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Technology use, work adaptation and economic vulnerability during COVID-19

Authors:

1) Kasra Khademorezaian, 2) Georgia Kosmopoulou, 3) Shane Connelly, 4) Mark Fichtel, 5) Yash Gujar, 6) Heshan Sun

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Affiliation:

1) Department of Economics, University of Oklahoma, Norman, Oklahoma

2) Department of Economics, University of Oklahoma, Norman, Oklahoma; georgiak@ou.edu (corresponding author)

3) Department of Psychology, University of Oklahoma, Norman, Oklahoma

4) Department of Psychology, University of Oklahoma, Norman, Oklahoma

5) Department of Psychology, University of Oklahoma, Norman, Oklahoma

6) Division of Management Information Systems, University of Oklahoma, Norman, Oklahoma

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Abstract

We explore how technology use helped to cope with the stresses of social distancing during the pandemic contributing insights about the impact of work adaptation enabled by technology on economic vulnerability and resilience. Using a three-wave survey conducted across ten states in the US, we found evidence that a high level of technology use was linked to a greater chance of maintaining employment during the pandemic. We evaluate job retention as a function of an index based on the prevalence of information technology (IT) usage in the workplace and psychological and somatic well-being, controlling for technology use outside of the workplace, and socioeconomic and demographic characteristics.

1 Introduction

In response to the COVID-19 pandemic, most state and local governments imposed measures of social distancing, that increased the need for remote work. However, these measures varied widely across the US and had different impacts on businesses, as some occupations were better suited for remote work than others. As a result, many firms intensified their use of technology to enable their employees to work from home while others were unable to do so. The change in working arrangements led to a shift in the direction of innovation towards technologies that would enable remote work (Bloom et al. 2021).

The impact of new work arrangements and COVID-19 restrictions on individuals' psychological responses has varied across the population. As previously demonstrated by Duarte et al. (2007) an individual's psychological and physical well-being can greatly impact their employment prospects. However, although a decline in well-being due to the pandemic-related stresses may reduce the likelihood of employment, viewing the new parameters of the work environment as a perceived opportunity for advancement could have a beneficial effect on work performance.

In this paper, we aim to explore the role of both technology adaptation and physical and mental well-being, during the COVID-19 pandemic on employment status. IT adaptation can affect employment in two ways: first, it can stimulate higher levels of productivity and lead to higher wages,[1] and second, it can provide flexibility, enabling workers to work remotely during periods that require mobility control.

Our work connects to the recent literature on work from home arrangements during the COVID-19 pandemic, while incorporating factors that have been studied in isolation thus far. The literature on this topic has mainly used two approaches to identify the impact of technological adaptation and the potential for remote work access on employment: one that uses the characteristics of each occupation to identify the feasibility of working from home[2] and another that uses surveys to capture the characteristics of workers who work remotely.[3] Our study aims to contribute to this literature by constructing surveys to study the role of IT as a tool to help individuals maintain employment while controlling for the psychosomatic effects induced by prolonged isolation or perceived opportunities for advancement.

Focusing on IT use, Pierri & Timmer (2020) showed that IT can shield individuals (except those with low levels of education) from the COVID shock associated with mobility restrictions, and Papanikolaou & Schmidt (2022) showed that sectors in which a higher fraction of the workforce is not able to work remotely experienced significantly greater decline in employment during periods of limited mobility in the pandemic. Beland et al. (2020) found that pandemic restrictions are significantly less likely to affect the labor market outcome of workers that can easily work remotely. Considering gender effects, Vernengo & Nabar-Bhaduri (2020) find that women were more likely to be affected by demand and supply shocks,[4] while Alon et al. (2020) find that a higher percentage of men work in jobs with telecommuting capabilities.

Our research combines information on IT use, education, and demographic characteristics with the psychological and somatic effects of the pandemic to study labor market changes and the differential vulnerabilities created by the pandemic. We show that the probability of employment increases for individuals using IT more intensively in the workplace as opposed to using technology for gaming or social media surfing outside of work. Further, a decline in psychological and physical well-being decreases the probability of employment while perceiving COVID-19 as an opportunity has a positive impact on job retention. Demographic considerations reveal that minorities and female workers have a lower chance of being employed. Education has the most profound impact on the probability of employment. A graduate degree increases the probability of employment by 27.8% relative to having a high school degree or less while some college education increases the employment probability by 16.9%. Our analysis shows that the age group 36-49 has the highest probability of employment followed by the youngest group of 18-35, and the age group 50-64.

