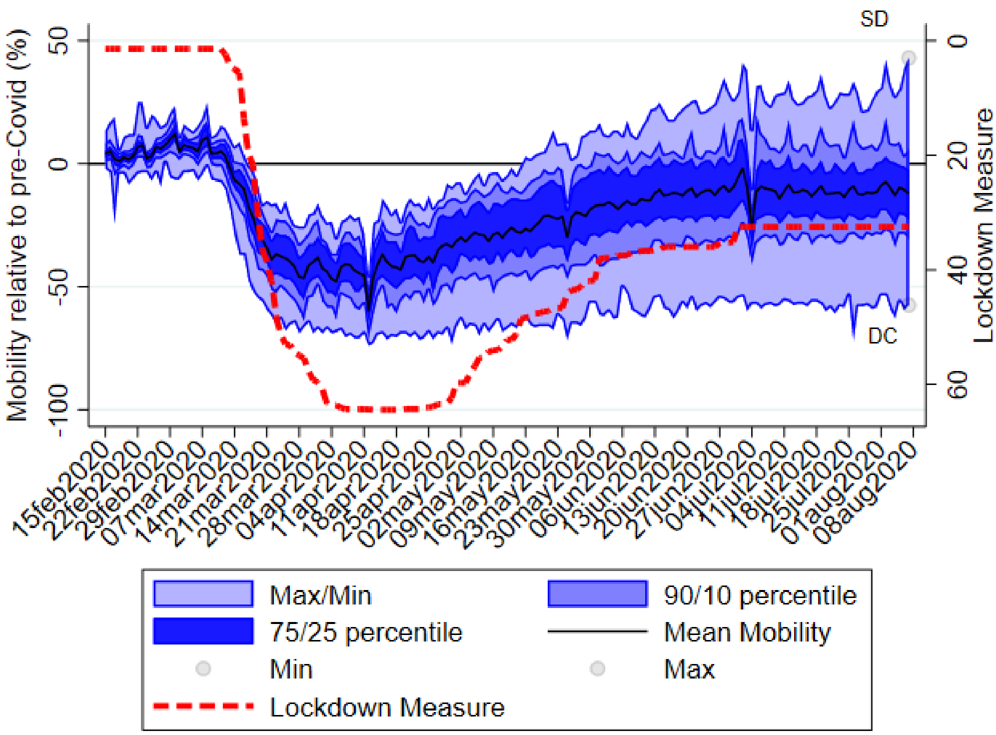
This figure plots the change in the unemployment rate between February and April by state on the average Lockdown stringency index (according to Keystone) over the same period. The red diamonds are states where IT adoption is above the median and the blue diamonds are states where IT adoption is below the median. The red line shows the linear fit for high-IT state and the blue line shows the linear fit for low IT states. See section 3 and subsection 5.2 for more details.

Figure 3: Lockdown across States



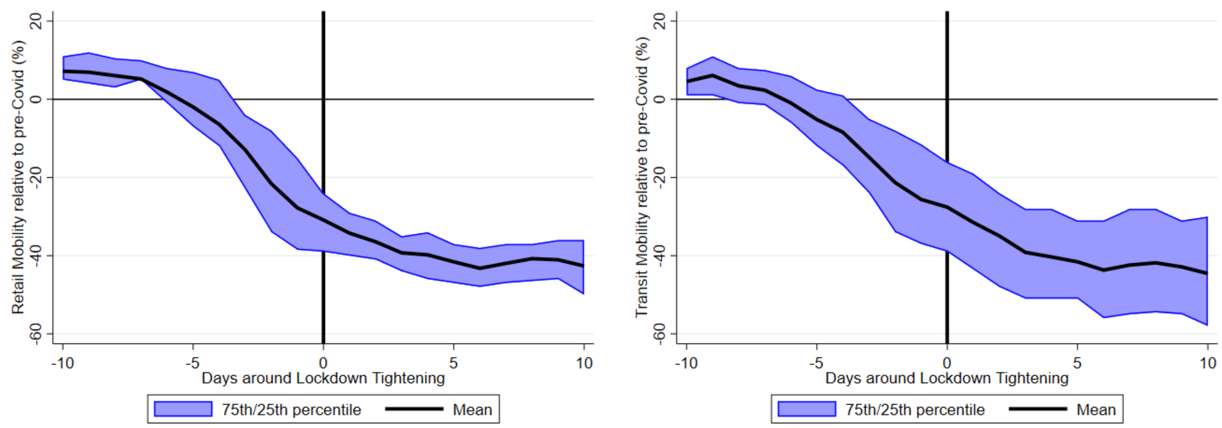
This figure plots the lockdown intensity by state in the beginning of April, May, June, July, respectively. Lockdown intensity is defined as the average across various NPI measures. See section 3 and section 4 for more details.

