INTERNATIONAL MONETARY FUND

Did the COVID-19 Recession Increase the Demand for Digital Occupations in the United States? Evidence from Employment and Vacancies Data

Jiaming Soh, Myrto Oikonomou, Carlo Pizzinelli,

Ippei Shibata, and Marina M. Tavares

WP/22/195

2022
SEP

WORKING PAPER

 WP/22/195

IMF Working Paper
Research Department

Did the COVID-19 Recession Increase the Demand for Digital Occupations in the United States? Evidence from Employment and Vacancies Data

Prepared by Jiaming Soh, Myrto Oikonomou, Carlo Pizzinelli, Ippei Shibata, and Marina M. Tavares

Authorized for distribution by Florence Jaumotte
September 2022

ABSTRACT: This paper investigates whether the COVID-19 recession led to an increase in demand for digital occupations in the United States. Using O*NET to capture the digital content of occupations, we find that regions that were hit harder by the COVID-19 recession experienced a larger increase in the share of digital occupations in both employment and newly-posted vacancies. This result is driven, however, by the smaller decline in demand for digital workers relative to non-digital ones, and not by an absolute increase in the demand for digital workers. While our evidence supports the view that digital workers, particularly those in urban areas and cognitive occupations, were more insulated during this recession, there is little indication of a persistent shift in the demand for digital occupations.

JEL Classification Numbers:	E24, J08, J22, J23, J24, J63
Keywords:	Digitalization, Labor Market, Employment, Vacancies, COVID-19
Author's E-Mail Address:	jiamings@umich.edu; moikonomou@imf.org; cpizzinelli@imf.org; ishibata@imf.org; mmendestavares@imf.org

* We thank Florence Jaumotte for invaluable comments and suggestions. A version of this paper was presented at the IMF's Jobs, Growth and Structural Reforms Seminar. We thank Romain Duval, Niels-Jakob Hansen and participants for useful suggestions and stimulating discussions. The views expressed in IMF Working Papers are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

Did the COVID-19 Recession Increase the Demand for Digital Occupations in the United States? Evidence from Employment and Vacancies Data

Jiaming Soh*
University of Michigan

Myrto Oikonomou
International Monetary Fund

Carlo Pizzinelli
International Monetary Fund

Ippei Shibata
International Monetary Fund

Marina M. Tavares
International Monetary Fund

September 22, 2022

Abstract

This paper investigates whether the COVID-19 recession led to an increase in demand for digital occupations in the United States. Using O*NET to capture the digital content of occupations, we find that regions that were hit harder by the COVID-19 recession experienced a larger increase in the share of digital occupations in both employment and newly-posted vacancies. This result is driven, however, by the smaller decline in demand for digital workers relative to non-digital ones, and not by an absolute increase in the demand for digital workers. While our evidence supports the view that digital workers, particularly those in urban areas and cognitive occupations, were more insulated during this recession, there is little indication of a persistent shift in the demand for digital occupations.

JEL Codes: E24, J08, J22, J23, J24, J63

Keywords: Digitalization, Labor Market, Employment, Vacancies, COVID-19

*Emails: jiamings@umich.edu; ishibata@imf.org.

We thank Florence Jaumotte for invaluable comments and suggestions. A version of this paper was presented at the IMF's Jobs, Growth and Structural Reforms Seminar. We thank Romain Duval, Niels-Jakob Hansen and participants for useful suggestions and stimulating discussions. The views expressed in IMF Working Papers are those of the authors and do not necessarily represent the views of the IMF, its Executive Board, or IMF management.

1 Introduction

COVID-19 has changed the way people live and work (e.g., Bloom et al. (2022); Forsythe et al. (2020); Hensvik et al. (2021)). The containment measures and voluntary social-distancing have shifted many activities from an in-person setting to online. From virtual work meetings to waiting staff in restaurants that place orders via smartphones and tablets, the interaction of workers with digital technology has been ever increasing. Such pandemic-induced shifts may have structurally increased the demand for skills that are needed to complement digital technologies. This paper sets out to evaluate the impact of the COVID-19 recession on the skills demanded in the labor market by investigating the following questions: i) did COVID-19 increase the demand for digital skills in the labor markets?; ii) if any, was the increase transitory or permanent?; iii) was the change in digital occupations broad-based, or concentrated in selected types of occupations or regions?

Central to our paper is how we define digital occupations. We follow Muro et al. (2017) and use O*NET measures on knowledge and work activity related to computers to calculate digital intensity scores for occupations in the US. We focus on digital skills instead of the teleworkability of occupations as in Dingel and Neiman (2022) because we aim to capture the underlying skills required to perform a job instead of looking at the nature of the job arrangement. Even though there is a significant overlap between digital skills and the teleworkability of a job, these do not map one-to-one.[1] Moreover, due to O*NET's data limitations, we construct the digital scores for each occupation in the US based on the latest pre-COVID-19 vintage of O*NET . Therefore, we capture the effect of COVID-19 on the *extensive* margin of digital employment and vacancies (i.e. changes in employment and vacancies given the pre-COVID19 digital scores for each occupation), rather than the *intensive* margin (i.e. within the same occupation, whether the digital scores have increased in the post-pandemic period).[2]

To address how the COVID-19 recession affected the demand for digital skills, we exploit the cross-sectional variation in the severity of the labor market contraction due to

[1]Indeed, using the 2019 Current Population Survey, we find that 70% of the digital occupations are teleworkable, while 30% of the digital occupations are non-teleworkable. Examples of the latter category include occupations such as Chemical Engineers, Avionics Technicians, Manufacturing Managers, Radio and TV Announcers.

[2]In O*NET, each year approximately 100 out of 900 occupations are updated on the information of occupational contents related to computers and technology. Moreover, for those 100 occupations with updated information on digital skills, it is not possible to isolate the upskilling that occurred during the pandemic period, as the previous update on these specific occupations occurred several years prior to COVID-19. However, we have conducted sensitivity analysis using digital scores based on the latest O*NET information (version 26.3 from May 2021) and our results remain robust.

the COVID-19 recession. To this aim, we construct a Bartik-type regional-level employment shock using the geographical variation in the economic exposure to COVID-19. We then investigate the changes in digital employment and vacancies as a function of this regional-level Bartik shock, while controlling for possible concurrent regional trends that may have affected the demand for digital employment and vacancies.

We find that regions that were hit harder by the COVID-19 recession experienced a larger increase in the share of digital employment and vacancies relative to regions that were less affected by the COVID-19 recession. This result holds even after controlling for a rich set of regional demographic characteristics and the pre-COVID-19 share of digital workers to account for the differential pre-pandemic trends between the hard-hit and the less-hit regions that may threaten the identification of the COVID-19 shock. The baseline results also hold when we employ alternative measures of the COVID-19 shock and alternative methods of classifying digital occupations. In addition, we find that the increase in the share of digital employment and vacancies in the harder-hit regions during the COVID-19 recession is not due to higher quit rates among the existing digital workers nor is it explained by the ability of digital workers to work from home.

These results raise the possibility of a structural shift in the demand for digital workers, particularly in harder-hit regions where their share increased disproportionately. This increase, however, was not permanent. By mid-2022, the difference in the share of digital employment and vacancies between the harder-hit and less-hit regions converged back to pre-pandemic levels. Therefore, our findings suggest that the COVID-19 recession has not generated a persistent shift in either the employment or the demand for more digital workers, contributing to the ongoing debate on whether COVID19 has induced large labor reallocation.[3]

We next disentangle whether the temporary increase in the *share* of digital employment and vacancies that we observe among the harder-hit regions was driven by an increase in the level of digital employment/vacancies in these regions in absolute terms or whether it was due to their relatively smaller decrease compared to non-digital employment/vacancies. We find evidence in favor of the latter: even though both types of occupations were negatively affected by the COVID-19 recession, digital occupations were shielded more from the shock relative to the non-digital occupations in the harder-hit regions.

[3]Our baseline result that COVID-19 did not induce a structural reallocation of labor is consistent with related literature (e.g., see Pizzinelli and Shibata (2020)).

Finally, to investigate whether our baseline results are driven by specific types of digital occupations, or by vacancies in specific regions, we zoom into the task intensity of digital occupations and we examine how our findings differ along geographic lines. Using data on vacancy postings, we find that the demand for digital occupations is relatively more shielded vis-a-vis non digital occupations in urban rather than rural areas. Additionally, we disaggregate total digital occupations into routine, cognitive, and manual occupations (following Autor et al. (2003)) and find that the labor demand for digital workers in cognitive occupations is more insulated from the COVID-19 shock than for digital workers in routine and manual occupations. This speaks to the importance of recognizing the heterogeneous impact of the COVID-19 recession not only across digital and non-digital occupations, but also within digital occupations.

The rest of the paper is organized as follows. Section 2 briefly discusses the related literature. Section 3 introduces the data for the regression analysis and discusses how we construct the occupation-specific digital scores. Section 4 summarizes the empirical strategy we use in this paper. Section 5 presents the baseline results. Section 6 discusses the results and our sensitivity analysis. Finally, section 7 concludes.

2 Literature Review

Our paper brings together three strands of macroeconomic literature. First, we contribute to the literature that studies the impact of recessions on the composition of labor markets. For instance, Jaimovich and Siu (2020) find that in the US past economic downturns greatly accelerated the process of job polarization, with approximately 88% of job losses in routine occupations occurring within a 12-month window of NBER recessions. This accelerated job polarization process during recessions, with routine occupations contracting and employment shifting towards non-routine manual and abstract ones, is one of the key drivers of the "jobless recoveries" that characterized previous US recessions. Focusing on the Great Recession and using data on US job vacancy postings, Hershbein and Kahn (2018) find that job postings in harder-hit metropolitan areas experienced a larger increase in their skill requirements, in line with an accelerated routine-biased technological change during recessions. The authors find that the "upskilling" occurred primarily *within* rather than *across* occupations, it was concentrated in routine-cognitive occupations, and persisted for several years following the Great Recession. Numerous papers examine the most recent downturn, the COVID-19 recession and its labor market impact.[4] We extend this literature

[4]See for instance Cajner et al. (2020); Crossley et al. (2021); Larrimore et al. (2022); Shibata (2021).

by focusing on digital skills, a dimension of workers' jobs that has been most salient given the changes in living and working conditions brought about by the pandemic.