The remainder of the paper is organized as follows. Section 2 provides a description of the data and outlines the empirical estimation model. Section 3 presents the estimation results.

2 Data

The longitudinal sample for this study was collected in three waves from 10 U.S. states through Qualtrics, a commercial survey company that recruits participants and administers online surveys. Individuals were reached through a personalized recruitment email and received $6.22 in compensation for completing each 15-20 minute survey. Participants were recruited from ten states in the U.S. that reflected variations in population size and minority representation, as well as variations in COVID-19 policies. The states from which our sample was drawn are New York, California, Texas, Massachusetts, Michigan, Georgia, Tennessee, Kentucky, Oklahoma, and Nevada. The data collection effort took place from September 28, 2020, to February 8, 2021. The sample consisted of work-age individuals (ages 18-64) and was restricted to those who were employed or were actively seeking employment. Quality checks were performed to ensure the quality of participant responses, and respondents who failed these checks were excluded from the final sample. The questions in all three waves were identical except for the first survey which inquired about demographic information. Participants were asked about their employment status in all three waves.

The strategy employed for sampling participants from these 10 states involved recruiting an initial sample of 2,675 participants at time 1, with 500 drawn from each of the large population states (NY, TX, CA), 200 drawn from each of the medium population states (MA, MI, GA, TN) and 125 drawn from each of the small population states (KY, OK, NV). After excluding responses from participants over the age of 65, conducting quality checks, and selecting only those who were employed or were seeking employment at time

1, the total number of participants with usable survey responses was 1783. All of these participants were invited to complete the survey again at time 2, which began two weeks after the end of the first survey period. All participants at time 2 (N=644) were invited for a third survey two weeks after the completion of the second survey. A total of 324 participants completed the last survey. The age, gender, education, and minority status of participants across the three time periods are reported in Table 1.

In all three waves, participants were asked about their employment status. Approximately 56.31% of the participants who were recruited at time 1 reported being employed. The employed individuals selected the amount of time spent at work using email, digital video technologies (e.g. watching video based training), video conferencing (e.g. Zoom, WebEx), chat systems (e.g. Slack), and specific work related software (word processors, spreadsheets etc.). The unemployed individuals answered the same questions except for the question about specific work related software.

Survey subjects answered questions about how many hours they spent on technology outside of the workplace using the same scale as in the questions on work-related IT use. Individuals answered questions about how many hours they watched or listened to the news, searched online for information about COVID-19, how many hours they spent on gaming, social networking, performing traditional errands (e.g. banking, ordering groceries), and technology for exercise purposes (e.g. Video classes).

Psychological and somatic well-being were assessed using the Griep et al. (2016) scale. Participants first indicated the extent to which they experienced 9 different states, including over-exhaustion, fatigue, apathy, sleeplessness, irritability, and depression, over the course of the previous two weeks. Participants also reported how much they suffered during the same period from various somatic ailments (e.g., headache, stomach troubles, mild illness, dizziness, irregular heartbeat).

Finally, we used an adapted version of a 3-item scale developed by Bala & Venkatesh (2016) to assess the extent to which participants perceived that COVID-19 presented them with opportunities.[5] Descriptive statistics of key variables constructed from the survey are presented in Table 2 and details on sample demographic statistics are presented in Table 1.

3 Model

The main objective of this study is to analyze how the COVID-19 restrictions affected employment and to gain insight into the role of IT and well-being in enabling individuals to adapt to the changing circumstances of the pandemic. In this section, we estimate the likelihood of employment as a function of individual demographic and occupational characteristics, state level varying information, and measures of well-being. We used the following standard Probit model to analyze the data for each separate wave, w, for $w = 1, 2, 3$

$$Pr[Y_{i,w} = 1|X_{i,w}, Z_{i,w}, C_i, \zeta_m] = \Phi(\alpha + X'_{i,w}\beta + Z'_{i,w}\gamma + C'_i\xi + \zeta_m). \tag{1}$$

The dependent variable ($Y_{i,w}$) indicates employment status for individual i at survey wave w. $X_{i,w}$ consists of technology measures such as IT use in the workplace, and technology use outside of workplace in the COVID-19 era. $Z_{i,w}$ consist of well-being measures. C_i are demographic characteristics including an age group classification (consisting of the age groups 18-35, 36-49 and 50-64), sex, race (white and non-white), and education (high school and below, some college, and college level) and ζ_m are state fixed effects.