Figure 4: Mobility and Lockdown in the US



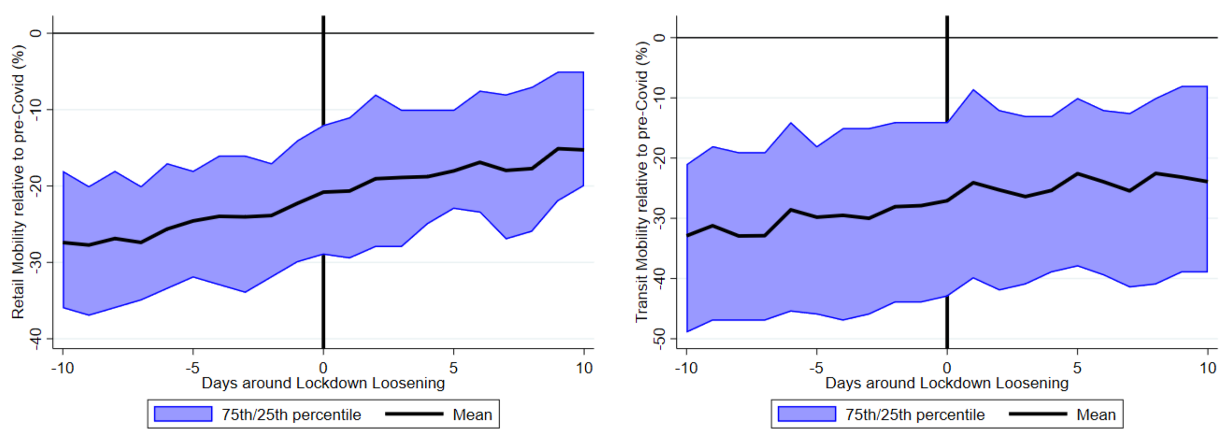
This figure plots the inverse of the weighted average lockdown intensity across states in red. The black line plots the average mobility across states. The dark/medium/bright shaded blue areas plot the 75th and 25th percentile/90th and 10th percentile and maximum and minimum in terms of the retail, recreation and transit mobility. The maximum and minimum states are labelled for the last available date. See section 3 and section 4 for more details.

Figure 5: Mobility around Lockdown Tightening



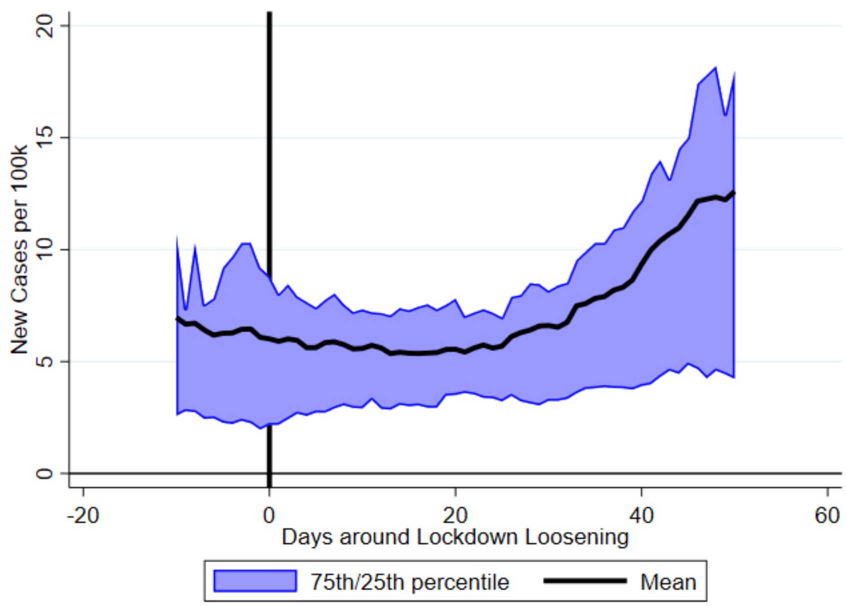
This figure plots the mobility for retail and recreation (left panel) and transit station (right panel) around when a state tightens its lockdown policy. The black line reflects the average state and the blue area reflects the states at the 75th and 25th percentile of the distribution. See section 3 and section 4 for more details.