Our paper also contributes to the growing literature that studies the evolution of labor markets during the COVID-19 recession. Barrero et al. (2021) argue that the COVID-19 shock resulted in a persistent reallocation in US labor markets, shifting relative employment growth towards industries with higher capacity for teleworkability. However, looking at job adverts, Adrjan et al. (2021) find that most of the increase in advertised ability to work remotely comes from a rise within industries that can accommodate telework rather than a permanent shift towards more teleworkable industires. Chernoff and Warman (2021) classify occupations based on their risk of automation and viral transmission and find that females with low- to mid-levels of education and wages are the demographic group with the highest risk of displacement. The paper that is most closely related to ours is Bellatin and Galassi (2022) which uses Canadian job vacancy postings data and finds that tighter containment measures during the pandemic resulted in a relatively smaller decline of openings for jobs broadly related to digital technologies. Focusing on the US, we also find that demand for digital occupations was more insulated during the COVID-19 crisis, but we do not find evidence that the relatively stronger demand for digital workers persisted through the recovery phase.

Finally, our work relates to literature that studies the shock-absorbing capacity of technological adoption. For instance, Pierri and Timmer (2020) use US establishment-level data on information technology (IT) adoption and find that areas with higher IT adoption by firms before the pandemic experienced a smaller increase of unemployment rate during the early stages of the pandemic.[5] They also find that IT adoption by firms had a cushioning effect for all workers apart from low-education individuals. Our analysis departs from theirs by focusing on the heterogeneity of the workers' occupations, besides investigating *both* the short-term and medium-term role of digitalization on employment and labor demand during the COVID-19 recession.

3 Data

3.1 Construction of Digital Occupations

This section describes how we construct the occupation-specific digital scores for US occupations using O*NET, a widely-used database which provides comprehensive informa-

[5]They focus on the period from February - April, 2020.

tion on the skills and characteristics of more than 900 occupation categories.[6] Importantly for our analysis, O*NET includes details on the digital content of each occupation. To classify occupations as "digital" or "non-digital", we utilize the following two pieces of information regarding the *knowledge* and the *work activity* related to computers and electronics:

- *"knowledge of computer and electronics"*, measuring the overall knowledge of computers and electronics required by a job (on a scale from 0 to 7)

- *"work activity–interacting with computers"*, quantifying the centrality of computers to the overall work activity of the occupation (on a scale from 1 to 5)

For any given occupation, O*NET scores each of these skills along two dimensions: i) their *importance* and ii) their *level*. Importance is a measure of how relevant it is to have skill X in an occupation, and level is a measure of how frequently skill X is used in an occupation.[7] We standardize the raw scores for each occupation so that resulting scores range from 0 to 100.[8] Finally, following Muro et al. (2017), we calculate the digital score for each occupation using the following formula:

$$\text{Digital Score} = \frac{\sqrt{K_L * K_I} + \sqrt{W_L * W_I}}{2} \tag{1}$$

where K_L is the standardized score of the knowledge-level, K_I of the knowledge-importance, W_L of the work activity-level, and W_I of the work activity-importance. The resulting digital scores range between 0 and 100.

To avoid potential endogeneity problems in our empirical strategy, we define digital occupations using the latest version of O*NET prior to COVID-19 (released on August 2019). This helps us address concerns that we may be over-selecting the digital occupations in our sample, thereby contaminating our empirical results, which could be the case if we were to use the post-COVID-19 version. However, we do test whether our baseline results hold when using the post-COVID-19 version of O*NET (released on May 2022) for the definition of the digital scores, and find that the results are robust to this alternative classification.[9]

[6] We use the SOC 2010 Occupation classification.

[7] For more information on the distinction between importance and level, see O*NET classification here.

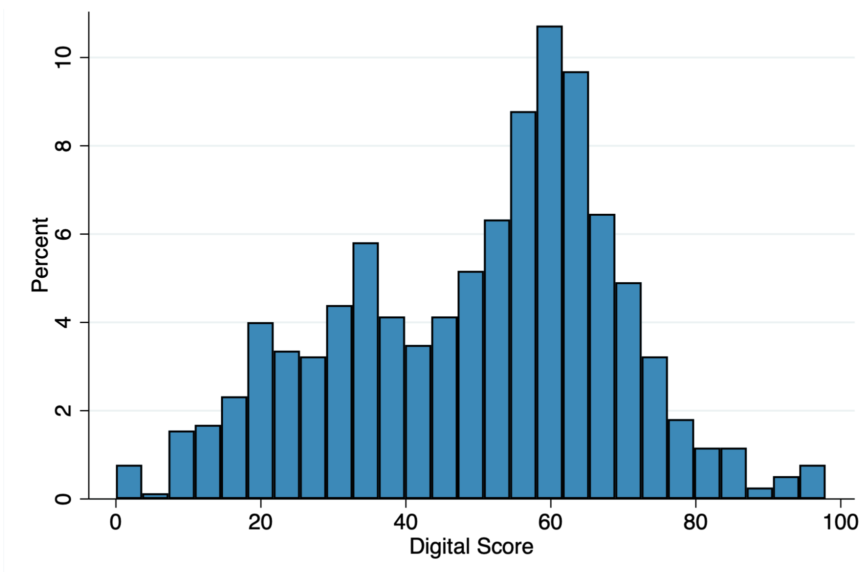
[8] We standardize following the O*NET's suggested formula: $S = ((O - L)/(H - L)) \times 100$, where O is the original rating score, and L and H are the lowest and higher raw scores across all occupations, respectively.

[9] O*NET updates the raw scores for a subset of occupations yearly. With regards to the scores on knowledge and activities related to computers, O*NET has currently updated 200 occupations out of roughly 900 occupations over the past two years. However, since occupations are updated sequentially, the previous update of these 200 occupations occured more than six years ago, making it impossible to detect whether upskilling took place during or prior to COVID-19.

Digital scores in Equation 1 are originally based on 8-digit O*NET occupation categories. These scores are then mapped to 6-digit SOC2010 codes by taking simple averages. We further map the digital scores from 6-digit SOC2010 to ISCO-08 4-digit occupation codes (unit-groups), to be consistent with the classification available for vacancy postings (from the Indeed dataset). Similarly, to identify digital workers using the employment data in the US Current Population Survey (CPS), we map the digital scores from 6-digit SOC2010 to the harmonized occupation codes (OCC2010) in the CPS.[10]

Figure 1 plots the distribution of digital scores across all SOC2010 occupation codes. The y-axis represents the percent of SOC2010 occupations with a given digital score. For our baseline specification, we define digital occupations as occupations with digital scores in the top 50th percentile (i.e., digital scores above 53).[11] We also perform robustness tests by classifying digital occupations using different percentile cutoffs (i.e. 75th percentile and 90th percentile as discussed in Section 6.3.2) and our results remain consistent regardless of the choice of cutoff used.

Figure 1: Distribution of Digital Scores



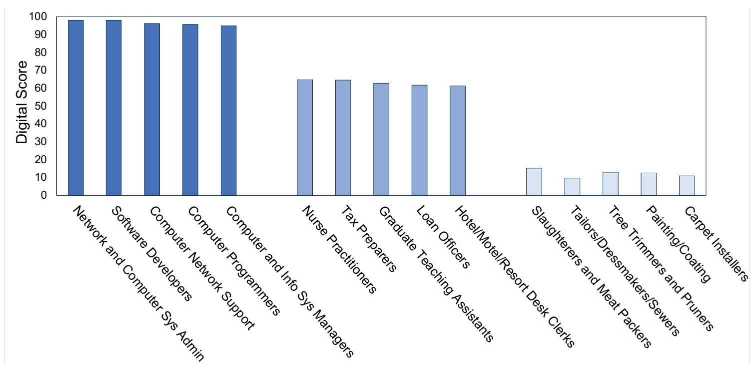
Notes: The figure plots the distribution of digital scores for all SOC2010 occupations. Y-axis indicates the % of US occupations that have the respective digital score from the x-axis. Occupation-specific digital scores are constructed using O*NET.
Source: O*NET and authors' calculations.

[10] OCC2010 is the harmonized occupation category that is consistent across all years

[11] Note that the 50th percentile is calculated based on raw occupation categories without employment weighting. Therefore, the share of digital employment or vacancies at the 50th percentile of the digital score distribution does not correspond exactly to 50% of the employed labor force.

To provide a general idea of how the scoring system characterizes occupations, Table 2 shows some selected examples of occupations with high digital scores (above 60), medium digital scores (between 33 and 60), and low digital scores (below 33) based on the SOC2010 classifications. Examples of US occupations with high digital scores include network and computer system administrators and other computer-related occupations. These are occupations with both high knowledge of and interactions with computers and electronics. Occupations with medium digital scores include nurse practitioners, tax preparers, and loan officers. Lastly, occupations with low digital scores include slaughterers and meat packers, carpet installers, and tailors. These are occupations with both low knowledge of and infrequent interactions with computers and electronics in their daily tasks.

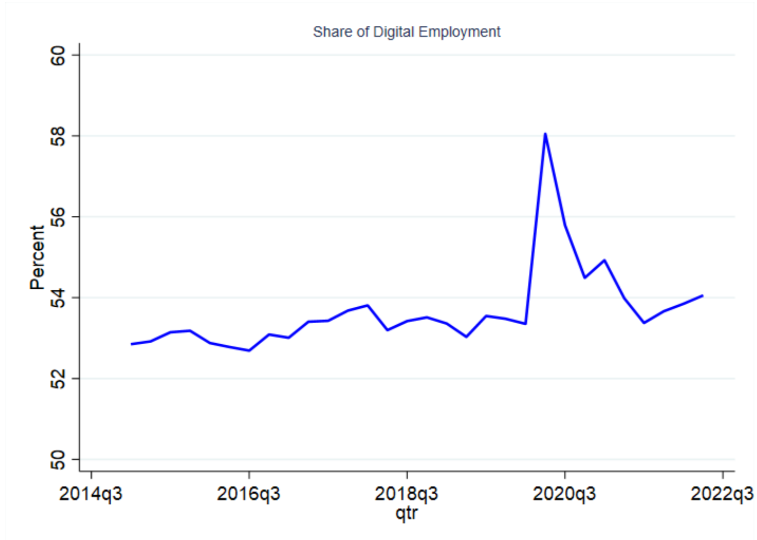
Table 2 Selected Examples of Occupations by Digital Score



Source: O*NET and authors' calculations.

Figure 2 plots the time series of the share of digital employment in the US between 2015Q1 and 2022Q2. On average, 53 percent of employed workers are working in digital occupations (based on the 50th percentile cut-off). During the COVID-19 period, there was a spike in the share of digital employment from around 53 percent to 58 percent. However, after the initial peak, the share of digital employment has declined and has seen a small uptick in 2022. Section 4 will present how we formally study whether COVID-19 shocks have induced an increase in the share of digital employment.

