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JEL classification: J21, J23, J24, J31, I26, O33

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1 Introduction

Working from home (WFH) is an efficient and important work arrangement as evidenced by, for instance, Bloom *et al.* (2015). It is also a promising direction for future modes of work as it can potentially reduce commuting time, improve work-life balance, and save capital costs. However, the WFH adoption has been relatively low.[1]. This under-adoption of WFH could be due to some barriers such as the uncertainties regarding WFH benefits to specific jobs and firms, technological and organizational transition costs facing firms, and inertia from working habits formed by employees in a traditional working environment.

During the Covid-19 pandemic, however, many jobs are forced to be done at home when lockdown and other social distancing policies were put in place[2]. A natural experiment offering a "compulsory" trial session of WFH to the firms and workers in cities where mobility was severely inhibited during the pandemic, the Covid-19 pandemic thus provides a unique opportunity to test the attractiveness of WFH absent the aforementioned barriers.[3]. Moreover, if remote working becomes a common practice after the pandemic, it might affect not only the work arrangement of incumbent employees[4], but also that of new hires in the labor markets.

In this paper, we exploit this large-scale quasi-experiment to test the following hypothesis: if WFH is productivity-enhancing for certain firms and jobs and if the barriers to shifting

[1] Dingel & Neiman (2020) points out that 37% of jobs in the United States can be performed entirely at home, which is far above the actual level of WFH adoption.

[2] To list a few, Bick *et al.* (2020) find that 35.2 % of the workforce worked entirely from home in May 2020, up from 8.2 % in February 2020. Brynjolfsson *et al.* (2020) find that the share of people switching to remote work can be predicted by the incidence of Covid-19. Gallacher & Hossain (2020) show that, under some specifications, workers in occupations for which the possibility of remote work is less likely experienced larger employment losses between March and April.

[3] Conceptually, if all firms are exogenously introduced to a practice and learning session about WFH, whether a firm chooses to opt in after the session ends could shed light upon how efficient WFH is to the firm. Empirically, it is yet be seen whether WFH is a temporary alternative work arrangement or a persistent shift from office-based to home-based working, which could vary vastly across different occupations, firms and industries.

[4] According to Bartik *et al.* (2020), over 1/3 of firms in the US that had employees switch to remote work believe that over 40% of workers who had switched to remote work during the Covid-19 crisis would continue with WFH after the crisis ends. Barrero *et al.* (2021) further show that 20% of full workdays will be supplied from home after the pandemic ends, while the percentage was just 5% prior to the pandemic.

to WFH can be overcome by obtaining relatively short-period learning experience, then these firms and jobs will have a *persistent* demand for WFH jobs after being temporarily hit by the pandemic. That is, a temporary shock can have a long-lasting effect on the job demand structure, which will show up in the new job ads posted by the firms after the pandemic subsides.

We test this hypothesis and its implications using detailed job postings data in collaboration with one of the largest online job posting platforms in China[5]. We have three main findings: (1) the Covid-19 pandemic leads firms to increase both the number and share of WFH job postings; (2) this increased demand for WFH jobs is persistent and long-lasting in the post-pandemic periods; and (3) firms' pre-Covid WFH experience and potential for remote work predict their post-Covid demand increase for WFH jobs. We first perform an event study around the Covid-19 shock (and corresponding lockdown policies), showing there is indeed a significant and persistent increase in both the number and the share of WFH job postings. We then identify the types of jobs and firms that see the most pronounced long-run shift to WFH induced by the temporary lockdown, using both the pre-Covid WFH adoption and the teleworkability measure introduced by Dingel & Neiman (2020). We also perform heterogeneity analyses using firm and occupation characteristics to gauge the welfare implications for the labor market.

Our paper makes unique contribution to the literature examining the impact of Covid-19 on WFH by exploiting job postings data, the actual presentation of firms' WFH labor demand. Compared with administrative or survey data, high-frequency job postings give us real-time data that record the dynamics of labor demand of WFH and non-WFH jobs in the pre- and post-Covid-19 periods. This allows us to avoid the recall noises inherent in surveys. Barrero *et al.* (2021), for instance, analyze the impact of Covid-19 on WFH through surveys of 30,000 Americans over multiple waves. Bick *et al.* (2021) document the evolution of commuting behavior in the U.S. based on survey data. Davis *et al.* (2021) construct a equilibrium model to

[5]This paper is most similar in approach to Forsythe *et al.* (2020), Campello *et al.* (2020), and Shuai *et al.* (2021) in terms of using job-vacancy postings to study the impact of Covid-19 on the labor market. While these papers examine the general labor demand, our paper takes a specific angle on WFH jobs.

study the impact of WFH. Additionally, information contained in job postings (such as tasks, skill requirements, and wages) can help us explore the labor demand adjustment to WFH in multiple dimensions. Moreover, adding to the existing studies in the context of more advanced economies, our paper provides empirical evidence from a developing country, highlighting the inclusiveness of digital technology in bridging the gap between developing and developed countries in the prospect of WFH adoption.

Our paper also deepens the understanding of the cross-sectional heterogeneity in the suitability and effectiveness of WFH. Complementing experimental studies within firms identifying the causal productivity impacts of WFH (e.g. Bloom *et al.*, 2015), our paper extends the analysis on WFH to a greater range of firms and jobs. Our panel analysis combined with quasi-natural experiment also adds identification power compared to the existing literature examining cross-sectional variation in the prevalence of WFH, as firms might face barriers to technology adoption for various reasons (Hall & Khan, 2002; Bloom *et al.*, 2013), including high adjustment costs and the lack of incentives to acquire information about the costs and benefits of WFH, which could themselves be endogenous to the productivity effects of WFH.