Figure 6: Mobility around Lockdown Loosening



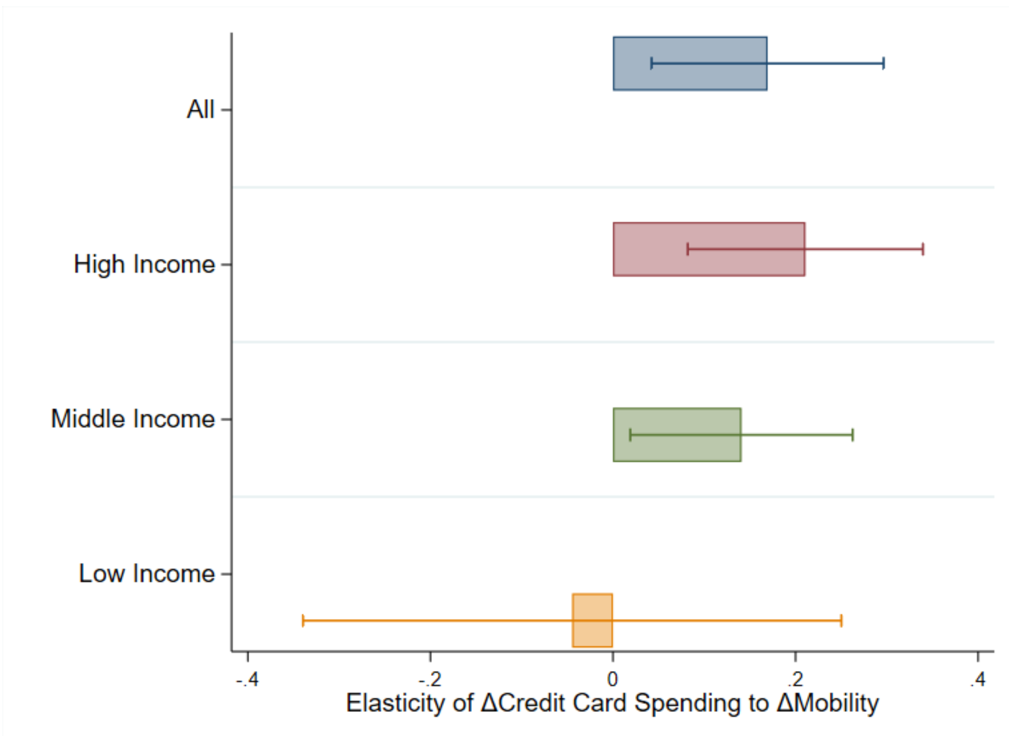
This figure plots the mobility for retail and recreation (left panel) and transit station (right panel) around when a state loosens its lockdown policy. The black line reflects the average state and the blue area reflects the states at the 75th and 25th percentile of the distribution. See section 3 and section 4 for more details.

Figure 7: Lockdown Loosening and New Cases



This figure plots the daily number of new infections per 100,000 people around when a state loosens its lockdown policy. The black line reflects the average state and the blue area reflects the states at the 75th and 25th percentile of the distribution. See section 3 and section 4 for more details.