Figure 2: Share of Digital Employment



Source: CPS, O*NET and authors' calculations.

3.2 Data for Regression Analysis

For the dependent variables, we use two separate datasets. In the employment regression, we use the Current Population Survey (CPS), which is a monthly survey, representative of the US population. We use this dataset to compute the stock of digital and non-digital employment for US states between 2019Q1 and 2022Q2. In the vacancies regression, we use firms' vacancy postings collected by Indeed from 2019Q1 to 2022Q2.[12] The unit of analysis for the vacancy data is at the Core-Based Statistical Area (CBSA) level, with a sample size of 937 observations per month. Both the state-level employment from CPS and CBSA-level vacancies from Indeed are categorized according to the standard occupation classifications: SOC 2010 for the former and ISCO-08 for the latter. We then classify the employment and vacancies into digital and non-digital occupations based on the score that we constructed from O*NET and mapped to each of the respective standard occupation classifications, as described in Section 3.1.

For the independent variables, we use state-level employment data from the CPS and CBSA-level employment data from the Quarterly Workforce Indicators (QWI) to construct the Bartik-type shock in the employment and vacancy regressions respectively. Our identification strategy lies on the regional-level differences in the exposure to the COVID-19 recession, and particularly the differences between the hard-hit regions and the less-hit

[12] Indeed data on vacancies are only available from January 2019 onwards. To match the period of analysis in the vacancies data, we also restrict our employment data from 2019Q1 onwards.

regions.

To alleviate concerns over differential pre-pandemic trends between the hard-hit and the less-hit regions, we control for a wide range of pre-COVID-19 regional characteristics. We include demographic controls such as educational attainment (share of population with Bachelor's degree), age composition (share of population with age between 25 and 44), race composition (share of population reported White), and migration in-flow that may influence employment and vacancy postings in certain regions.[13] We also include GDP per capita in each region to control for the pre-COVID-19 income level.[14] To address concerns that the historically higher quit rates in some regions may drive the vacancy postings in these areas, we also control for the pre-COVID-19 state-level quit rates that we obtain from JOLTS.[15] These regional controls allow us to account for differences across states and CBSAs in their pre-existing tendency to hire digital workers which is independent of the COVID-19 recession.

4 Empirical Strategy

The empirical analysis aims to understand how the COVID-19 recession affected the demand for digital skills. Our empirical specification, which builds on Hershbein and Kahn (2018), exploits the cross-sectional geographical variation in the severity of the labor market contraction during the COVID-19 pandemic in order to capture the effect of the COVID-19 shock on the composition of employment and vacancies since 2020Q2. The baseline empirical framework in our paper is the following:

$$\mathrm{Y}_{m,q,t} - \mathrm{Y}_{m,q,2019} = \alpha_0 + \boldsymbol{\alpha_1}\left[shock_m * \boldsymbol{I_t}\right] + \alpha_2 shock_m + \boldsymbol{\alpha_3} I_t + \boldsymbol{\beta}' controls_{m,q,t} + \varepsilon_{m,q,t}. \tag{2}$$

where Y refers to the share of digital employment (vacancies), m refers to state (CBSA), q refers to quarter, and t to year. We separately run the regressions for employment at the state level and vacancies at the CBSA level. [16] The term $\mathrm{Y}_{m,q,t} - \mathrm{Y}_{m,q,2019}$ is the change in the share of digital employment or vacancies in region m at quarter q, year t relative to the same quarter q in the year 2019. We choose 2019 as the pre-COVID-19 base year because this is the earliest available year for the US vacancies data in Indeed. Taking the difference of the same quarter relative to 2019 addresses the potential seasonality in employment and vacancies data. The quarter q and year t includes each post-recession period from 2020Q2

[13]The demographic controls are obtained from the American Community Survey, and we averaged values from the year 2017 and 2018 which we define to be the pre-COVID-19 years.

[14]We obtain the average values of 2017 and 2018 from the Bureau of Economic Analysis.

[15]Similarly, we average the values from the year 2017 and 2018.

[16]In our data, we have 937 CBSAs.

to 2022Q1.

The key independent variable of interest is the COVID-19 shock measure for each region m ($shock_m$). This is a Bartik-type measure of the local employment shock due to the COVID-19 recession, which is described in greater detail further below. $\boldsymbol{I_t}$ represents the vector of quarter-year dummies from 2020Q2 to 2022Q1. Our coefficient of interest is the vector $\boldsymbol{\alpha_1}$ which captures the impact of the local employment shock due to the COVID-19 recession on the cumulative change in the share of digital employment/vacancies between 2020Q2-2022Q1. The vector $controls_{m,q,t}$ includes pre-COVID-19 demographics controls in each region m to account for differential pre-pandemic trends between the hard-hit and the less-hit regions. These are trends that may threaten the identification of the COVID-19 shock if the change in the share of digital employment/vacancies is more prevalent in regions with, for example, higher population density, education level, or other demographic characteristics.[17]. The term $\varepsilon_{m,q,t}$ is the idiosyncratic error term for each region m at quarter q and year t.

Following Hershbein and Kahn (2018), we define $shock_m$ as the change in the projected employment growth between the peak in 2019Q2 and the trough in 2020Q2. Specifically, we construct the plausibly exogenous COVID-19 $shock_m$ as follows:

$$\Delta \hat{E}_{m,2020Q2} = \sum_{j=1}^{J} \phi_{m,j,2017-2018} \left(\ln E^{US}_{j,2020Q2} - \ln E^{US}_{j,2019Q2} \right) \tag{3}$$

$$\Delta \hat{E}_{m,2019Q2} = \sum_{j=1}^{J} \phi_{m,j,2017-2018} \left(\ln E^{US}_{j,2019Q2} - \ln E^{US}_{j,2018Q2} \right) \tag{4}$$

$$shock_m = \Delta \hat{E}_{m2020Q2} - \Delta \hat{E}_{m2019Q2} \tag{5}$$

where the subscript j stands for the 2-digit NAICS industries in the US; $\ln E^{US}_{j,2019Q2} - \ln E^{US}_{j,2018Q2}$ is the national annual employment growth rate for industry j in 2019Q2, and $\phi_{m,j,2017-2018}$ is the average employment share of industry j in the state (CBSA) m over 2017-2018.[18] Note that the variable $shock_m$ is fixed at each regional level for our entire

[17]Specifically, we include demographic characteristics in each region prior to the COVID-19 recession to account for the differential pre-trends that may drive the share of digital employment. These characteristics include the share of the population with i) a Bachelor's degree; ii) that between 25-44 years of age and iii) that is reported White. We also control for iv) the real GDP per capita as a proxy for income in each region; v) the log migration in-flow to control for potential migration movements driving the changes in the vacancies posted in a region, and vi) log population size. In addition, to alleviate concerns that some regions may post more vacancies due to a historically higher quit rate in these areas, we also control for the pre-COVID-19 quit rate in each region.

[18]For the employment regression, we construct the national growth rate of employment in industry j and

sample period. It captures the projected contraction growth from peak to trough during the COVID-19 recession. This shift-share approach is commonly used in empirical studies since it was first proposed by Bartik (1991). The benefit of using the Bartik-projected employment growth instead of the actual employment growth is that the Bartik measure is arguably less influenced by factors unrelated to COVID-19 (e.g., regional idiosyncratic shocks or changes in labor supply) that may also cause changes to the share of digital employment and vacancies during the pandemic period.

In addition, the reason for using the Bartik-projected employment growth instead of Bartik-projected employment level is that the former, being a flow, better captures the sudden shift in employment conditions during the pandemic period, whereas the employment stock may respond with significant lags to sudden changes in labor market conditions.[19] For ease of interpreting the coefficients $\boldsymbol{\alpha_1}$, following Hershbein and Kahn (2018), we normalize the variable $shock_m$ with the difference between the 10$^{\text{th}}$ and 90$^{\text{th}}$ percentiles of the Bartik shock's distribution across regions (i.e., state for the employment, CBSA for vacancies regressions). Hence, a larger value of $shock_m$ corresponds to a harder hit state or CBSA, and a one-unit positive change is equivalent to the difference between the 10$^{\text{th}}$ and the 90$^{\text{th}}$ percentiles.

Finally, we control for the time fixed effects by including a series of quarter-year dummies $\boldsymbol{I_t}$ from 2020Q2 to 2022Q1. The time fixed effects control for the national-level shock, so that $\boldsymbol{\alpha_1}$ is driven entirely by the relative difference between the harder hit regions and the less hit regions at any point in time during the COVID-19 pandemic periods. Finally, we cluster standard errors at the regional level to account for potential serial correlation within a region. Each cell is weighted using the regions' pre-COVID-19 share of national employment, computed as its average value over 2017-2018, so that regions with a larger employed population are given greater weight in the regression relative to regions with a smaller employed population.

the average employment share $\phi_{m,j,2017-2018}$ using the state-level data from the Current Population Survey. For the vacancies regression, the data source for the same measures at the CBSA level is calculated using the Quarterly Workforce Indicators.

[19] In the robustness section, we also re-run our results using the Google mobility measure as an alternative measure of the COVID-19 shock. Our results remain broadly consistent regardless of the choice of COVID-19 shock we use.

5 Results

This section presents our baseline results. First, we show that the composition of employment shifts toward digital occupations at the onset of the COVID-19 recession. This is true for vacancies as well. Second, we find that the initial increase in the share of digital occupation is not driven by the absolute increase in demand for digital occupations, but by digital occupations being insulated from the COVID-19 recession.