For the second and third waves, we estimated equation (2) below in addition to equation (1). Equation (2) uses the lagged technology, and well-being measures to account for past information, and short and long term choices affecting a person's well-being that may have contributed to the current employment status

$$Pr[Y_{i,w} = 1|X_{i,w-1}, Z_{i,w-1}, C_i, \zeta_m] = \Phi(\alpha^* + X'_{i,w-1}\beta^* + Z'_{i,w-1}\gamma^* + C'_i\xi^* + \zeta_m). \tag{2}$$

The advantage of using the lagged values is in avoiding potential endogeneity issues in the determination of employment as a function of well being measures. The trade off is in the reduced participation of subjects who filled out the survey across the different time periods.[6]

3.1 Unobserved Heterogeneity

The use of IT at work could be affected by unobservable factors that also impact employment status, raising issues of endogeneity. To alleviate this concern and show that our findings are not likely driven by omitted variable bias, we employ two methods that are based on developments in Altonji et al. (2005), refined in Oster (2019) (under the assumption of exogenous controls) and Diegert et al. (2022) (under the assumption of endogenous controls). The paper by Oster (2019) develops an estimation method based on the idea that the amount of selection on observables provides a guide to the selection on unobservables. Those estimates come in the form of breakdown points used to find the largest magnitude of selection on unobservables relative to observables needed to overturn a specific baseline finding of our original model. In Panel B of Table 5, we report estimates of the breakdown points (δs) along with our baseline estimates of the linear probability model corresponding to the marginal effects of the original model in equation (1). Oster (2019) suggests that when $|\delta| > 1$ the unobservables are less likely to explain the baseline results. A potential shortcoming of the Oster (2019) method is in the assumption that the controls are exogenous. Therefore, we augmented our analysis to include a newly developed method by Diegert et al. (2022) that relaxes the assumption of exogenous controls. Their proposed parameter ($\bar{r}_x$) allows us to test the hypothesis that the coefficient of IT use is different from the baseline results. In their case, if $\bar{r}_x$ is less than one, the selection on unobservables is smaller than the selection on observables, implying a limited scope for unobservables to explain observed data. Those results are reported in in Panel C of Table 5 the next section.

4 Results

Table 3 contains the results of our estimation of equation 1. The table is divided into five columns: (1) - (3) correspond to estimations limited to observations from the first, second, or third wave, and (4) and (5) are panel Probit estimations, with and without survey fixed effects. Our analysis indicates that a higher number of hours spent using IT at work, as measured by our index, increases the likelihood of employment while an increase in the amount of technology use outside of work reduces the probability of employment. These findings shed light on the complex interplay between technology use and employment outcomes. The probability of employment is negatively impacted by a decrease in psychological and somatic well-being. Conversely, perceiving COVID-19 as an opportunity increases the likelihood of employment. These results underscore the importance of both mental and physical health, as well as individual perceptions and attitudes, in shaping employment outcomes during the pandemic.

Table 3 provides further evidence that women and individuals from racial minorities face significant barriers to employment during the pandemic. Moreover, individuals between the ages of 50-64 are less likely to be employed than the reference group of 18-35 years old. Although the age group of 36-49 years old appears to have a higher probability of employment, the result is not statistically significant. These findings suggest that sex and age were important factors determining employment prospects during the pandemic, with the probability of employment decreasing markedly for those above the age of 50.

In our estimations, education has demonstrated the most significant impact on the probability of employment. Higher levels of education enhance the likelihood of employment, with individuals holding a college degree or some college education having a 16.9% (average partial effect) higher probability of employment relative to those having a high school diploma or less. The effect of a graduate degree is the largest (27.8% higher probability) suggesting that individuals who have received more formal education were more likely to be employed during the COVID-19 restrictions. We also considered the interactions between gender and education in addition to the interaction between gender and race but the effects were not statistically significant.