Figure 8: Mobility and Credit Card Spending by Income

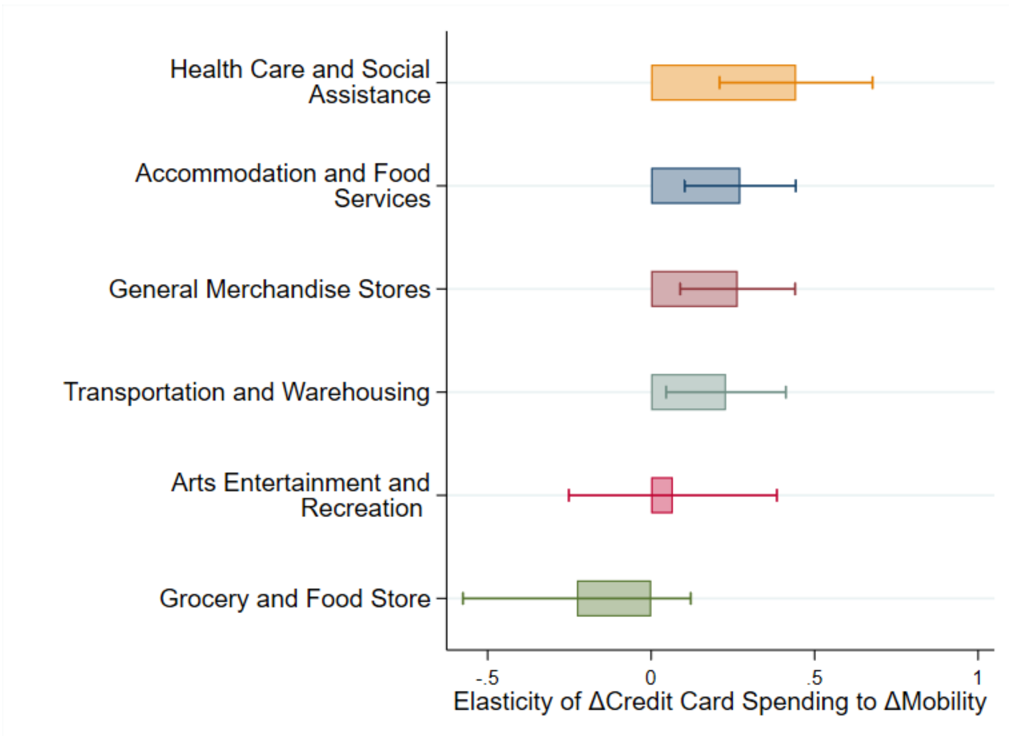


This figure plots the coefficient and the 90% confidence interval of β_k from Equation 2:

$$\Delta Spending_s^k = \alpha + \beta_k \Delta Mobility_s + X'\gamma + \epsilon_s$$

where $\Delta Spending_s^k$ is the percentage change in spending between April and the pre-COVID baseline in state s for income group k. $\Delta Mobility_s$ is the change in mobility in April 2020 relative to the pre-COVID baseline. X includes GDP per capita, population density and the minority share. See section 3 and subsection 5.1 for more details.