Furthermore, our paper contributes to the debate on whether and how adverse economic shocks can accelerate adjustments to technological advances. A long theoretical literature, beginning with Schumpeter (1939)'s "creative destruction", suggests that recessions can produce sufficiently large shocks to overcome frictions that could inhibit the optimal reallocation of resources in the face of technological change. This argument is applied to the Great Recession as well as routine-biased technological change (Hershbein & Kahn, 2018). The Covid-19 pandemic could leave persistent impacts on various aspects of the organization of production activities within and between firms, and the adoption of WFH and other flexible work arrangements might be one of those welfare-enhancing impacts in the long run. Hern (2020) argues that Covid-19 could cause permanent shift towards home working. Molino *et al.* (2020) argues that the use of remote working increased during the pandemic and is expected to maintain high levels of application even after the emergency. Kramer & Kramer (2020) describe the pandemic as a "work from home experiment" that may enable organizations and researchers to better designate occupational groups to working (or not working) from home. But none of these papers provide systematic evidence. Our paper fills the gap by demonstrating extensive evidence that the impact of Covid-19 on remote working is going to persist.

More broadly, our paper connects to the literature on how technology is shaping the future of work. One important aspect is that the internet and IT advances have made it easier for employers to allow workers to work remotely and to provide workers with flexible schedules (Oettinger, 2011; Golden *et al.*, 2014; Katz & Krueger, 2019). The past decades have witnessed a sharp increase in WFH internationally, especially in developed countries.[6] Contributing to the ongoing debate over how technology is shaping the future of work, we investigate whether and how the short-term lockdown and social distancing during the Covid-19 pandemic induced long-run adoption of WFH, which in turn could permanently alter the demand for different skills.

Methodologically, our paper is among the first attempts to study job task and skill requirements using textual analysis on job posting data in the context of China, while this methodology has been adopted in the studies on the US labor markets (e.g. Deming & Kahn, 2018; Hershbein & Kahn, 2018). In previous studies on the Chinese labor markets, researchers mainly used worker surveys such as the China Urban Labor Survey (e.g. Lewandowski *et al.*, 2019) to measure tasks and skills associated with jobs, and job ads have been used to study gender discrimination and matching in terms of education in the Chinese labor markets (e.g. Kuhn & Shen, 2013; Shen & Kuhn, 2013; Kuhn *et al.*, 2020). Applying textual analysis on job postings in China to measure skill requirements, if successful, could be adopted in the research in a variety of topics other than WFH, such as the impacts of globalization and robot adoption, either for

[6] For example, 3.6% of the U.S. employee workforce worked at home at least half-time in 2018 according to the American Community Service (ACS), while the number was 0.75% in 1980 and 2.4% in 2010, and for some occupations and industries the shares are much higher (Mateyka *et al.*, 2012).

cross-country comparisons or focusing on China alone.

Last but not the least, this paper is related to the literature that is concerned with inequality in the time of global pandemic, noting that the ability to WFH differs systematically by age, race, education, and gender. For instance, Bick *et al.* (2020) and Mongey & Weinberg (2020) find that highly educated, high-income and white individuals are much more likely to shift to remote work. Angelucci *et al.* (2020) show that job losses are up to three times as large for non-remote workers in the pandemic. Irlacher & Koch (2021) find a substantial wage premium for workers performing their job from home. They also find evidence for substantial regional variations in the share of jobs that can be done from home in Germany. Yancy (2020) argues that being able to maintain social distancing while working from home is a privilege not accessible to some African Americans. Brynjolfsson *et al.* (2020) find that states with a higher share of employment in information work including management, professional and related occupations are more likely to shift toward working from home. Other studies also find that the WFH take-up during the pandemic may enhance inequality (Kawaguchi & Motegi (2021)). The good news is that the flexible working arrangements adopted in the Covid-19 pandemic may ultimately promote gender equality Alon *et al.* (2020).

The rest of our paper proceeds as the following: Section 2 introduces the background information on the Covid-19 pandemic and related lockdown policies in China. Section 3 summarizes our data and explains the strategy we use to construct our sample. In Section 4, we present regression results exploiting variations in firms' potential for telework and their pre-Covid WFH take-up. We discuss the heterogeneity of firms in Section 5. Section 6 concludes the paper and prescribes policy recommendations.

2 Background Information on WFH and Covid-19 in China

China offers some unique opportunities for our study. First, China was hit hard by the initial round of Covid-19 outbreak, and the Chinese government launched a top-down lockdown and other social distancing policies in many cities. The prevalence and severity of the disease and the strictness and length of lockdown periods varied greatly across different cities, and we are able to exploit the geographical variation in the presence and intensity of the lockdown treatment and the extent to which firms are forced into adopting WFH in the short run. Second, the pandemic was quickly controlled and followed by relatively full and now lengthy recovery, making it ideal to study the persistent impacts of the crisis. In addition, remote working remains relatively less prevalent in China compared in the years before the pandemic, even with the rapid spread of laptops and cell-phone connectivity and rising traffic congestion in the urban areas in the past two decades (CNNIC, 2018), creating high potential for the medium and long-run adoption of WFH.

2.1 Timeline of the Covid-19 pandemic

The Covid-19 pandemic first broke out in Wuhan, the capital city of Hubei province, in mid January, 2020. By late January, local governments across China had adopted lockdown policies, which proved to be very effective in controlling the spread of the Covid-19 virus. By the middle of March, the pandemic was already under control in most parts of the country, with daily confirmed cases kept at a very low level.

We obtain data of confirmed Covid-19 cases released by the National Health Commission (NHC) of the People's Republic of China from CSMAR. Data are available at the national, provincial, and prefecture-city level. The national and provincial data distinguish mainland cases from cases imported from overseas (including Hong Kong, Macau, Taiwan, and other countries and regions.) Since they were mainly found in airports and directly treated, imported

Covid-19 cases were not associated with any communities. Therefore we only use the number of confirmed mainland cases for this paper. City-level macroeconomic indicators such as GDP and population come from CEIC Data, a data science firm in Hong Kong.

Based on the spread and containment of the Covid-19 pandemic in China, we define January 23 to March 31, 2020 as the lockdown period and the months following March as the recovery period. As shown by Figure 1, newly confirmed Covid-19 cases peaked in February and dropped close to zero starting from March 11, 2020, marking the success of disease control efforts and the end of the first and major wave of mainland cases. Although there were scattered broke-outs afterwards, their impacts were limited. Chinaâs economic performance also supports our definition of the lockdown period. In the first quarter of 2020, China's GDP fell by 6.8% as a result of the strict lockdown, while in the second and third quarter, China's GDP rebounded, growing at year-on-year rates of 3.2% and 4.9%, respectively.