The estimation results controlling for lagged values of the variables are shown in Table 4. Columns (1) and (2) are Probit estimations restricting the data to the second and third waves and columns (3) and (4) are panel Probit estimations with and without survey fixed effects. The estimates in columns (1) and (2) in Table 4 are not significantly different to those in columns (2) and (3) in Table 3 suggesting that the effect of IT use (both in and outside the workplace) in the data collection period of the previous wave have almost the same positive effect as the IT use in the past two weeks based on the latest wave of data collection. Our analysis, however, indicates that well-being measures from earlier waves had a stronger impact on the probability of employment compared to current well-being measures. More precisely, a decline in well-being, as assessed in the last wave, had a more substantial effect on employment prospects than current well-being.

In Table 5, we present the results of our analysis to assess the potential for omitted variable bias. Panel A displays the linear probability estimation results needed to perform the tests of Oster (2019) and Diegert et al. (2022), with the coefficients corresponding to the partial marginal effects from Tables 3 and 4. Panel B reports estimates of the breakdown points used to find the largest magnitude of selection on unobservables relative to observables needed to overturn a specific baseline finding of our original model. To estimate a breakdown point, δ, we selected a comparison group of observed variables that included demographics and state fixed effects. Our estimated values of δ range from 1.8 to 2.5. To interpret these values, we first look at the comparison group, which explains around 20% of the variation in employment. The breakdown points imply that the selection on unobservables should be at least 1.8 to 2.5 times the selection on observables that explain 20% variation in employment. This suggests that unobservables have more limited scope in driving our findings. Panel C presents the estimated values of $\bar{r}_x$ from Diegert et al. (2022), which by design should be less than one for the selection on unobservables to be smaller than the selection on observables. Specifically, the estimate of $\bar{r}_x$ in our case ranges from 60.1 to 71.6, indicating that relaxing the assumption of exogenous observables in Oster, the selection on unobservables is at most 60.1%-70.6% as large as the selection on observables. In conclusion, both tests indicate that the impact of selection on unobservable factors is less significant than the impact of selection on observable factors.

5 Conclusion

In this paper, we explore the role of technology adaptation on job retention controlling for demographic characteristics of participants, psychological and somatic well-being, actions that help cope with stress as well as attitudes towards the pandemic. Our findings suggest that work adaptation associated with intensive IT use is a key factor to job retention during the period of data collection while demographic characteristics and attitudes towards the pandemic play a significant role in job market participation. Females, minorities, older participants, and those with a lower level of formal education were affected adversely the most. Those who perceived the pandemic as an opportunity for advancement fared well. The pandemic has created yet another rift in opportunities that could create setbacks and shifts in labor market participation for many years to come. Job adaptation to technology use and flexibility of work from home in turn will likely be a factor determining the willingness of workers to return to certain occupations.[7]

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Notes

1. The share of workers in IT intensive jobs is expanding across the last few decades and IT has a significant contribution to U.S. labor productivity growth (Gallipoli & Makridis 2018, Byrne et al. 2013).

2. Dingel & Neiman (2020) introduce a method to classify the feasibility of working at home for all occupations and merge this classification with occupational employment counts on O*NET. They find that 37% of jobs can be done from home and these jobs account for 46% of all US wages. Mongey et al. (2021) extend their method to incorporate the degree of physical proximity to others, that the job requires. Their results show that workers in jobs that cannot be done remotely are most likely to be affected by the pandemic restrictions. These workers are disproportionately less educated, have limited healthcare, have income within the low end of the distribution, and limited liquidity of assets.

3. Bick et al. (2020) report that 8.2 percent of their US survey respondents in February 2020 worked from home as opposed to 35 percent in May. Based on their sample, highly educated, high-income, and white survey participants were much more likely to shift to remote work and maintain employment following the virus outbreak. Using a two-wave survey in April and May 2020, Brynjolfsson et al. (2020) find that the age of people and the number of COVID cases are good predictors of a switch to remote work with younger individuals adopting more easily to new conditions.

4. Women reduced their hours more than twice as much as during the Great Recession, a change that could be signaling exit from the labor force, leading to a possible increase in the gender pay gap. This trend has intensified during the pandemic. See https://www.npr.org/2021/06/03/1002402802/there-are-complex-forces-keeping-women-from-coming-back-to-work

5. Items in this scale included "I am confident that COVID-19 is having positive consequences for me", "I feel that COVID-19 opens new avenues for success in my life or career", and "COVID-19 provides opportunities to improve my performance". Items were rated on a seven-point scale ranging from 1=Strongly Disagree to 7=Strongly Agree. We also constructed a mindfulness measure to capture the extent to which participants engaged in a variety of mindful activities. Example items included writing in a personal journal, engaging in physical exercise, practicing yoga, meditating, praying, and intentionally taking a break from the news. The estimates were not statistically significant and were omitted from the analysis. The results are available upon request.