Figure 9: Mobility and Credit Card Spending by Category

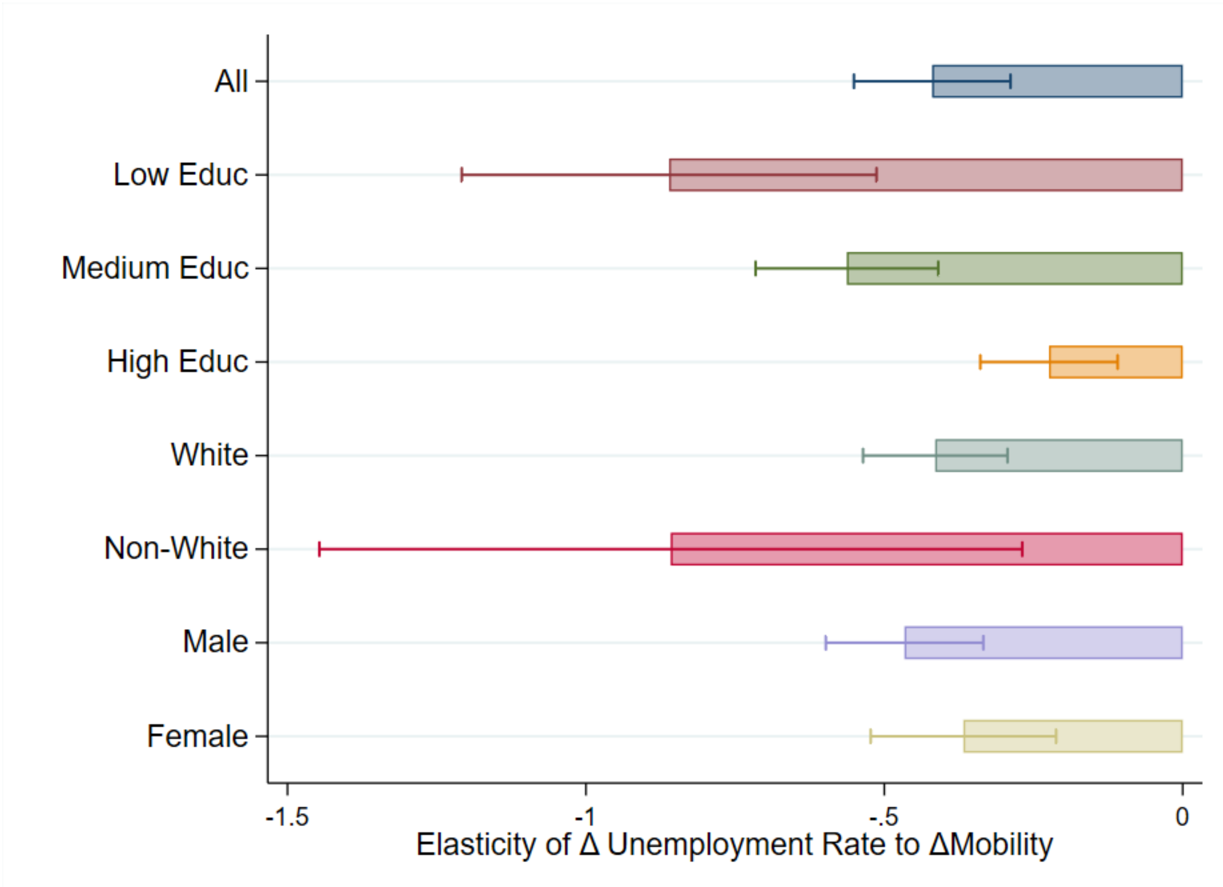


This figure plots the coefficient and the 90% confidence interval of β_k from Equation 2:

$$\Delta Spending_s^k = \alpha + \beta_k \Delta Mobility_s + X'\gamma + \epsilon_s$$

where $\Delta Spending_s^k$ is the percentage change in spending between April and the pre-COVID baseline in state s for spending category k. $\Delta Mobility_s$ is the change in mobility in April 2020 relative to the pre-COVID baseline. X includes GDP per capita, population density and the minority share. See section 3 and subsection 5.1 for more details.