2.2 Government lockdown policies

To battle the COVID-19 pandemic, the Chinese government introduced strict lockdown policies that inhibited human mobility and normal economic activities. On January 23, 2020, Wuhan became the first city to introduce a lockdown measure, which includes the shutdown of intra-city public transportation as well as the shutdown of airports and railway stations. On February 11, Wuhan declared closed-off management measures for all residential communities. Residents could only enter or leave the community through a designated gate. Each household was allowed to send out only one person for living essentials every three days. The epicenter was not the only city that went through strict lockdown. People in almost all parts of China were subject to mobility restrictions although their severities varied.

Besides following the central government's guidelines, local governments took initiatives to implement lockdown policies depending on their local situations. On February 10, 2020, Zhejiang became the first province to introduce a pandemic risk rating system, which assigned each county (or district) a risk level ranging from "high risk" to "low risk". Initially, there were five levels of risk in Zhejiang's risk rating system. Other provinces soon followed suit, and almost all provinces started to release risk ratings by early March, 2020. Most provinces adopted three levels of risk: high risk, medium risk, and low risk. This categorization was adopted nationwide and commonly used thereafter.

Risk rating has had real effects on human mobility and economic recovery (and thus corporate hiring), since local governments dynamically changed lockdown measures based on their concurrent risk level: low risk areas were supposed to "prevent imported COVID cases", medium risk areas were supposed to "prevent imported cases and local infections", and high risk areas were supposed to "prevent imported cases and local infections with tough measures". Specifically, the State Council announced a prolonged Chinese New Year vacation ending at February 2, 2020, extending the 7-day long vacation to a 10-day long vacation. Many provinces gave their people an even longer vacation depending on the local transmission of the virus. For instance, Zhejiang Province announced that people should not go to work until February 10, unless their jobs were related to the supply of daily essentials or battling the pandemic. Zhejiang's government further requested that all institutions in the province should "postpone and reduce off-line meetings and crowded activities, and make good use of 'video meetings' and 'online working' ".[7]

Starting in the middle of February, going back to work was encouraged in most provinces in China. On February 18, the State Council announced to waive firms of expenses of pension and unemployment insurances. Local governments subsidized firms that recruited employees and firms that facilitated their employees back to their workplaces. For large numbers of migrant workers, gate-to-gate transportation – including specially designated trains – was arranged.[8] On March 4, 2020, the State Council prohibited low risk level counties from postponing em-

[7] For more information, see https://www.zj.gov.cn/art/2020/1/27/art$_1$2289966604$_4$1860935.$html$.

[8] See http://www.gov.cn/xinwen/2020-02/19/content$_5$481020.htm.

ployees' resumption of work. Medium and high risk level areas were encouraged to simplify the procedures required for restarting work.[9] The risk rating system has been in place since March 2020. There have been scattered lockdowns afterwards, but their impacts were limited.

3 Data and Methodology

3.1 Online job posting data

Our primary data source is an internal database of job vacancies from December 2017 to June 2021 provided by Zhaopin.com (hereafter, Zhaopin), one of the largest online job market platforms in China[10].

Job postings. For each job vacancy entry in the database, we have the following information: date of the posting, type of the position, occupation code (defined by Zhaopin, of around 900 in total), number of workers to be hired, wage range, education requirement (if any), work experience requirement (if any), firm ID, industry, firm size, firm type, work location of the position, and the open text of job descriptions.

We draw a roughly 7% random sample of the universe of job postings on Zhaopin.com between December 2017 and June 2021. The random sample consists of 3,964,881 online job postings and is representative of the job posting population, as shown in Table 2 and 3.

Labeling WFH positions. We perform textual analysis on the job descriptions to create indicators of working from home. We use key words that are related to WFH, such as "working from home", "remote working", "online working", "flexible work schedule", and "flexible work location", to identify WFH postings[11]. Table 2a summarizes these key words and their

[9]See http://www.gov.cn/zhengce/content/2020-03/04/content$_5486767.htm$.

[10]Founded in 1994, Zhaopin now has around 1.4 billion users in the job market, and more than 4 million firms in collaboration. Kuhn & Shen (2013) first used the "scraped" job postings on Zhaopin to analyze gender discrimination in job ads China.

[11]We have explored different definitions of WFH that vary in terms of their strictness to examine the internal consistency of our WFH measures and evaluate whether under-measurement (especially possible non-classical measurement error) is likely a severe issue and if so what are the corresponding robustness checks. The results

corresponding share in terms of the number of related job postings.

Teleworkability. Drawing on the results of Dingel & Neiman (2020), we match the industry-specific teleworkability index to the postings provided by Zhaopin. A higher teleworkability index predicts higher feasibility and chance for a job to be performed remotely.

In a trial analysis performed by Zhaopin.com on job postings from December 2018 to May 2020 using two keywords "remote working" and "online woking", 0.93 percent of the jobs were identified as WFH jobs,[12] and the occupational and industrial distributions of WFH jobs are highly consistent with the distributions of all jobs weighted by occupation- and industry-specific teleworkability scores proposed by Dingel & Neiman (2020) using the O*Net survey datasets in the US, showing positive signs of the external consistency of the WFH measures we use (see Figure 2b)[13].

Sample construction. Using the WFH job postings identified by the aforementioned key words search, we trace back the job posting history of the corresponding firms that issued these postings in the random sample. We refer to these WFH job postings as "sample A1" and non-WFH postings by the same firms as "sample A2", which together form sample A. There are 111,644 firms (categorized into 52 industries) that issued at least one WFH job posting in the random sample between December 2017 and June 2021.