6. To address the possible endogeneity issues with the well-being measures in our original specification, we

used an instrumental variable approach. We used as instruments three measures developed by Surgo Ventures (Sociodemographic Barriers, Resource constrained Health System, and Healthcare Accessibility Barriers). While these factors that represent long term systemic issues could have significant psychosomatic effects on participants during the pandemic they are unlikely to change the likelihood of employment in the short term. The results, however, were not different from the Probit model.

7. See https://www.grantthornton.com/library/press-releases/2021/october/gt-survey-employees-value-flexibility-over-salary-increases-one-third-looking-for-new-jobs.aspx

Table 1: Demographics by Sample Wave

	T1	T2	T3
Female	1004 (56.31%)	355 (55.12%)	190 (58.64%)
Employed	1115 (62.54%)	408 (63.35%)	213 (65.74%)
Minority	826 (46.33%)	335 (52.02%)	163 (50.31%)
Age:			
18-35	464 (26.02%)	101 (15.68%)	42 (12.96%)
36-49	628 (35.22%)	205 (31.83%)	93 (28.70%)
50-64	691 (38.75%)	338 (52.48%)	189 (58.33%)
Education:			
Highschool and below	615 (34.49%)	171 (26.55%)	80 (24.69%)
Some college	849 (47.62%)	326 (50.62%)	165 (50.93%)
Graduate degree	319 (17.89%)	144 (22.36%)	79 (24.38%)

Table 2: Summary Statics of Continuous Controls by Sample Wave

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
T1 (n=1,783)				
IT use (work)	2.120	0.917	1.0	5.0
Technology use (non work)	2.258	0.725	1.0	5.0
Well-being	1.470	0.465	1.0	3.0
Perceived opportunity	3.185	1.628	1.0	7.0
T2 (n=644)				
IT use (work)	1.990	0.835	1.0	5.0
Technology use (non work)	2.047	0.595	1.0	4.7
Well-being	1.343	0.388	1.0	2.8
Perceived opportunity	3.197	1.529	1.0	7.0
T3 (n=324)				
IT use (work)	2.008	0.849	1.0	5.0
Technology use (non work)	1.987	0.588	1.0	4.7
Well-being	1.327	0.374	1.0	2.8
Perceived opportunity	3.147	1.553	1.0	7.0

Table 3: Estimation Results

	Employment				
	(1)	(2)	(3)	(4)	(5)
IT use (work)	0.594***	0.705***	0.799***	2.836***	2.875***
	(0.050)	(0.084)	(0.129)	(0.251)	(0.256)
Technology use (non work)	-0.253***	-0.332***	-0.258	-0.756**	-0.762**
	(0.067)	(0.124)	(0.185)	(0.302)	(0.306)
Well-being	-0.222***	-0.233	-0.129	-0.999***	-1.043***
	(0.084)	(0.164)	(0.233)	(0.384)	(0.388)
Perceived opportunity	0.063***	0.071*	0.128**	0.210**	0.212**
	(0.023)	(0.041)	(0.059)	(0.090)	(0.091)
Female	-0.338***	-0.296**	-0.496***	-2.411***	-2.453***
	(0.071)	(0.118)	(0.173)	(0.419)	(0.426)
Age (36-49)	0.116	0.136	0.411	0.622	0.631
	(0.091)	(0.194)	(0.302)	(0.470)	(0.473)
Age (50-64)	-0.418***	-0.540***	-0.256	-2.774***	-2.785***
	(0.094)	(0.182)	(0.269)	(0.496)	(0.500)
Minority	-0.204***	-0.265**	-0.058	-1.193***	-1.218***
	(0.075)	(0.130)	(0.194)	(0.405)	(0.410)
Education (Some college)	0.520***	0.386***	0.071	3.712***	3.776***
	(0.074)	(0.133)	(0.197)	(0.420)	(0.422)
Education (Graduate degree)	0.913***	0.714***	0.260	6.260***	6.346***
	(0.115)	(0.178)	(0.261)	(0.829)	(0.865)
State Fixed Effects	Y	Y	Y	Y	Y
Survey Wave Fixed Effects	N	N	N	N	Y
Pseudo R^2	0.214	0.240	0.254	0.180	0.180
Number of observations	1783	644	324	2751	2751

Notes: Standard errors in parentheses; ***, ** and * denote statistical significance at, the 1%, 5% and 10% level respectively. The dependent variable, *Employment*, is equal to one if the individual is reported as currently employed and zero otherwise. Columns (1) to (3) present Probit estimates corresponding to the 3 survey waves. Columns (4) and (5) present panel random effect Probit estimates. All estimations included a constant.