Figure 10: Mobility and Unemployment Rates

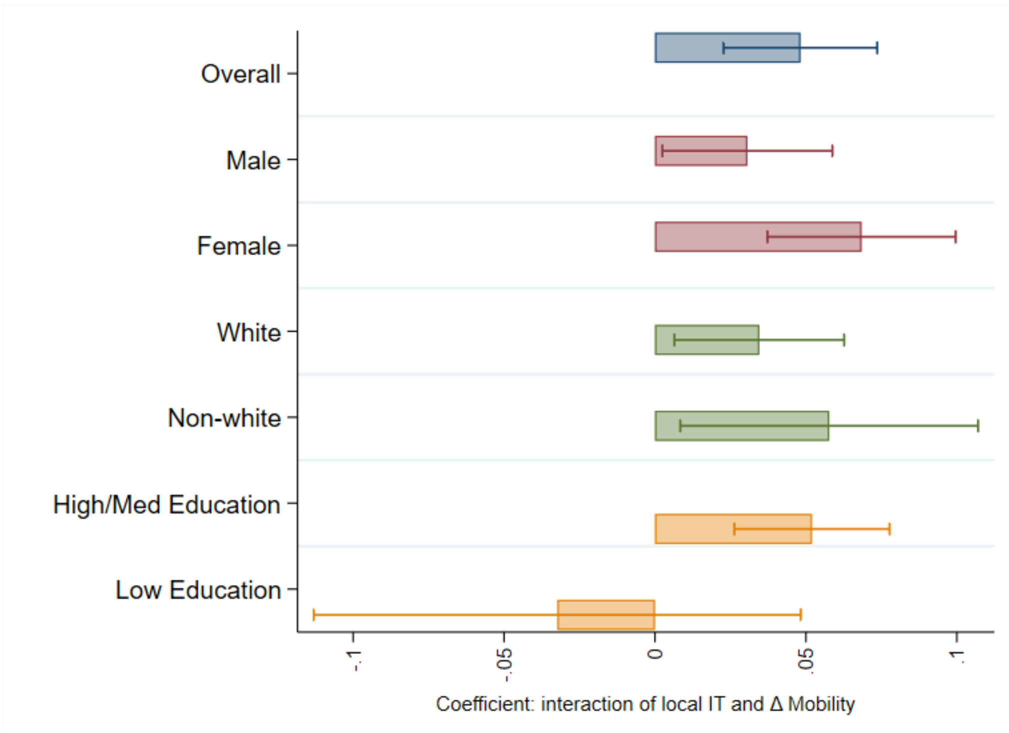


This figure plots the coefficient and the 90% confidence interval of β_k from Equation 4:

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

where ΔUR_s is the change in the unemployment rate between April and February in state s for category k. $\Delta Mobility_s$ is the change in mobility in April 2020 relative to the pre-COVID baseline. X includes GDP per capita, population density and the minority share. See section 3 and subsection 5.1 for more details.

Figure 11: Mitigating Impact of IT across Individuals

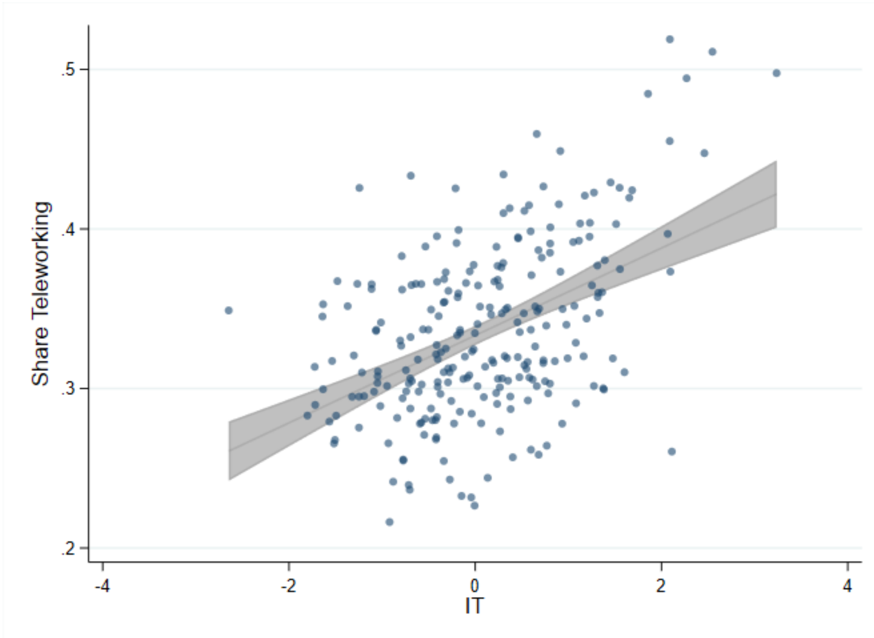


This figure plots the coefficient and the 90% confidence interval of β_5 and β_6 from Equation 6:

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

where $Unemployed_{i,t}$ is a dummy variable that takes the value one if the individual i is unemployment in month t (April/May 2020) and zero if the individual is employed. $\Delta Mobility_{msa(i),t}$ is the change in mobility in month t relative to the pre-COVID baseline. $IT_{msa(i)}$ is the average level of IT adoption in the MSA. A_i and B_i are dummy variables for gender, race, and education subgroups. X includes GDP per capita, population density and the minority share. See section 3 and subsubsection 5.2. 1 for more details.

Figure 12: 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 subsubsection 5.2. 1 for more details.

Table 1: Unemployment, Mobility and IT

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

Results of estimating Equation 4 :

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

where ΔUR_s is the change in the unemployment rate in state s between April and February in state s for category k. $\Delta Mobility_s$ is the average decline in mobility in state s in April. IT_s is a dummy that indicates whether a state is above the median in terms of IT adoption and zero if it is below the median. X includes the level and the interaction between mobility and GDP per capita, the population density and the manufacturing share of the state as control variables in the regressions. Robust standard errors are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsection 5.2 for more details.