Our key variable is the WFH ratio, defined as the number of WFH posts ($A1$) divided by all job postings (A), including both WFH and non-WFH positions, by firm f in period t, which captures the share of WFH jobs in firms' demand for labor,

$$WFHRatio_{ft} = \frac{A1_{ft}}{A_{ft}} \tag{1}$$

are very similar as long as we capture the two most important key word categories, "remote working" and "online working".

[12] This number is smaller but comparable in the order of magnitude to the numbers in the US generated from the American Community Service (ACS). See Footnote 6.

[13] We have created industry and occupation crosswalk between the ones defined by Zhaopin and the ones used in Dingel & Neiman (2020): NAICS and Standard Occupational Classification (SOC).

3.2 Summary Statistics of WFH Jobs

Table 1 shows the summary statistics of the main variables in firm-month level and firm-city-month level panels.

Time-trend analysis. As shown in Figure 1b, the time trends of the number of WFH and non-WFH job postings followed each other closely prior to the pandemic, although WFH jobs constitute only about 10% of all jobs released by the same firms. The total number of WFH job postings (dashed line) drops to the bottom during the Covid-19 shock, rises afterwards, and stays at a level higher than before. In contrast, non-WFH jobs experienced a very weak rebound, fluctuating at a level lower than before. In Figure 3a, we capture the shift in job demand composition by the WFH ratio, which is the fraction of WFH jobs in all jobs posted by the same company. Shown by the solid line in Figure 3a, this WFH ratio is almost constant before the Covid-19 shock, falls upon the Covid-19 shock, and bounces back and keeps increasing post-pandemic.

One may argue that the slack season around the Chinese New Year could confound the impact of Covid-19 shock and lockdown policies on WFH job postings. To take in account the seasonal fluctuations of corporate hiring, we seasonally adjust the number of WFH jobs and the WFH ratio using the 12-month moving average. As shown in Figure 3b, both the number of WFH job postings and the WFH ratio rose dramatically after the lockdown, and continued to increase afterwards. The increase of WFH's share in the job demand composition is closely connected to the pandemic shock and seems to stay in the post-pandemic era.

4 The Impact of the Covid-19 Pandemic on WFH Demand

4.1 Event study

We first estimate an event study model to illustrate the impact of COVID-19 lockdown on WFH ratio,

$$Log(WFHRatio_{ft} + 1) = \alpha + \Sigma_{t=n}^{m} \beta_t Month_t + \lambda_f + \varepsilon_{ft} \tag{2}$$

where $WFHRatio_{ft}$ is the share of WFH job postings amongst all job postings released by the same firm i in month t. $Month_t$ are a set of month dummies ranging from December, 2017 to June, 2021. We compact the January to March, 2020 into one single lockdown period, and omit this period in our regression to rule out the possible noise introduced by the pandemic and lockdown. So the lockdown period is actually set as the base level. The coefficients of interest are β_t, which capture the change in WFH ratio that is independent of firm characteristics. We expect β_t to increase after the pandemic shock.

Indeed, we find a significant trend break around the lockdown period, with the share of WFH being higher after the COVID shock. Figure 4b plots β_t on the month dummies in equation (2) at the firm level. We also replicate the above event study at the industry level, replacing firms' WFH ratio with industries' WFH ratio. Doing so, we not only find out the impact of Covid-19 on firm's shift in WFH demand, but also its impact on industrl-level WFH demand. We control for firm and industry fixed effects and cluster standard errors at the firm and industry level, respectively. In both settings, the event study suggests a notable increase in WFH ratio following the pandemic.

4.2 Difference-in-differences

The Covid-19 shock provides firms and workers with a unique opportunity to try out and learn about the working from home (WFH) arrangement. Other things equal, it should have a larger impact on firms less accustomed to WFH hiring prior to the Covid-19 shock through mandatory WFH trials during the lockdown period. We test this hypothesis by estimating a difference-in-differences model to see the impact of the Covid-19 shock on the WFH ratio at firm level :

$$Log(WFHRatio_{fit}+1) = \alpha + \beta PostCovid_t \times WFHRatio2019_f + \lambda_f + f(t) + \varepsilon_{fit} \quad (3)$$

where $WFHRatio_{fit}$ is the share of WFH job postings amongst all job postings released by firm f in industry i in month t. $PostCovid_t$ takes value 1 for months after March 2020 when the pandemic was brought under control, and 0 for months before January 2020, when the pandemic first broke out. The key treatment variable is $WFHRatio2019_f$, the annual average of each firm's $WFHRatio$ in 2019.

We drop the lockdown period (January to March, 2020) in our regressions, focusing only on the comparison of pre- and post-Covid era. We also control for firm fixed effects λ_f, and time trends $f(t)$. Standard errors are clustered at the firm level. The coefficient of interest β captures the WFH ratio gap of high-teleworkbility firms and low-teleworkability firms induced by Covid related lockdown policies.

Table 4 presents the regression results of specification 3. The coefficients on the interaction term between $PostCovid$ and $WFHRatio2019$ are significantly negative in all columns, indicating that firms with previously lower WFH ratio witnessed a larger increase in WFH ratio post Covid. To be specific, we find that a 10 percentage points' increase of pre-Covid WFH ratio of a firm can reduce the WFH ratio gap before and after the pandemic by around 3.65%.

Another possibility is that firms with fewer WFH hiring are intrinsically different from those with more WFH job postings prior to the Covid-19 shock. For instance, firms in industries with greater potential to shift to remote working may have already done so even without any exogenous push. To tackle this problem, we control for industry and firm fixed effects, respectively, in Table 4, to control for any time-invariant industry and firm characteristics. We also control for time fixed effects to rule out the firm-invariant time trends. The results we obtain above are robust even when controlling for industry, firm and month fixed effects.

One may concern that as time goes by since the lockdown period, our estimated impact of the pandemic on WFH may pick up the effects of some other factors. To eliminate that concern, we replicate the DID estimation in Table 4 by restricting the sample to 6 months before & after the pandemic and 12 months before & after the pandemic, respectively. As shown in Table 6, we find the results are largely the same as the baseline.