Result 1. ***Composition of employment shifts towards digital occupations during COVID, similarly for vacancies***

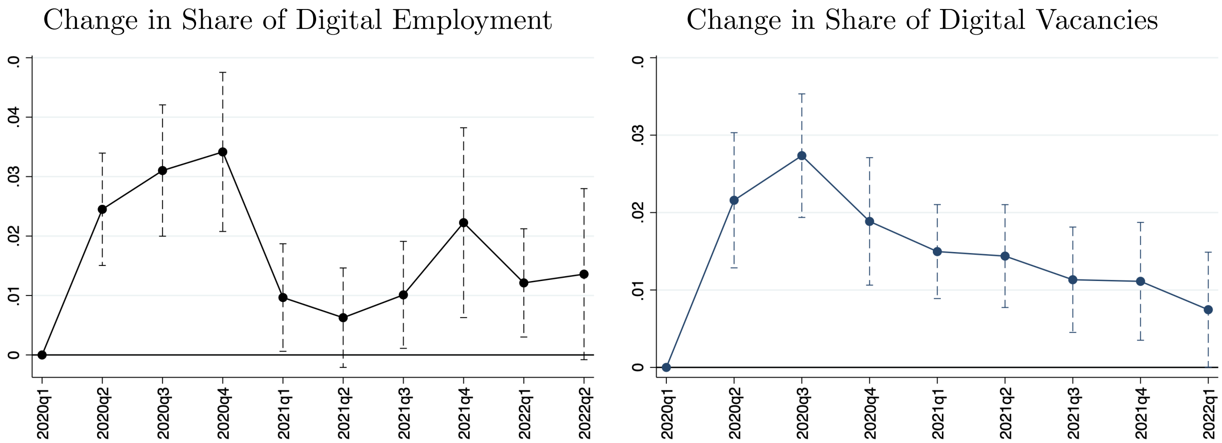
Figure 3 shows our baseline regression results to answer the first question of our paper: "Did COVID-19 increase the relative demand for digital skills in the labor markets?" It summarizes the results from Equation 2 for the two different dependent variables of interest, by plotting the estimated ($\boldsymbol{\alpha_1}$ coefficients and the 90% confidence intervals for each post-pandemic period over 2020Q1-2022Q2 relative to the same quarter in 2019. The left panel plots the estimated impact of the Bartik shock on the change in the share of digital employment at the state level. The right panel reports the estimated impact for the share of digital vacancies at the CBSA level.

We find that relative to the same quarter in 2019, states that were hit harder by the COVID-19 shock experienced a larger increase in the share of digital employment relative to states that were affected less. Quantitatively, we find that in a region that experienced a one unit change in the Bartik shock[20], the share of digital employment and vacancies in this hard-hit region increased up to 3.5 and 3 percentage points respectively within the first year of the COVID-19 shock. The effect, however, did not persist. The increase in the share of digital employment among the harder-hit states peaked after only three quarters. It started to decline in 2021, and the difference is no longer statistically significant by 2022Q2.

The result using the share of digital vacancies (right panel) shows a remarkably similar pattern in magnitudes and persistence to the employment results. CBSAs hit hard by the COVID-19 shock experienced a larger increase in the labor demand for digital occupations than regions that experienced a smaller shock. The difference, however, was not persistent. It started to decline only two quarters after the COVID-19 shock and approached zero in 2022.

[20] which is equivalent to the difference in the employment contraction between a region in the bottom 10th percentile shock and a region in the top 90th percentile shock

Figure 3: Effect of COVID-19 on the change in the share of digital employment and vacancies



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 2 separately for the change in share of digital employment (LHS chart) and share of digital vacancies (RHS chart). 90% confidence interval is plotted in dashed line. Employment data is at the state level, and vacancies data is at the CBSA level. Pre-Covid regional demographic controls are included in the regression to control for any preexisting trends within the region that may drive the share of digital employment/vacancies. The key source of variation to identify $\boldsymbol{\alpha_1}$ is the differences across the region in the employment shock during COVID-19. All standard errors are clustered at the regional level, and the regression is weighted by the region's pre-covid employment share (average of 2017-2018) to upweight areas with larger employment population. A larger value of $shock_m$ corresponds to a harder hit region.
Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

Overall, the employment and vacancies results suggest no evidence of a permanent shift in the composition of labor demand towards digital employment and vacancies due to COVID-19.

Result 2. ***Digital occupations were more insulated from the COVID-19 recession, but there is no evidence of a permanent or temporary increase in the level of the demand for this type of occupations***

To better understand the mechanisms underlying the baseline results in Figure 3, we further decompose the share change results. In particular, given that the shares of digital employment and vacancies are defined to be i) $ShareDigEmp_t = \frac{\text{Digital Employment}}{\text{Total Employment}}$ and ii) $ShareDigVac_t = \frac{\text{Digital Vacancies}}{\text{Total Vacancies}}$ respectively, there are two possible cases that will cause an increase in the share:

- Case 1: Digital Employment rises even as total employment falls, indicating an increase in the absolute demand for digital occupations.

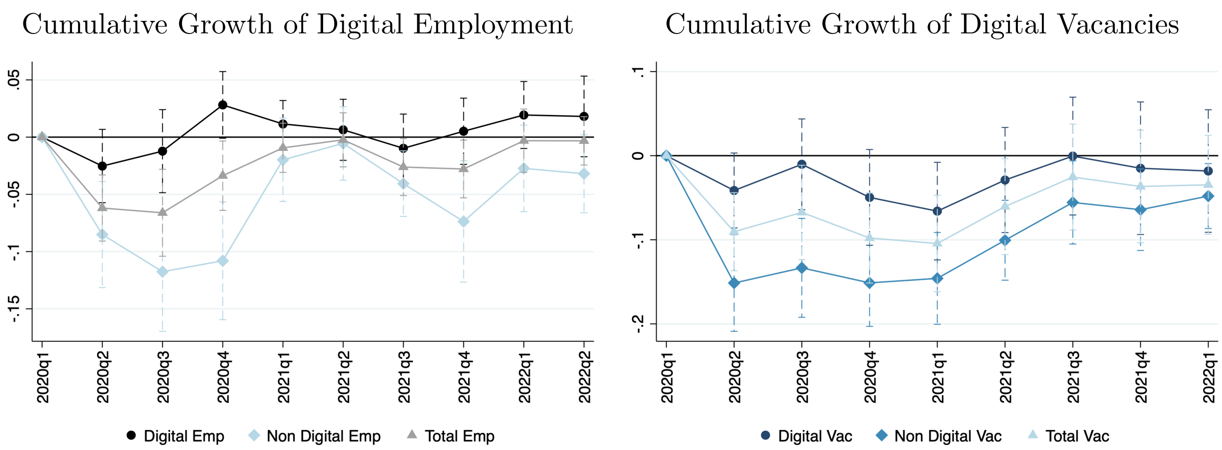
- Case 2: Digital employment falls but to a lesser extent than total employment, indicating that digital occupations were more insulated from COVID-19.

The first case corresponds to the increased demand for digital occupations during the COVID-19 recession. However, the second case corresponds to digital occupations being more insulated from the COVID-19 recession. The baseline results using the share of digital employment and vacancies are insufficient to disentangle Case 1 from Case 2. This limitation motivates our following empirical specification:

$$ln(\mathrm{Z}_{m,q,t}) - ln(\mathrm{Z}_{m,q,2019}) = \alpha_0 + \boldsymbol{\alpha_1}\left[shock_m * \boldsymbol{I_t}\right] + \alpha_2 shock_m + \boldsymbol{\alpha_3} I_t + \boldsymbol{\beta}' controls_{m,q,t} + \varepsilon_{m,q,t}.. \tag{6}$$

where Z refers to the level of digital employment/vacancies in region m, quarter q, year t. The set of explanatory variables remains similar to the baseline Equation 2. This specification allows us to investigate the change in the absolute level of digital employment and vacancies, which is the key to identifying the underlying mechanism driving the increase in the share from the baseline results.

Figure 4: Effect of COVID-19 on the cumulative growth of digital employment and vacancies



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 6 separately for the change in log level of digital employment (LHS chart) and digital vacancies (RHS chart). 90% confidence interval is plotted in dashed line. Employment data is at the state level, and vacancies data is at the CBSA level. Pre-Covid regional demographic controls are included in the regression to control for any preexisting trends within the region that may drive the share of digital employment/vacancies. The key source of variation to identify $\boldsymbol{\alpha_1}$ is the differences across the region in the employment shock during COVID-19. All standard errors are clustered at the regional level, and the regression is weighted by the region's pre-covid employment share (average of 2017-2018) to over-weigh areas with larger employment population. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

Figure 4 provides the regression results for the change in the log level of digital employment and vacancies in the left and right panels, respectively. The hypothesis at test is the following: if the increase in the share of digital employment and vacancies is due to an increase in the demand for digital occupations (Case 1), then we should observe a positive growth in the level of digital employment and vacancies during the COVID-19 recession. On the other hand, if the increase in the share is due to digital occupations being more insulated from the COVID-19 recession, we should observe a decline in both digital and non-digital occupations. However, the decline would be much smaller for digital occupations than non-digital ones (Case 2).

Figure 4 suggests Case 2 is the mechanism behind the increase in the share of digital employment and vacancies. We observe that in regions that were hit harder by the COVID-19 recession, the level of both digital employment and vacancies declined. However, the

employment and vacancy postings for non-digital occupations declined substantially more than for digital occupations in these regions. Digital occupations were therefore more insulated from the shock than non-digital ones. However, there is no evidence of a structural increase in the demand for digital occupations. We do not observe positive, statistically significant results for the growth rate of digital occupations both in the short and medium-run after 2020Q1.

5.1 Are all digital occupations insulated from the COVID-19 recession?

The analysis above finds that regions hit harder by the COVID-19 shock experienced a temporary increase in the share of digital employment and vacancies relative to regions that were affected less, as these occupations were more insulated from the COVID-19 recession than non-digital ones. In this section, we explore heterogeneity of this baseline result across the types of regions and types of digital occupations. Here, urban (rural) areas are defined to be metropolitan (micropolitan) CBSA regions, where metropolitan areas have at least 50,000 people. This analysis is important in light of anecdotal evidence of people moving away from urban to rural areas given the flexible work arrangements in many companies.[21]

Result 3. ***In urban areas, digital occupations are much more insulated from the COVID-19 recession than non-digital occupations. This difference, however, is less evident in rural areas***