Table 2: Unemployment, Mobility and IT

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

Results of estimating Equation 5:

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

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 subsubsection 5.2. 1 for more details.

Table 3: Probit: Unemployment, Mobility and IT

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

Results of estimating Equation 5 with Probit:

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

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives and $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. Z_i are individual level controls. $X_{msa(i)}$ are MSA level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsubsection 5.2. 1 for more details.

Table 4: Unemployment, Mobility and IT

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

Results of estimating Equation 6 :

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

where $Unemployed_{i,t}$ is a dummy variable that takes the value one if the individual i is unemployment in month t (April/May 2020) and zero if the individual is employed. $\Delta Mobility_{msa(i),t}$ is the change in mobility in month t relative to the pre-COVID baseline. $IT_{msa(i)}$ is the average level of IT adoption in the MSA. A_i and B_i are dummy variables for gender, race, and education subgroups. X includes GDP per capita, population density and the minority share. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsubsection 5.2. 1 for more details.

Table 5: Unemployment, Mobility, Teleworking abilities and IT

	Dependent variable: Unemployed		
	(1)	(2)	(3)
Δ Mobility	0.0236	-0.553	0.635
	(1.358)	(1.243)	(1.550)
IT	0.0292***		0.0305***
	(0.011)		(0.011)
Δ Mobility × IT	0.0677***		0.0539**
	(0.025)		(0.025)
Teleworking		0.237	0.164
		(0.190)	(0.185)
Δ Mobility × Teleworking		1.100**	1.002**
		(0.517)	(0.506)
R-squared	0.0384	0.0385	0.0387
N	71812	71812	71812
Controls	Yes	Yes	Yes
FEs	Yes	Yes	Yes

Results of estimating the following equation:

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

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. $\Delta Mobility_{msa(i),t}$ is the change in mobility in the MSA where the individual lives. $IT_{msa(i)}$ is the level of IT adoption in the MSA where individual i lives. $Teleworking_{msa(i)}$ is the share of jobs that can be done from home in the MSA where individual i lives, taken from *Dingel and Neiman* [2020]. Z_i are individual level controls. $X_{msa(i)}$ are MSA level controls. $\alpha_{s(i)}$ are state fixed effects. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsubsection 5.2. 1 for more details.

Table 6: Unemployment, Mobility and IT: Robustness

	Dependent variable: Unemployed				
	(1)	(2)	(3)	(4)	(5)
Δ Mobility	-0.151***	-0.397**	-0.176***	-0.150***	-0.269***
	(0.023)	(0.159)	(0.029)	(0.023)	(0.031)
IT	0.0186**	0.00136	0.0185	0.00836	0.00698
	(0.008)	(0.001)	(0.015)	(0.009)	(0.010)
Δ Mobility × IT	0.0488***	0.00391*	0.0880**	0.0388**	0.0457**
	(0.016)	(0.002)	(0.037)	(0.017)	(0.021)
R-squared	0.0202	0.0201	0.0202	0.0202	0.0246
N	71812	71812	71812	71812	71812
Controls	No	No	No	No	No
FEs	Yes	Yes	Yes	Yes	Yes
Specification	Baseline	High-Speed Internet	High IT	PCs/Emp	U6 Unemployment

Results of estimating the following equation:

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

where $Unemployed_{i,t}$ is a dummy that equals one if the individual is unemployed in month t, where t (April/May 2020) and zero otherwise. Column (1) is the baseline specification. Column (2) replaces our baseline IT measure with the share of people who have access to high-speed internet in the given MSA. Column (3) defines the IT variable as a dummy that equals one if the MSA has an above-median IT adoption and zero otherwise. Column (4) replaces the IT measure with a measure of the share of personal computers per employee. Column (5) classifies individuals as unemployed according to the U6 unemployment rate. Standard errors are clustered at the MSA level. The regressions are weighted by the assigned weight of the respondent. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. See section 3 and subsubsection 5.2. 1 for more details.