4.3 Teleworkability

Dingel & Neiman (2020) find that 37% of jobs in the US can be performed entirely at home, and that these jobs account for 46 % of all US wages. Bartik *et al.* (2020) show that the Dingel & Neiman (2020) measure of suitability for remote work does a remarkably good job of predicting the industry level patterns of remote work, and that remote work is much more common in industries with better educated and better paid workers. Across countries, teleworkability also differs. Gottlieb *et al.* (2020) find that in urban areas the share of employment suitable for WFH is 20% in poor countries and 40% in rich ones.

We use the following DID model to examine the predictive power of the teleworkability measure à la Dingel & Neiman (2020):

$$Log(WFHRatio_{fit} + 1) = \alpha + \beta PostCovid_t \times Teleworkability_i + \lambda_f + f(t) + \varepsilon_{fit} \quad (4)$$

where the treatment variable $Teleworkability_i$ is the teleworkability index of industry i as given in Dingel & Neiman (2020).

Table 5 reports the regression results of 4. We find that with month and industry being controlled, an 0.1 increase in the industrial teleworkability of the firm significantly increases the gap between the share of WFH job postings before and after the COVID shock by 0.16%, as shown in column 4. The coefficients on $PostCovid_t$ and $Teleworkability_i$ also have intuitive signs, both being postitive. This suggests that WFH ratio is higher after the pandemic and higher for firms in high-teleworkability industries.

However, column 5 and 6 of Table 5 show that this effect becomes insignificant when controlling for firm fixed effect. One possible hypothesis is that firms with higher WFH ratio prior to the pandemic tend to experience smaller increase of WFH ratio after the pandemic. To test this hypothesis, we then estimate the following triple difference model:

$$\begin{aligned} Log(WFHRatio_{fit}+1) = & \alpha + \beta PostCovid_t \times WFHRatio2019_f \times Teleworkability_i \\ & + PostCovid_t \times WFHRatio2019_f \\ & + PostCovid_t \times Teleworkability_i + \lambda_f + f(t) + \varepsilon_{fit} \end{aligned} \tag{5}$$

Table 7 reports the regression results. We find that the triple interaction term $PostCovid_t \times WFHRatio2019_i \times Teleworkability_i$ stays significantly positive, indicating that given the same take-up rate of WFH in 2019, firms with higher teleworkability tend to experience larger increase in the difference-in-differences of WFH ratio, when controlling for firm and month fixed effect, as shown in column 6.

5 Firm Characteristics and Heterogeneity Analysis

5.1 Firm Type

In this section, we examine firm characteristics which could possibly predict the degree to which COVID-19 affected the WFH ratio. We first look at the heterogeneity of firms' ownership.

Table 8 presents the results of regressing specification (3) on the sub samples of private firms and state-owned enterprises (SOE), respectively. Panel A shows the results on private firms and Panel B shows the results on SOEs. In private firms' sub-sample, a 10 percentage points' increase in pre-Covid WFH ratio leads to around 3.7% decrease in the WFH ratio gap before and after the pandemic. For SOEs, that number is 3.5%. In other words, the private firms are quicker at learning to shift to WFH than SOEs with all else being equal, although the difference between private firms and SOESs is small in magnitude.

Table 9 reports the results of regressing specification (4) on the two different types of firms using teleworkability as the treatment variable. Panel A shows the results of private firms. We find that with month and industry being controlled, teleworkability of the firm significantly increases its WFH ratio gap before and after the pandemic, as shown in column 4. However, column 5 and 6 show that the coefficient of the interaction term becomes statistically insignificant after controlling for firm fixed effect. Panel B shows the results on SOEs. The coefficients on the interaction terms are consistently positive, and become statistically significant at the 10% level in the columns 5 and 6, where firm fixed effects are controlled. This indicates a positive effect of teleworkability on the post-Covid WFH share of SOEs.

5.2 Average Wages of the Firms

In order to look into the influence of other firm characteristics, we introduce a triple interaction term into the DID specifications:

$$\begin{aligned} Log(WFHRatio_{fit}+1) =& \alpha + \beta PostCovid_t \times WFHRatio2019_i \times Characteristic_f \\ & + \lambda_f + f(t) + \varepsilon_{fit} \end{aligned} \tag{6}$$

$$\begin{aligned} Log(WFHRatio_{fit}+1) =& \alpha + \beta PostCovid_t \times Teleworkability_i \times Characteristic_f \\ & + \lambda_f + f(t) + \varepsilon_{fit} \end{aligned} \tag{7}$$

where $Characteristic_f$ is a firm characteristic, and other variables are defined in the same way as in equation (3) and (4). Standard errors are clustered at the firm level.

Table 10 presents the regression results of specification (6). Panel A shows the results with $Characteristic_f$ being the logarithm of the average wage of jobs posted by the firm. We find that among firms with the same WFH ratio in 2019, those with higher average wage tend to experience significantly larger increase in WFH ratio post Covid, with firm and month fixed effects being controlled.

Panel A of Table 11 presents the regression results of specification (7) with $Characteristic_f$ being the teleworkability of the firm's industry. The effect of average wage on WFH ratio post Covid among firms with the same teleworkability remains unclear. In column 4, when controlling for both time and industry fixed effect, the influence of wage becomes insignificant. In columns 5 and 6, after adding the firm fixed effect, the influence of average wage even becomes significantly negative. This suggests the higher the wage level of the firm, the smaller the impact of teleworkability on WFH ratio after the pandemic.

5.3 Firm Scale

Panel B of Table 10 presents the results of specification (6) with $Characteristic_f$ being the logarithm of firm scale measured by the number of employees in the firm. As shown in column 4, when controlling for month and industry fixed effect, firms with the same pre-Covid WFH ratio but larger scale tend to experience slightly though significantly larger increase in WFH ratio post Covid. In column 5 and 6, however, the effect becomes negative and insignificant when controlling for the firm fixed effect.

Panel B of Table 11 presents the results of specification (7) with $Characteristic_f$ being the logarithm of firm scale measured by the number of employees in the firm. When not controlling for firm fixed effect, among firms with the same teleworkability, those with larger scale tend to experience slightly though significantly larger increase in WFH ratio post Covid. Also, the effect becomes negative and insignificant when controlling for the firm fixed effect.