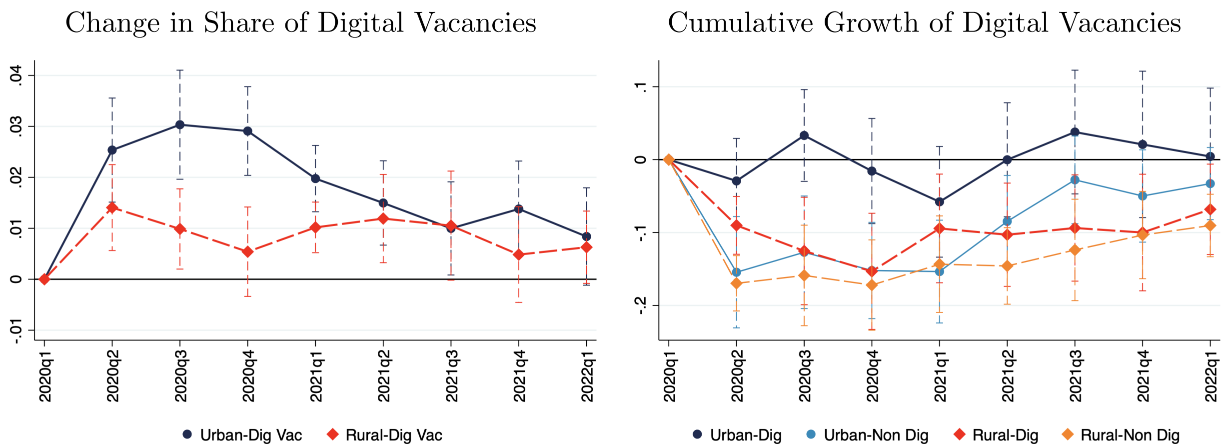
Figure 5 shows the baseline results separately for the urban and rural CBSA regions based on the definition provided by the US Census Bureau.[22] From the left panel, we observe that within urban areas, regions hit hard by the COVID-19 recession experienced an increase in the share of digital occupation vacancies relative to non-digital occupations. However, the increase in digital occupation vacancies is less obvious among rural regions. Underpinning the larger share of digital vacancies in the urban areas is a much smaller decline in the level of labor demand for digital occupations relative to the non-digital occupations (blue lines, right panel). However, in rural areas, the magnitude of the decline in the level of labor demand is quite similar for both digital and non-digital occupations, thus suggesting only

[21]Given that employment regressions are run at state level, there is not a clear way to define urban vs rural states for the employment analysis. Therefore, we conduct this analysis only for vacancies.

[22]The graphs are constructed by running Equation 2 and Equation 6 separately for the urban/metropolitan and rural/micropolitan CBSA regions. Only vacancy regression can be separated into the urban and rural regions. Given the ambiguity in categorizing a state into urban and rural states, we do not have a similar region separation for the employment regression.

limited shielding of digital jobs from the recession. This finding may reflect the fact that although some people may move to rural areas during the COVID-19 pandemic, the job postings may be still listed in urban areas.

Figure 5: Effect of COVID-19 on the share and cumulative growth of digital vacancies



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 2 (LHS) and Equation 6 (RHS) separately for the urban and rural areas. 90% confidence interval is plotted in dashed line. Vacancies data is at the CBSA level. CBSA are separated into urban/metropolitan (≈40% of CBSA) and rural/micropolitan areas (≈60% of CBSA). Equation 2 and Equation 6 are run separately for the urban and rural areas. Pre-Covid regional demographic controls are included in the regression to control for any preexisting trends within the region that may drive the share of digital employment/vacancies. All standard errors are clustered at the urban/rural regional level, and the regression is weighted by the urban/rural region's pre-covid employment share (average of 2017-2018) to upweight areas with larger employment population. A larger value of $shock_m$ corresponds to a harder hit region.

Source: Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

Result 4. ***Labor demand for digital workers in cognitive occupations are more insulated from the COVID-19 recession than for digital workers in routine and manual occupations***

We further investigate whether all types of digital occupations are insulated from the COVID-19 recession. For example, Jaimovich and Siu (2020) found that 88% of job losses that occurred during recessions in the US are from routine occupations. We therefore examine whether the increase in the share of vacancies for digital occupations from the baseline result is driven by selected types of digital occupations based on their task content.

To see this, we disaggregate total digital occupations into three task-based occupational groups: routine, cognitive, and manual occupations, following the approach in Autor et al. (2003). This categorization is based on the skill content that is required to perform the

tasks in the occupations. Cognitive occupations refer to jobs that require establishing and maintaining interpersonal relationships: guiding, directing, and motivating subordinates; flexibility, creativity, and problem-solving. Routine occupations refer to jobs that are characterized by a set of well-defined instructions and procedures, and involve high repetition of the same tasks. Manual occupations refer to jobs that involve working with the hands and physical activities[23].

We find that there are cognitive, manual, and routine occupations within digital occupations. For example, digital cognitive occupations include software developers, computer programmers, and computer system managers. Digital routine occupations include statistical assistants, sales engineers, and industrial equipment repairers, which tend to be more repetitive. Digital manual occupations include dental assistants, gaming surveillance officers, and pharmacy aides. Table 1 shows the composition of digital vacancies and employment by the three occupation groups in the US in 2019.

Table 1: Distribution of Digital Employment and Vacancies in the US

Digital Vacancies Postings/Employment (2019)	
Indeed	
Digital Occupation Threshold	>50 percentile
Total Digital Vacancies	55%
Cognitive	69%
Routine	28%
Manual	3%
Current Population Survey	
Total Digital Employment	53%
Cognitive	59%
Routine	36%
Manual	5%

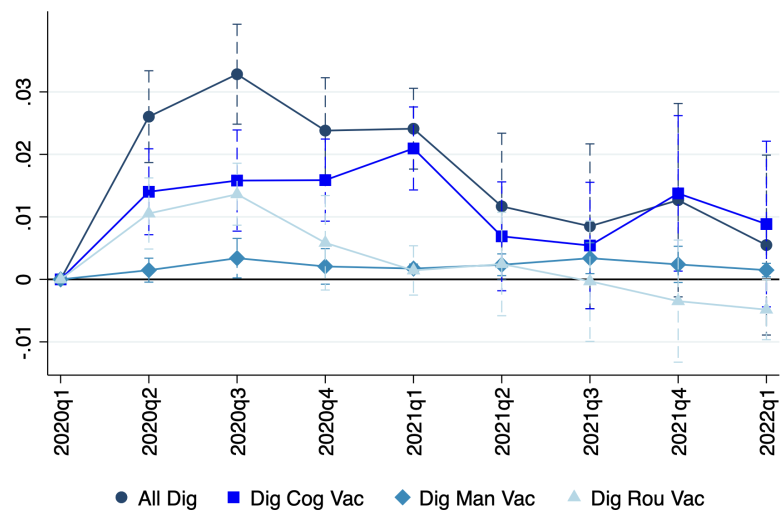
Notes: Calculations are based on the US Current Population Survey for employment data and Indeed for vacancy data. Digital occupations are those with a digital score above the 50th percentile of the digital score distribution. Top row corresponds to the distribution of digital vacancies, bottow row corresponds to the distribution of digital employment. For example, 55% of the total vacancy postings in Indeed in 2019 are related to digital occupations. Within the 55%, 69% are cognitive occupations, 28% are routine occupations, and 3% are manual occupations.
Source: Indeed, CPS, and authors' calculations.

Figure 6 shows the results for digital cognitive, routine, and manual occupations separately. As is evident from the figure, the composition shift in labor demand towards

[23] Autor et al. (2003) provides more detailed information on these categorizations

digital occupations during COVID-19 in the baseline result is driven mainly by digital cognitive ones. Approximately 60% of the total increase in the share of digital vacancies during COVID-19 is accounted for by digital cognitive occupations. This stands in contrast to the contribution of digital routine and digital manual occupations, whose contributions are much smaller relative. This suggests that the shielding observed on the labor demand for digital workers mainly concerns those in cognitive occupations.[24]

Figure 6: Effect of COVID-19 on the share of digital cognitive, routine and manual vacancies.



Notes: The figure plots the effect of COVID-19 on the share of digital cognitive, routine, and manual occupations estimated using from Equation 2. 90% confidence interval is plotted in dashed line. Vacancies data is at the CBSA level. Vacancy posting for digital occupations are separated into cognitive, routine and manual occupations and Equation 2 is run separately for these three different types of occupations. Pre-Covid regional demographic controls are included in the regression to control for any preexisting trends within the region that may drive the share of digital vacancies. All standard errors are clustered at the regional level, and the regression is weighted by the region's pre-covid employment share (average of 2017-2018) to upweight areas with larger employment population. A larger value of $shock_m$ corresponds to a harder hit region.

Source: Indeed, ACS, QWI, BEA, JOLTS.

[24]The result for manual occupations is also less informative given that only 3% of digital vacancies fall under the manual occupations

6 Discussion and Robustness

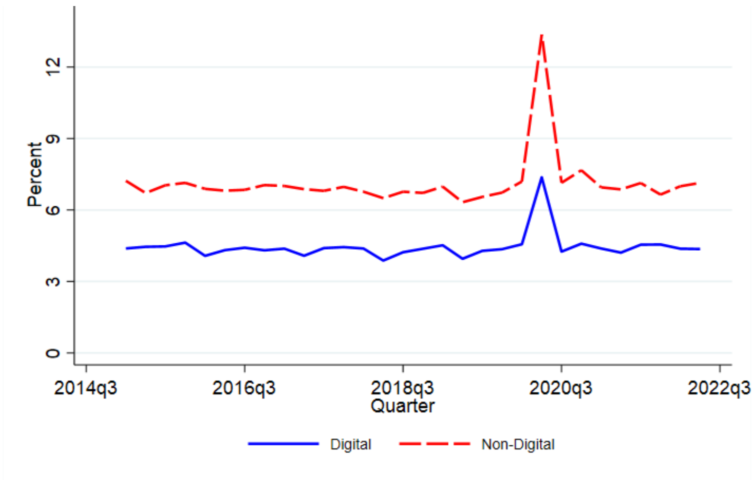
In this section, we present a series of discussions on our baseline results and potentially competing explanations to our findings.

6.1 Is the higher share of digital vacancies postings by firms due to a higher quit rate among the digital workers?

Instead of reflecting the labor demand channel, a potential concern is that the higher share of job postings by firms for digital occupations during the COVID-19 recession is due to a higher quit rate among the existing digital workers in the same period. Hence the higher share of vacancies would reflect the need to replace quitting workers more than sustained demand for these occupations. To investigate this mechanism, we look into the total separation rates for digital and non-digital workers separately.[25] using the data from the Current Population Survey. Historically, the total separation rate is consistently higher for non-digital workers than for digital ones, including during the COVID-19 recession. The total separation rate (which includes quitting behavior) for non-digital workers is almost twice the rate for digital workers during the COVID-19 recession. This suggests that the higher share of digital vacancies relative to non-digital vacancies is not due to the higher quit rate among the existing digital workers.

[25]Similar to the baseline results, digital workers are those occupations with a digital score above the median digital score in the distribution

Figure 7: Total Separation Rate



Notes: The figure plots the total separation rate for the digital and non-digital workers, respectively. Similar to the baseline results, digital workers are those occupations with a digital score above the median digital score in the distribution. Total separation is the sum of i) transition from employment to employment, ii) transition from employment to unemployment, iii) transition from employment to out of labor force.
Source: CPS, O*NET, and authors' calculations.