Table 4: Estimation Results (w/ lagged variables)

	Employment			
	(1)	(2)	(3)	(4)
Lagged IT use (work)	0.705***	0.827***	2.738***	2.771***
	(0.091)	(0.126)	(0.438)	(0.427)
Lagged Technology use (non work)	-0.239*	-0.410**	-1.052*	-1.043*
	(0.126)	(0.191)	(0.588)	(0.605)
Lagged Well-being	-0.509***	-0.220	-2.764***	-2.785***
	(0.163)	(0.256)	(0.675)	(0.679)
Lagged Perceived opportunity	0.019	0.141**	0.167	0.177
	(0.039)	(0.064)	(0.172)	(0.180)
Female	-0.281**	-0.480***	-2.095***	-2.074***
	(0.119)	(0.176)	(0.637)	(0.630)
Age (36-49)	0.117	0.513	0.838	0.828
	(0.191)	(0.312)	(0.965)	(0.942)
Age (50-64)	-0.607***	-0.351	-3.769***	-3.787***
	(0.181)	(0.275)	(1.007)	(0.963)
Minority	-0.254**	-0.140	-1.072	-1.031
	(0.128)	(0.195)	(0.846)	(0.883)
Education (Some college)	0.405***	0.038	2.849***	2.740***
	(0.132)	(0.201)	(0.893)	(0.975)
Education (Graduate degree)	0.746***	0.386	5.389***	5.286***
	(0.178)	(0.260)	(1.073)	(1.207)
State Fixed Effects	Y	Y	Y	Y
Survey Wave Fixed Effects	N	N	N	Y
Pseudo R^2	0.231	0.270	0.176	0.176
Number of observations	644	324	968	968

Notes: Standard errors in parentheses; ***, ** and * denote statistical significance at the 1%, 5% and 10% level respectively. The dependent variable, *Employment*, is equal to one if the individual is reported as currently employed and zero otherwise. Columns (1) and (2) present Probit estimates corresponding to the first and second survey waves. Columns (3) and (4) present panel random effect Probit estimates. All estimations included a constant.

Table 5: Regression Sensitivity Analysis

	Employment			
	(1)	(2)	(3)	(4)
Panel A. Baseline Results				
IT use (work)	0.177***	0.213***	0.227***	0.190***
	(0.014)	(0.023)	(0.033)	(0.011)
Technology use (non work)	-0.074***	-0.113***	-0.093*	-0.086***
	(0.019)	(0.034)	(0.048)	(0.015)
Well-being	-0.075***	-0.083*	-0.059	-0.076***
	(0.024)	(0.047)	(0.066)	(0.020)
Perceived opportunity	0.017**	0.019	0.032*	0.019***
	(0.007)	(0.012)	(0.016)	(0.005)
Female	-0.106***	-0.087**	-0.148***	-0.105***
	(0.021)	(0.035)	(0.050)	(0.017)
Age (36-49)	0.021	0.016	0.052	0.025
	(0.026)	(0.053)	(0.080)	(0.023)
Age (50-64)	-0.138***	-0.176***	-0.103	-0.142***
	(0.028)	(0.052)	(0.076)	(0.023)
Minority	-0.052**	-0.055	0.011	-0.048***
	(0.022)	(0.037)	(0.054)	(0.018)
Education (Some college)	0.179***	0.125***	0.009	0.152***
	(0.023)	(0.041)	(0.061)	(0.019)
Education (Graduate degree)	0.261***	0.203***	0.047	0.226***
	(0.031)	(0.051)	(0.074)	(0.025)
State Fixed Effects	Y	Y	Y	Y
Survey Wave Fixed Effects	N	N	N	Y
R^2	0.247	0.275	0.276	0.251
Number of observations	1783	644	324	2751
Panel B. Sensitivity Analysis (Exogenous Controls)				
δ	2.5	2.5	1.8	2.4
Panel C. Sensitivity Analysis (Endogenous Controls)				
$\bar{r}_x$ ($\times 100$)	65.0	71.6	60.1	66.7