5.4 City

To identify the impact of Covid-19 on WFH take-up, we estimate the following DID model:

$$Log(WFHRatio_{fct}+1)=\alpha+\beta PostCovid_t\times CovidShock_c+\eta X_{ct}+\lambda_f+\gamma_c+f(t)+\varepsilon_{fct} \quad (8)$$

where $WFHRatio_{fct}$ is the share of WFH job postings amongst all job postings released by firm f in city c in month t. $CovidShock_c$ is the logarithm of the ratio of the number of confirmed Covid cases in city c by March, 2020 to the population of that city in 2019. $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. X_{ct} is a vector of city-level controls, including the annual GDP, population, urbanization rate, and the share of primary industry and secondary industry value added in its GDP. λ_f is firm fixed effects, γ_c is city fixed effects and $f(t)$ is month fixed effects.

Table 12 reports the regression results. As shown in column 6, when controlling for all the city-level control variables and month and city fixed effects, the covid shock a city experienced has a small though significant effect on the post-Covid WFH ratio of a firm. The smaller WFH share increase in cities hit harder by the pandemic within firms may suggest a intra-firm hiring restructure, i.e. firms may shift their teleworkable jobs to cities hit less hard by the pandemic because these jobs allow remote work. Jobs that cannot be done online or in another place, however, continue to be posted in the original city. This restructuring of WFH and non-WFH jobs within firm may explain the seemingly unintuitive result that the Covid-19 pandemic seems to decrease remote work.

6 Conclusion

The Covid-19 pandemic serves as a large-scale natural experiment inducing short-run WFH takeup in places where lockdown and social distancing policies were implemented. We find this temporary shock has a persistent impact on firms' demand for WFH reflected in the job posting data. We further exploit the variation in firms' pre-Covid WFH take-up to identify the learning effect of this temporary shock. Our findings show that firms with smaller pre-Covid WFH take-up experience a larger increase in WFH hiring after the Covid-19 lockdown. This effect is more pronounced in firms with greater potential of remote work, with private ownership, and with larger size. These characteristics are useful not only for tracing back the causes of higher WFH demand after the Covid-19 shock, but also for predicting future trends of hiring in the labor market.

Given large heterogeneities in the productivity impacts of WFH and other flexible work arrangements across firms and job types, it remains an open empirical question what firm and occupation characteristics are more likely to make WFH a profitable option to adopt (Mas & Pallais, 2020). A good answer to these questions can guide policymakers to direct WFH-fostering industry policies to the right groups. Our research highlights two aspects of the high-stake policy relevance. First, once the characteristics of the firms that permanently shift their jobs to WFH after the pandemic are identified, the government can choose to offer or subsidize short-run WFH training programs targeting similar firms which are not heavily affected by the pandemic and therefore still remain on-site. This one-time policy, similar to the pandemic in terms of its potential to permanently shift WFH-profitable jobs to being performed remotely, could generate large welfare enhancement in the long run. In addition, documenting what skills are likely to be in greater demand in the future, resulting from the permanent adoption of WFH in some jobs after the COVID-19 crisis, can provide guidance for education policies in terms of curriculum designs and vocational training programs, etc.

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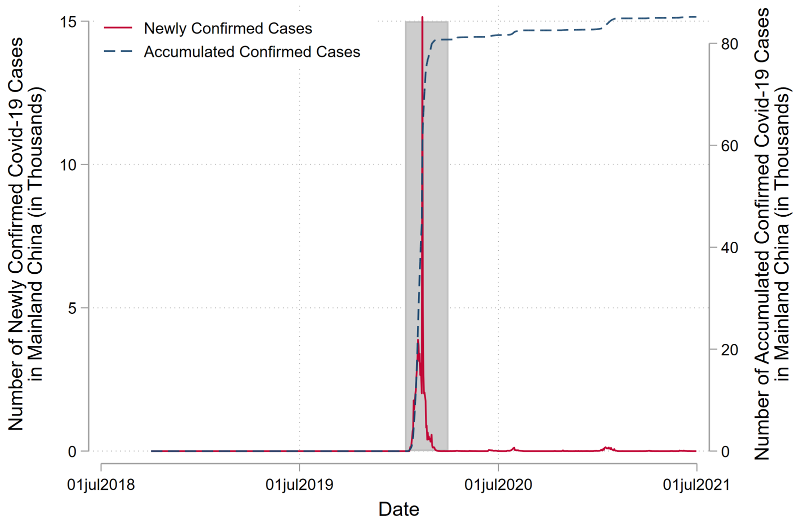
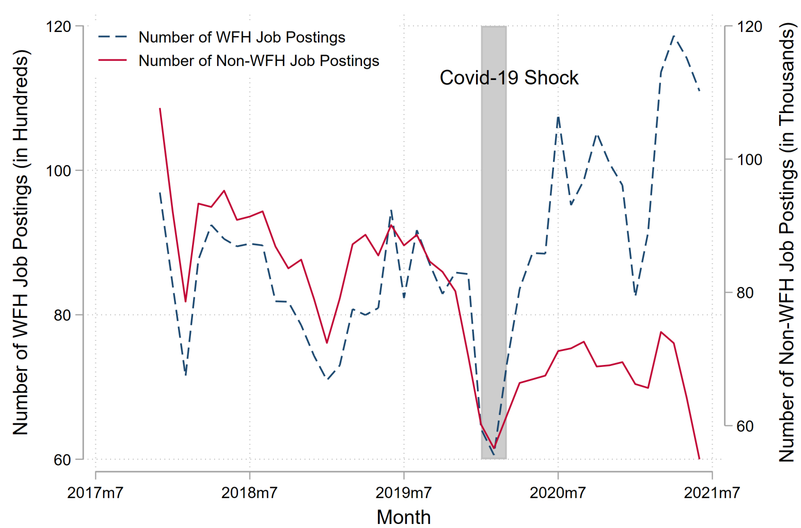
FIGURE 1: THE COVID-19 SHOCK IN CHINA

Note: Panel A shows the daily data on newly confirmed mainland cases and accumulated mainland cases since October 1, 2018. Panel B compares the number of WFH job postings and the number of Non-WFH job postings in our sample.