6.2 Is the higher share of digital vacancy postings by firms due to the ability of digital workers to work from home?

Another concern is that the baseline results for digital vacancies could reflect the teleworkability nature of these occupations.[26] We thus explore whether the teleworkability of these occupations drives our baseline results for digital vacancies.

Based on the 2019 Current Population Survey, we found that 70% of the digital occupations are teleworkable and 30% of the digital occupations are non-teleworkable[27]. There is indeed a significant overlap between digital occupations and teleworkable occupations. However, not all digital occupations are teleworkable. Hence, the main analysis focuses on digital occupations instead of teleworkable occupations. While teleworkablility is the occupation's

[26]We define teleworkable occupations as occupations that can be done entirely from home. We use the occupational classification from Dingel and Neiman (2022) to define whether an occupation is teleworkable or not. For more information on how the teleworkable classification is done for the US occupation, Dingel and Neiman (2022) describes how they construct the occupation-specific work-from-home measure using surveys from O*NET.

[27]Examples of digital occupations that are teleworkable are network and computer system administrators, software developers, computer network specialists, computer programmers, and computer system managers. Examples of digital occupations that are non-teleworkable include chemical engineers, avionics technicians, manufacturing managers, radio and television announcers, and electrical equipment repairers.

working arrangement, digital skills capture the *skills required* to perform specific tasks in an occupation, which could go beyond the initial COVID-19 shocks.

Figure 8 shows the results for digital teleworkable and digital non-teleworkable occupations. The hypothesis that we would like to test is whether the baseline results for digital occupations are driven by the ability of digital workers to work from home. If this is true, we should expect a one-to-one relationship between the results digital teleworkable and for all digital occupations. The left panel displays the change in the share of digital teleworkable and digital non-teleworkable vacancies during the COVID-19 recession estimated using Equation (2), and the right panel shows the log level difference estimated separately for digital teleworkable and digital non-teleworkable vacancies using Equation (6).

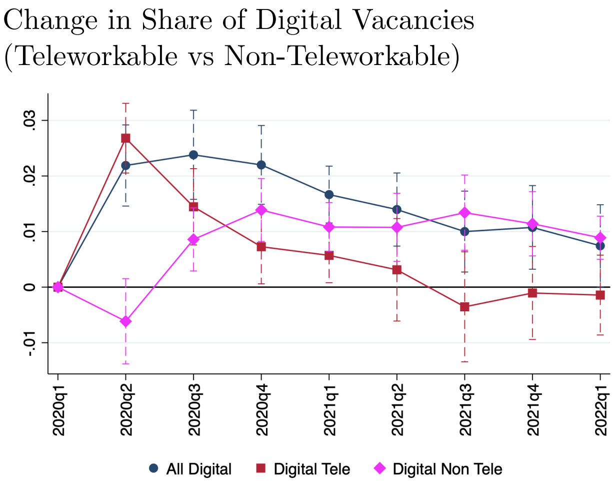
Looking at the left panel, in the immediate short-run following the COVID-19 shock, the increase in the share of digital vacancies in 2020Q2 is driven entirely by digital teleworkable occupations. Digital teleworkable occupations are more insulated from the immediate impact of the COVID-19 shock relative to digital non-teleworkable occupations, as shown in the right panel. However, an interesting shift occurs after 2020Q2, as non-teleworkable digital occupations recovered much faster than teleworkable ones and subsequently drove the increase in the share of digital vacancies from 2020Q3 onwards. A similar pattern emerges from the level change in the right panel, where digital non-teleworkable occupations recovered much faster than digital teleworkable occupations in the subsequent quarters. Our baseline results for all digital occupations are, therefore, not driven entirely by the teleworkability of digital occupations.

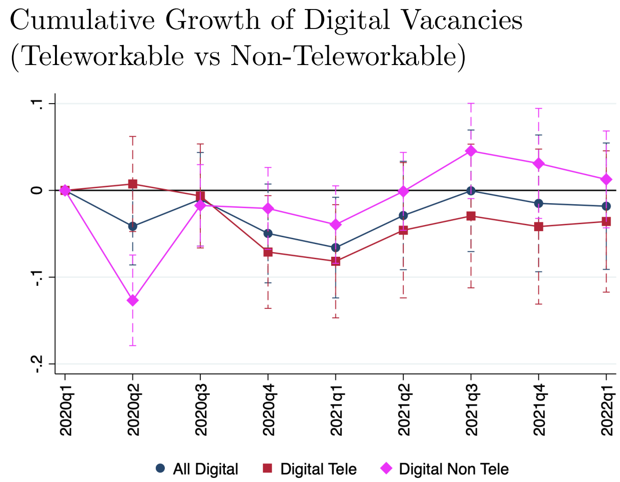
6.3 Other Robustness Checks

Thus far, we have provided evidence that regions that are more severely affected by the COVID-19 shock experience a compositional shift towards digital occupations, and this compositional shift is driven by the more resilient nature of digital occupations relative to non-digital occupations. However, there may be concerns with the validity of the measure $shock_m$ used in Equations (2) and (6) to capture the effect of the COVID-19 recession. The baseline results may also be sensitive to how we classify digital and non-digital occupations based on the percentile cutoff. In addition, there may be additional endogeneity concerns with the parallel-trend assumptions on the share of digital employment and vacancies between the hard-hit and the less-hit regions in the pre-COVID-19 period.

This section, therefore, discusses how we address these three concerns. In summary,

Figure 8: Effect of COVID-19 on the share and cumulative growth of digital teleworkable and non-teleworkable vacancies





Notes: The figure plots the effect of COVID-19 on the share of digital teleworkable and non-teleworkable occupations estimated using Equation 2 (LHS chart) and Equation 6 (RHS chart). 90% confidence interval is plotted in dashed line. Vacancies data is at the CBSA level. Vacancy posting for digital occupations is separated into teleworkable and non-teleworkable occupations based on the classification in Dingel and Neiman (2022). Teleworkable occupations are jobs that can be done entirely from home. Equation 2 (LHS chart) and Equation 6 (RHS chart) is run separately for the teleworkable and non-teleworkable digital occupations. Pre-Covid regional demographic controls are included in the regression to control for any preexisting trends within the region that may drive the share of digital vacancies. All standard errors are clustered at the regional level, and the regression is weighted by the region's pre-covid employment share (average of 2017-2018) to upweight areas with larger employment population. A larger value of $shock_m$ corresponds to a harder hit region.
Source: Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

our baseline results remain robust to i) alternative measures of the shock, ii) alternative percentiles to define digital occupations, and iii) including among the explanatory variables the regions' pre-COVID-19 share of digital employment and vacancies to control for pre-existing differential trends in the share of digital employment and vacancies between the hard-hit and less-hit regions.

6.3.1 Alternative Measure of the COVID-19 Shock

We use monthly data from Google's COVID-19 Community Mobility Reports to construct an alternative measure of the COVID-19 shock. In particular, we measure the drop in the time spent away from retail, recreation, and transit locations to construct the shock. Following the approach of Chetty et al. (2020), we measure the drop in mobility for each region m as the percent change in time spent away from home relative to the base

period of January - February 2020.[28]. We then construct the shock for each region using the peak-to-trough method as in the baseline method:

$$shock_m = G_{m,\text{April,2020}} - G_{m,\text{Jan - Feb,2020}} \tag{7}$$

where G is the Google mobility measure of time spent away from retail and recreation and transit locations in each region m; April, 2020 is the trough of the Google mobility measure, and January -February , 2020 is the national-level peak of the Google mobility measure, which we take as the reference period.

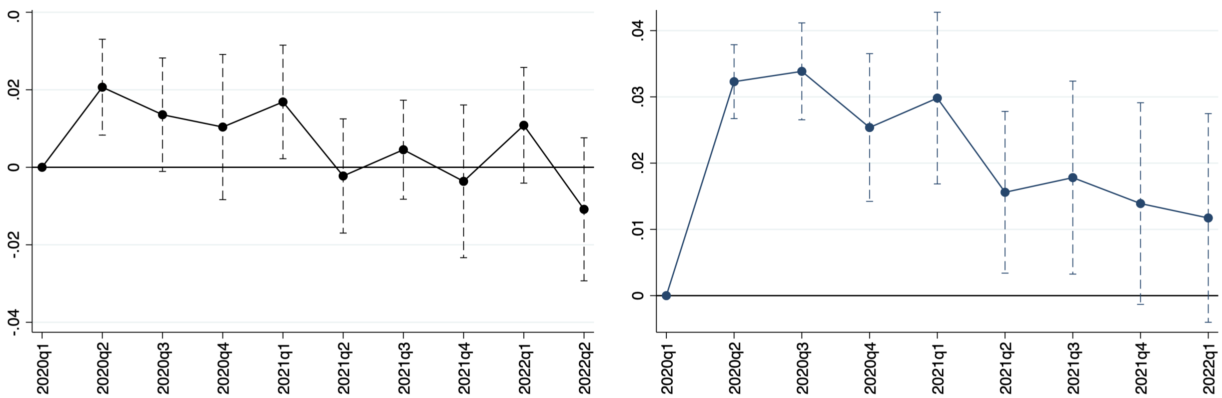
Figure 9 and 10 show the results for i) the share of digital employment/vacancies and ii) the cumulative growth of digital employment/vacancies estimated via Equations (2) and (6), respectively, using the Google mobility COVID-19 shock. In general, our baseline results remain robust to this alternative measure: regions that are more severely affected by the COVID-19 shock experienced a compositional shift towards digital occupations, and this compositional shift was due to digital occupations being relatively more insulated from the COVID-19 recession.

[28]The monthly mobility data is made available at the county and state-level by Chetty et al. (2020). CBSA-level mobility data is constructed using the averages of county-level data.