Note: Panel A. shows the baseline Linear Probability estimations. The dependent variable, *Employment*, is equal to one if the individual is reported as currently employed and zero otherwise. Columns (1) to (3) present estimates of the three survey waves and column (4) of the pooled regression. All regressions included a constant. Standard errors in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% level. Panel B presents the Oster (2019) tests for each specification with reference to the coefficient of *IT use (work)* in Panel A. Panel C presents the Diegert et al. (2022) tests for each specification with reference to the coefficient of *IT use (work)* in Panel A. The comparison group for Panels B and C contains gender, age groups, minority status, education, and state fixed-effects.

Appendix

Survey details

The longitudinal sample for this study was collected in 3 time periods through Qualtrics, a marketplace of suppliers that provides access to thousands of research participants who have agreed to be contacted for research studies.

Participants were recruited from ten states in the U.S. that reflected variations in geographic location, demographics, and employment.

Subject recruitment came from 3 states with large populations (19.5, 29.0, and 39.5 million), 4 states with medium-sized populations (6.8, 6.9, 10.0, and 10.6 million), and 3 states with small populations (3.1, 4.0, 4.5 million). In this selection process, we also sought variation in the level of statewide restrictions of COVID-19 policies including mask mandates, public school, and non-essential business closures, stay-at-home orders, and mass gathering restrictions as seen in the table A1.[1] Among other dimensions, those states varied in the Governor's political affiliation (half had a Republican as Governor and half had a Democrat as Governor).

The participants who indicated an interest in the study accessed the survey from a link that directed them to an informed consent page and the survey. Several data quality checks were performed to ensure the quality of participant responses, including attention checks (i.e., survey items that instructed respondents to provide a specific response), speeding checks, and internal consistency checks across two items. Respondents who failed any of these quality checks were excluded from the final sample.

Finally, our survey tested the impact of technology avoidance and the use of mindfulness

[1] The data on the number of confirmed COVID-19 cases in each state and employment comes from the Economic tracker (https://tracktherecovery.org/). We used the daily employment level for all workers in the state from three different sources. The Paychex (https://www.paychex.com/) data is the base for the series, and Earnin (https://www.earnin.com/) and Intuit (https://www.intuit.com/) helped to refine the series (Chetty et al. 2020). The daily number of COVID-19 infections for each state also has three sources. The Economic tracker used data from The New York Times, The Johns Hopkins Coronavirus Resource Center, and The Centers for Disease Control and Prevention (Chetty et al. 2020))

Table A1: Estimation results from the third wave

	Statistics			Policies				
State	Population	Female	Minorities	Days of State-wide Mask mandates	Public Schools related bills	Days of non-essential businesses closure	Days of Stay-at-home order	Days of Gathering restrictions
California	39.51	50.3%	63.5%	236	15	327	313	327
Georgia	10.62	51.4%	48.0%	0	1	24	28	84
Kentucky	4.47	50.7%	15.9%	214	6	320	47	320
Massachusetts	6.89	51.5%	28.9%	279	2	318	56	217
Michigan	9.99	50.7%	25.3%	289	6	319	71	333
Nevada	3.08	50.0%	51.8%	229	2	317	39	322
New York	19.45	51.4%	44.7%	300	12	318	68	324
Oklahoma	3.96	50.5%	35.0%	0	1	31	0	42
Tennessee	6.83	51.2%	26.3%	0	8	314	31	50
Texas	28.99	50.3%	58.8%	221	10	315	29	313

Note: Population is reported in millions. The percentage reported as minorities are the percentage of non-white in the state. The number of days for implemented policies is calculated for the duration of the survey (September 28 of 2020 to February 8, 2021).
Sources: US Census Bureau, Education Commission of States(https://www.ecs.org/), Economics Tracker (https://tracktherecovery.org/), and Ballotpedia (ballotpedia.org)

apps associated with a range of positive outcomes, including reduced stress, improved well-being, and better cognitive functioning. The estimated coefficients were not significant contrary to the literature that shows mindfulness being connected to many aspects of workplace functioning Glomb et al. (2011).[2]

[2] Results are available upon request.