(A) NEWLY CONFIRMED CASES IN MAINLAND CHINA



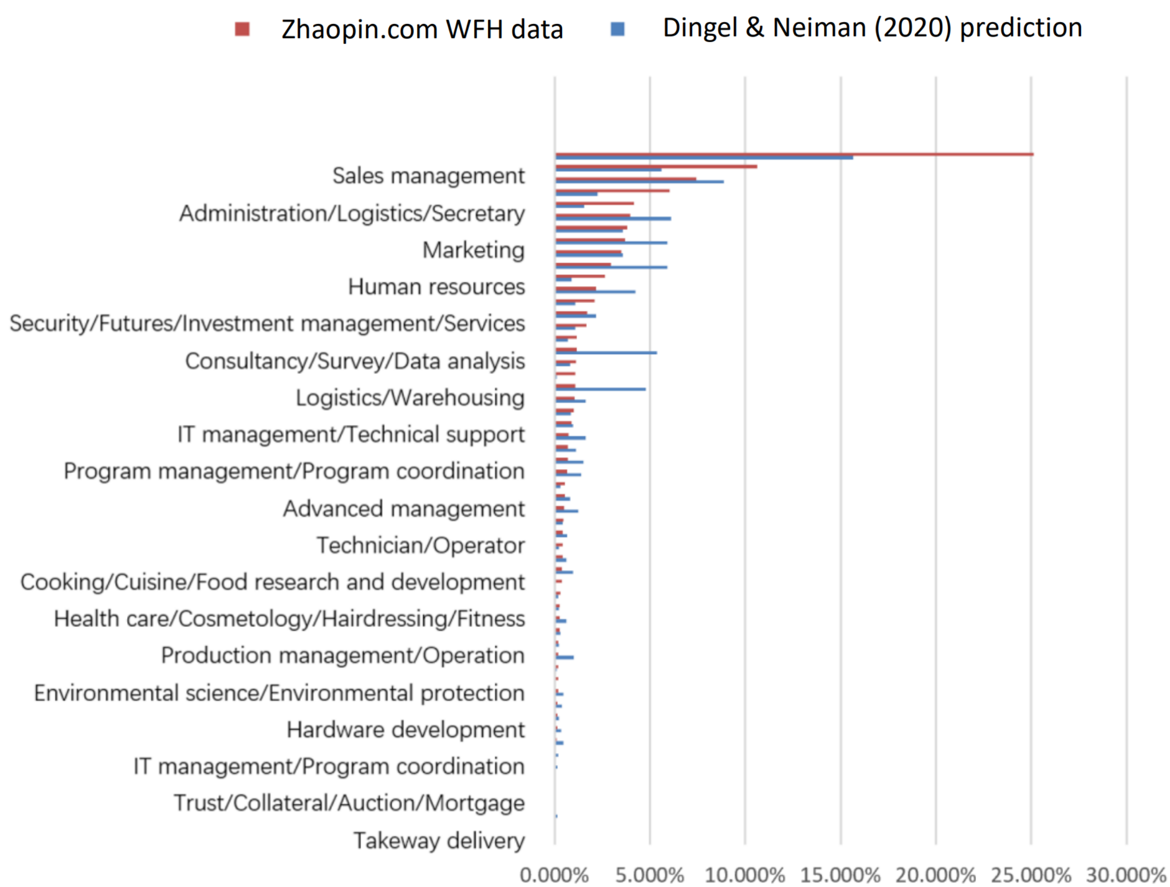
(B) COMPARISON OF THE NUMBER OF WFH AND NON-WFH JOB POSTINGS

FIGURE 2: WORKING FROM HOME (WFH) JOB POSTINGS

Note: This figure shows the distribution of key words used to draw the WFH sample as well as a comparison of the predicted and actual distribution of WFH jobs by industry. Panel A demonstrates the share of observations by key words in the WFH sample. "Inverse" refers to deducing that a job allows WFH from expressions like "no need to be onsite", etc. "Free" refers to jobs that allow employees to freely decide when and where to work. Panel B presents the predicted values of the share of remote work based on Dingel & Neiman (2020), and the actual values calculated with Zhaopin's data.

WFH Key Words	Percentage
Remote	2%
Flexible	75%
Online	12%
At home	13%
Inverse	1%
Free	1%

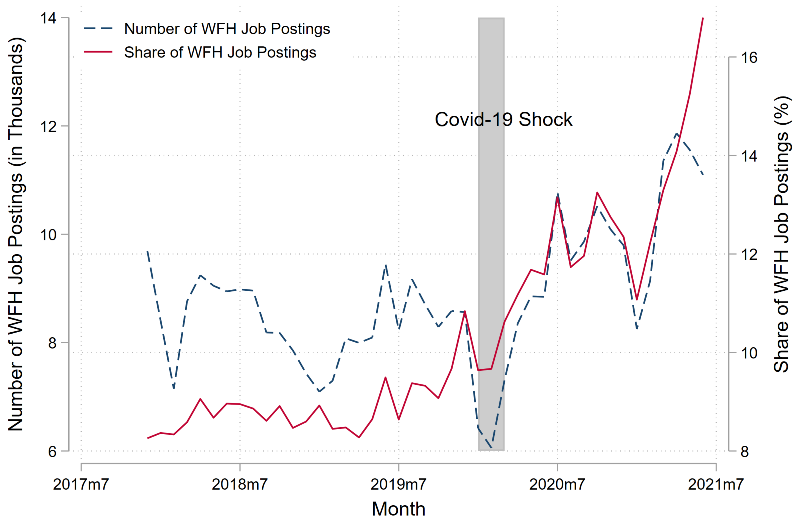
(A) KEY WORDS USED TO DRAW THE WFH SAMPLE