Figure 9: Effect of COVID-19 on the change in the share of digital employment and vacancies (Google Mobility)

Change in Share of Digital Employment (Google Mobility)

Change in Share of Digital Vacancies (Google Mobility)



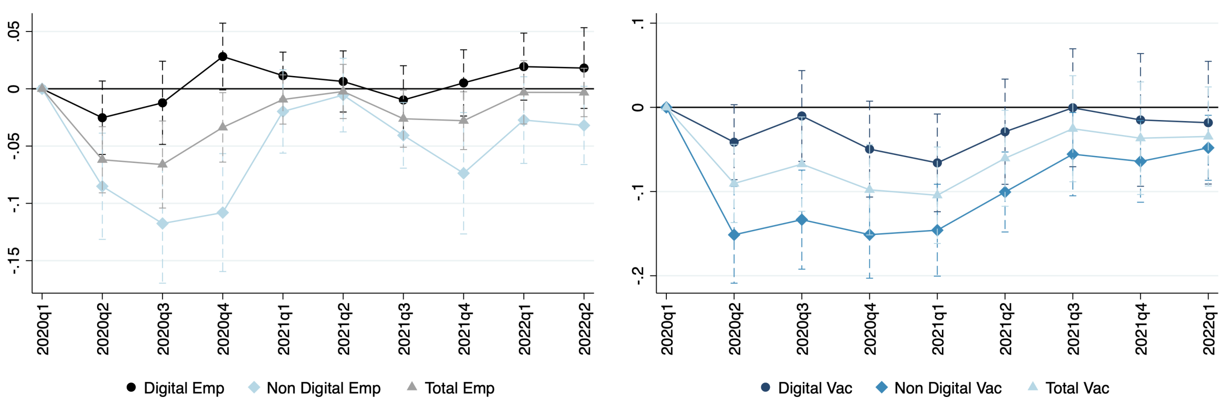
Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 2 separately for the change in share of digital employment (LHS chart) and share of digital vacancies (RHS chart) using the Google Mobility COVID-19 shock. 90% confidence interval is plotted in dashed line. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

Figure 10: Effect of COVID-19 on the cumulative growth of digital employment and vacancies (Google Mobility)

Cumulative Growth of Digital Employment (Google Mobility)

Cumulative Growth of Digital Vacancies (Google Mobility)



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 6 separately for the change in log level of digital employment (LHS chart) and digital vacancies (RHS chart) using the Google Mobility COVID-19 shock. 90% confidence interval is plotted in dashed line. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

6.3.2 Alternative Method of Classifying Digital Occupations

The baseline results in Figures 3 and 4 use the 50^{th} percentile digital score as the cutoff to classify occupations as digital or non-digital. In this section, we explore the robustness of the results when using different thresholds of the digital score to construct the binary categorical variable. Specifically, we compare the baseline thresholds with thresholds corresponding to the 75^{th} and 90^{th} percentiles of the score's distribution.

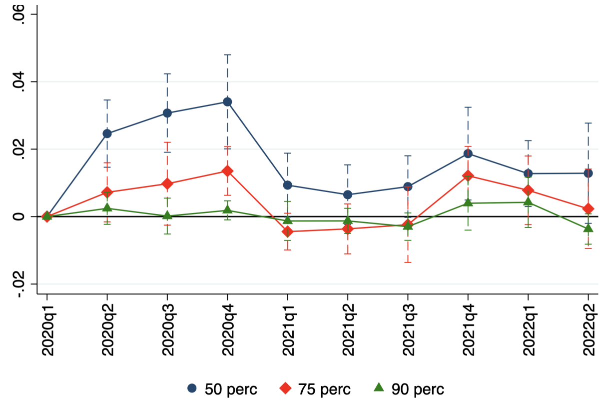
Higher thresholds imply that the definition of digital occupations includes a smaller subset of jobs that involve a greater intensity of digital skills compared to the baseline definition. From a qualitative perspective, comparing the results with the baseline definition can shed light on whether the observed shielding pattern concerned all jobs with medium-to-high digital intensity, or whether it was greater or milder for the highly-digital occupations at the right tail of the distribution.[29] In other words, using the occupations listed in Figure **??** as an example, were tax preparers and software programmers equally insulated from the COVID-19 recession?

Figures 11 and 12 show the baseline results for employment and vacancies, respectively, using different percentile cutoffs to define digital occupations. In general, regardless of the choice of the percentile cutoff, we do not observe a permanent increase in either the share or the absolute level of digital employment and vacancies in both figures during the COVID-19 recession. The fact that there seems to be less increase in the share of digital employment and vacancies with stricter cutoffs suggest that the "medium" digital occupations were the most shielded.

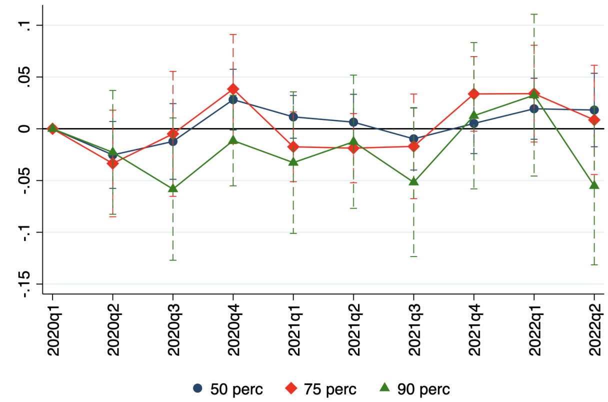
[29] Intuitively, since these jobs comprise a smaller portion of the full labor force, it is likely that the ensuing change in vacancies is also smaller in terms of the percentage-point share. However, the log level change should not be directly affected by the use of a higher cutoff.

Figure 11: Effect of COVID-19 on the change in the share and cumulative growth of digital employment (Different Cutoff Percentile)

Change in Share of Digital Employment
(Different Cutoff Percentile)



Cumulative Growth of Digital Employment
(Different Cutoff Percentile)



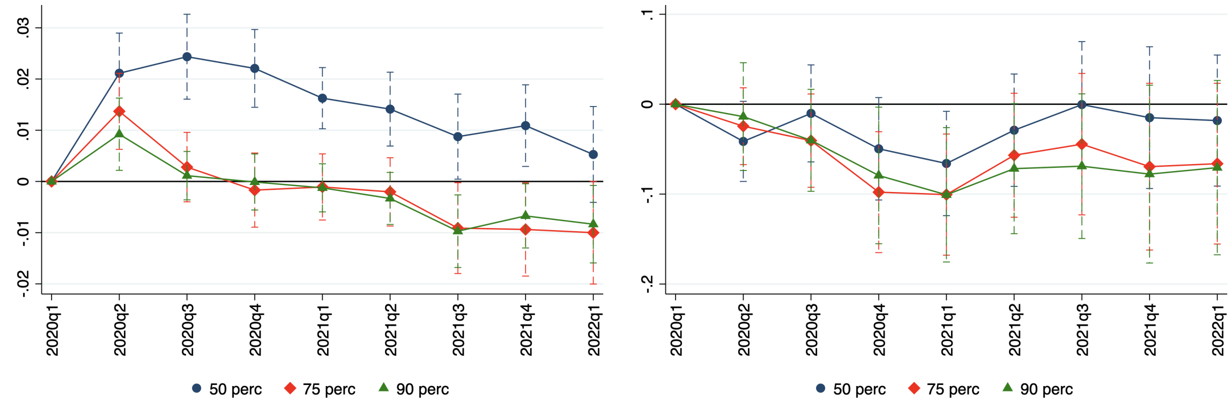
Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient for the change in share of digital employment (LHS chart) and the cumulative growth of digital employment (RHS chart). 90% confidence interval is plotted in dashed line. Digital occupations are classified using three different percentile cutoffs of digital scores: above 50th percentile, 75th percentile, and 90th percentile. Equation 2 (LHS chart) and Equation 6 (RHS chart) are run separately on these three different percentile cutoff. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

Figure 12: Effect of COVID-19 on the change in the share and cumulative growth of digital vacancies (Different Cutoff Percentile)

Change in Share of Digital Vacancies (Different Cutoff Percentile)

Cumulative Growth of Digital Vacancies (Different Cutoff Percentile)



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient for the change in the share of digital vacancies (LHS chart) and the cumulative growth of digital vacancies (RHS chart). 90% confidence interval is plotted in dashed line. Digital occupations are classified using three different percentile cutoffs of digital scores: above 50th percentile, 75th percentile, and 90th percentile. Equation 2 (LHS chart) and Equation 6 (RHS chart) are run separately on these three different percentile cutoff. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

6.3.3 Accounting for Differential Pre-trends in Digital Employment and Vacancies

As discussed above, there may be concerns with the parallel-trend assumption on the share of digital employment/vacancies between the harder-hit and the less-hit regions before the COVID-19 recession. In this section, we formally test for the parallel-trend assumptions by regressing the pre-COVID-19 change in the share of digital employment and vacancies on the regional-level COVID-19 shock. This will allow us to test whether there is a difference in the share of digital employment/vacancies between the harder-hit and the less-hit regions in the pre-COVID-19 period.

The equation that we use to test whether there is a differential pre-trend in digital employment between the harder-hit and the less-hit regions before the COVID-19 recession is the following:

$$\mathrm{Y}_{m,q,2019} - \mathrm{Y}_{m,Q1,2019} = \alpha_0 + \boldsymbol{\alpha_1} \left[\text{ shock }_m * \boldsymbol{I_t} \right] + \alpha_2 shock_m + \boldsymbol{\alpha_3 I_t} + \boldsymbol{\beta}' control_{m,q,t} + \varepsilon_{m,q,t}. \tag{8}$$

where Y refers to the share of digital vacancies, m refers to CBSA, q is quarter $\in \{2, 3, 4\}$ in the year 2019. The dependent variable is the change in the 2019 share of digital vacancies in each quarter relative to the base period of 2019Q1[30]. Similarly, $\boldsymbol{I_t}$ refers to the time period from 2019Q2-2019Q4.

Ideally, we would want to compare quarterly levels in 2019 (or even earlier years) with the corresponding quarters from the previous year. Unfortunately, due to the data for vacancies starting in 2019, we can only compare quarters 2-3-4 to the first quarter of 2019. To be consistent in the comparison of employment and vacancies, we adopt the same specification for employment even though we could use the more appropriate approach. That is, we restrict the pre-trend analysis to only looking at the change in 2019 relative to the 2019Q1.[31]

Figure 13 shows the results for the parallel-trend test for employment and vacancies using Equation 8 respectively. For both the employment and vacancies parallel-trend test, almost all the estimated coefficients $\boldsymbol{\alpha_1}$ are close to zero and statistically insignificant, implying that the harder-hit regions had fairly similar digital employment and vacancies trends relative to the other regions before the COVID-19 recession. The only exception is the estimate for 2019Q2, which is negative and statistically significant. This suggests the harder-hit regions experienced a *decline* in the share of digital employment and vacancies relative to the less-hit regions in 2019Q2 before the COVID-19 recession. However, this difference only lasted temporary and disappeared in the subsequent quarters. In any case, all the estimated coefficients $\boldsymbol{\alpha_1}$ are somewhat noisy and, at worst, point in the opposite direction for the harder-hit regions compared to post-COVID-19 developments. There is no evidence of any composition shift in labor demand towards *more digital occupations* in the harder-hit regions prior to the COVID-19 recession. If any, the evidence instead indicates a trend toward a lower share of digital employment and vacancies in the harder-hit regions relative to the less-hit regions before the COVID-19 recession.

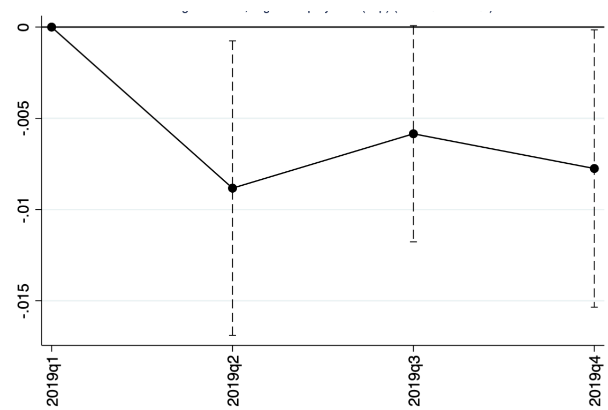
[30] We have to use 2019Q1 as the base period instead of the year 2018 due to the data limitation in the vacancy data.

[31] When we run equation 8 using the quarters in 2018 for employment as a robustness robustness check, and the results are similar.

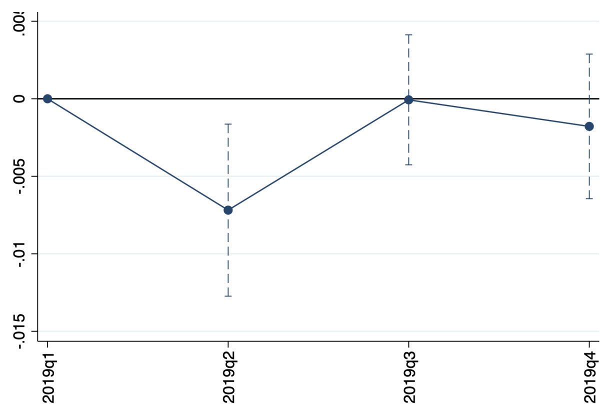
Thus, this finding reduces the concerns about pre-existing *increasing* trends in digital employment and vacancies among the harder-hit regions.

Figure 13: Differences in the share of digital employment and vacancies between the harder-hit and the less-hit regions before the COVID-19 recession

Change in Share of Digital Employment
(Pre-COVID-19 period)



Change in Share of Digital Vacancies
(Pre-COVID-19 period)



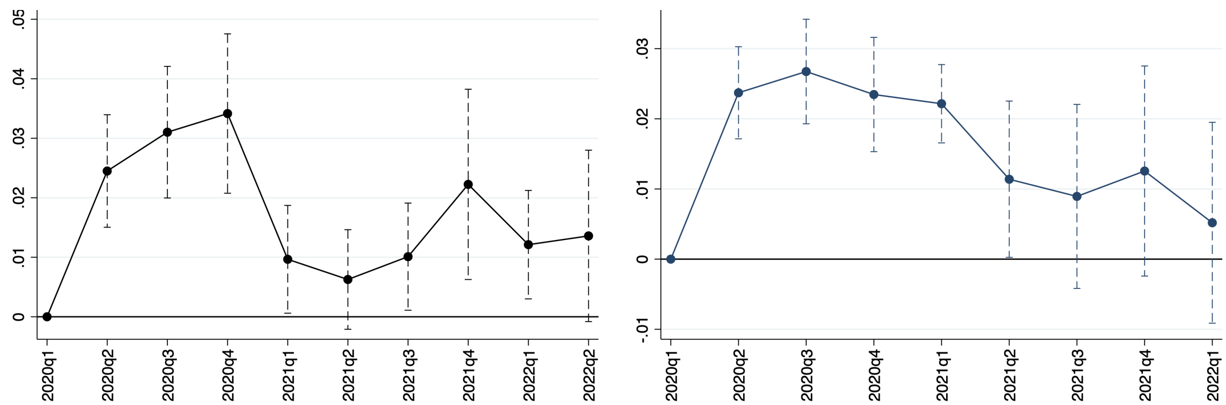
Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient for digital employment (LHS chart) and for digital vacancies (RHS chart) estimated using Equation 8 for the period 2019Q1-2019Q4. This is to test whether the harder-hit and less-hit regions have a similar trend in the share of digital employment and vacancies before the COVID-19 recession. 90% confidence interval is plotted in dashed line. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

To further alleviate any remaining concerns about differential pre-trends, we also directly control for the regions' pre-COVID-19 share of digital employment and vacancies in Equation (2) to account for the potential differential pre-trend between the hard-hit and the less-hit regions. Figure 14 shows that the baseline results remain robust to the inclusion of this control.

Figure 14: Effect of COVID-19 on the change in the share of digital employment and vacancies (Controlling for Pre-Trend)

Change in Share of Digital Employment (Controlling for Pre-Trend) | Change in Share of Digital Vacancies (Controlling for Pre-Trend)



Notes: The figure plots the $\boldsymbol{\alpha_1}$ coefficient from Equation 2 separately for the change in share of digital employment (LHS chart) and share of digital vacancies (RHS chart) after controlling for the regions' pre-COVID-19 share of digital employment and vacancies in the respective regressions to account for potential differential pre-trend. 90% confidence interval is plotted in dashed line. A larger value of $shock_m$ corresponds to a harder hit region.

Source: CPS, Indeed, ACS, QWI, BEA, JOLTS, and authors' calculations.

7 Conclusion

This paper studies whether the COVID-19 recession led to an increase in the demand for digital occupations in the U.S. We use O*NET to measure the digital content of occupations and classify them as digital or non-digital. Utilizing geographical variation in the exposures to COVID-19 at the state or CBSA level, we find that regions that were hit harder by the COVID-19 recession experienced a larger increase in the share of digital employment and vacancies relative to less-affected regions. This result holds even after controlling for a rich set of regional demographics and pre-COVID-19 shares of digital workers to account for the differential pre-pandemic trends between the hard-hit and the less-hit regions. In addition, the baseline results are also robust to alternative measures of the COVID-19 shock and alternative methods of classifying digital occupations. We also conclude that the increase in the share of digital employment and vacancies in the harder-hit regions during the COVID-19 recession is not due to higher quit rates among the existing digital workers nor to the ability of the digital workers to work from home.

The baseline results, therefore, raise the possibility of a structural shift in the demand for digital workers that increased disproportionately in the harder-hit regions. However, we find that the increase in the share of digital employment and vacancies within the harder-hit regions was driven by the smaller decline in demand for digital workers than for non-digital workers, and not by an absolute increase in the demand for the former.

While our evidence supports the view that digital workers, particularly those in urban areas and cognitive occupations, were more insulated during this recession, there is little indication of a permanent shift in the demand for digital occupations due to the COVID-19 recession. In fact, the increase in the share of digital occupations was not permanent. By mid-2022, the difference in the share of digital employment and vacancy between the harder-hit and less-hit regions converged back to pre-recession levels. Our findings thus suggest the COVID-19 recession has not generated a permanent shift in the demand for digital workers.

References

Adrjan, P., G. Ciminelli, A. Judes, M. Koelle, C. Schwellnus, and T. Sinclair (2021). Will it stay or will it go? analysing developments in telework during covid-19 using online job postings data. OECD Productivity Working Papers 30, Organization for Economic Cooperation and Development.

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

Barrero, J. M., N. Bloom, S. J. Davis, and B. H. Meyer (2021, May). Covid-19 is a persistent reallocation shock. *AEA Papers and Proceedings 111*, 287–91.

Bartik, T. J. (1991). *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute.

Bellatin, A. and G. Galassi (2022). What covid-19 may leave behind: Technology related job postings in canada. *Bank of Canada Staff Working Paper 2022-17*.

Bloom, N., R. Han, and J. Liang (2022, July). How hybrid working from home works out. Working Paper 30292, National Bureau of Economic Research.

Cajner, T., L. D. Crane, R. A. Deker, J. Grigsby, A. Hamins-Puertolas, E. Hurst, C. Kurz, and A. Yildrmaz (2020). The us labor market during the beginning of the pandemic recession. *Brookings Papers on Economic Activity*, 3–34.

Chernoff, A. and C. Warman (2021, May). COVID-19 and Implications for Automation. Staff Working Papers 21-25, Bank of Canada.

Chetty, R., J. N. Friedman, N. Hendren, M. Stepner, and O. I. Team (2020). The economic impacts of covid-19: Evidence from a new public database built using private sector data. *Working Paper*.

Crossley, T. F., P. Fisher, and H. Low (2021). The heterogeneous and regressive consequences of covid-19: Evidence from high quality panel data. *Journal of Public Economics 193*, 104334.

Dingel, J. I. and B. Neiman (2022). How many jobs can be done at home? *Becker Friedman Institute White Paper*.

Forsythe, E., L. B. Kahn, F. Lange, and D. Wiczer (2020). Labor demand in the time of covid-19: Evidence from vacancy postings and ui claims. *Journal of Public Economics 189*, 104238.

Hensvik, L., T. Le Barbanchon, and R. Rathelot (2021). Job search during the covid-19 crisis. *Journal of Public Economics 194*, 104349.

Hershbein, B. and L. B. Kahn (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review 108 (7)*, 1737–1772.

Jaimovich, N. and H. E. Siu (2020). Job polarization and jobless recoveries. *Review of Economics and Statistics 102 (1)*, 129–147.

Larrimore, J., J. Mortenson, and D. Splinter (2022). Earnings shocks and stabilization during covid-19. *Journal of Public Economics 206*, 104597.

Muro, M., S. Liu, J. Whiton, and S. Kulkarni (2017). Digitalization and the american workforce. *Brookings Paper*.

Pierri, N. and Y. Timmer (2020). It shields: Technology adoption and economic resilience during the covid-19 pandemic. *IMF Working Papers 2020/208*.

Pizzinelli, C. and I. Shibata (2020). Has covid-19 induced labor market mismatch? evidence from the us and the uk. *IMF Working Paper 2022/005*.

Shibata, I. (2021). The distributional impact of recessions: The global financial crisis and the covid-19 pandemic recession. *Journal of Economics and Business 115*, 105971. COVID-19 – Economic and Financial Effects.