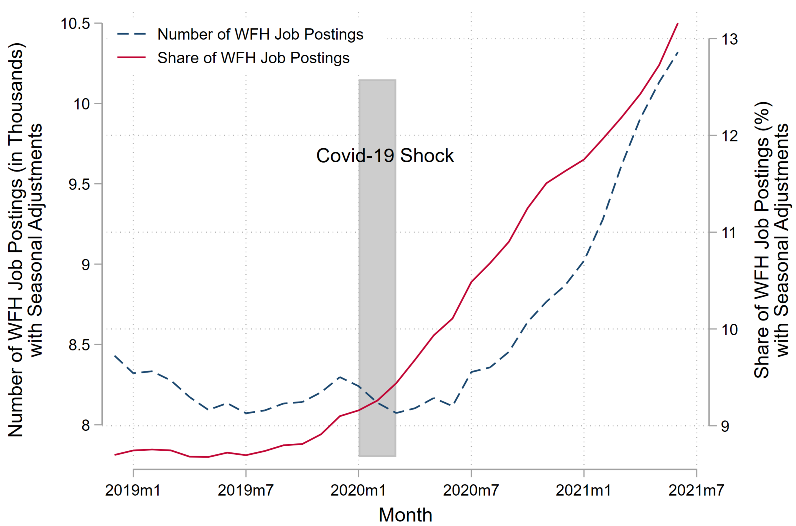
(B) SHARE OF WFH BY INDUSTRY, PREDICTED VALUES AND AVERAGE VALUES

FIGURE 3: THE COVID-19 SHOCK AND INCREASE IN WFH POSTINGS

Note: This figure shows the time trend of the total number of WFH jobs postings, and the time trend of the WFH ratio defined as the share of WFH job postings amongst all job postings. Panel A shows the time trends without seasonal adjustment, while Figure Panel B makes seasonal adjustments by taking a 12-month moving average of the two variables.



(A) NUMBER AND SHARE OF WFH JOB POSTINGS OVER TIME



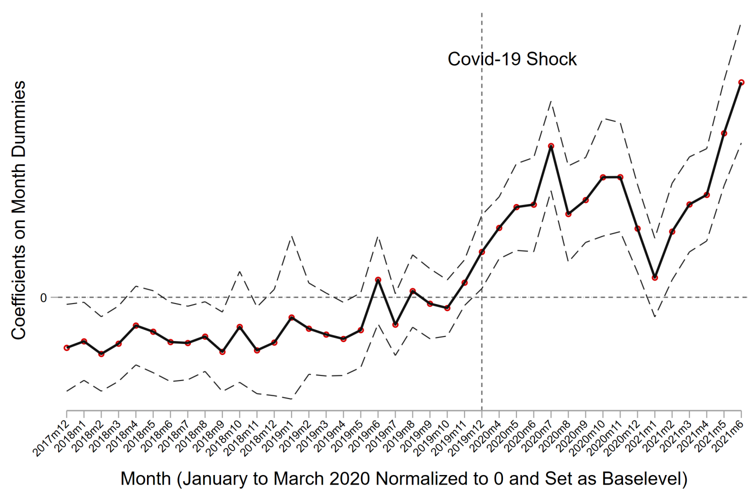
(B) NUMBER AND SHARE OF WFH JOB POSTINGS OVER TIME (WITH SEASONAL ADJUSTMENTS)

FIGURE 4: EVENT STUDY

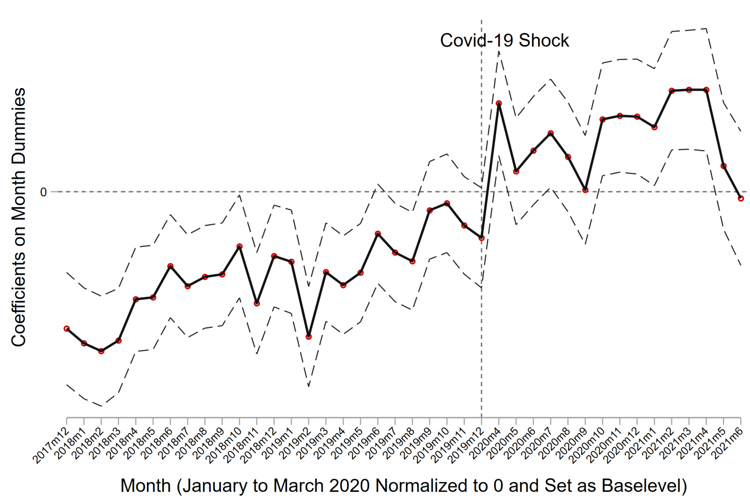
Note: This figure shows the results of the event study by estimating the following regression:

$$Log(WFHRatio_{ft} + 1) = \alpha + \Sigma_{t=n}^{m} \beta_t Month_t + \lambda_f + \varepsilon_{ft}$$

where $WFHRatio_{ft}$ is the share of WFH job postings amongst all job postings released by the same firm i (or industry i) in month t . $Month_t$ are a set of month dummies ranging from December, 2017 to June, 2021. λ_f is firm (or industry) fixed effects. We compact the January to March, 2020 into one single lockdown period, and set this period as the base level. Panel A presents the results of the industry-month panel, and Panel B presents the results of the firm-month panel.



(A) COEFFICIENTS ON THE MONTH DUMMIES (INDUSTRY LEVEL)



(B) COEFFICIENTS ON THE MONTH DUMMIES (FIRM LEVEL)

Table 1: Summary Statistics

Note: This table summarizes the key features of the sample data. Panel A presents the summary statistics of firm-month data. $WFHRatio2019$ is the annual average of each firm's $WFHRatio$ in 2019, right before the outbreak of the Covid-19 pandemic. $FirmScale$ is a proxy for the firm size using the number of employees hired by each firm. Panel B presents summary statistics of the firm-city-month panel.

(a) Summary Statistics of Firm-month Panel Data

VARIABLES	N	mean	sd	min	max
Teleworkability	747,646	0.660	0.302	0.076	1.000
Wages	734,875	8,458	4,312.957	500.000	25,000.000
WFHRatio	747,646	0.144	0.316	0.000	1.000
FirmSize	732,794	1,720.692	3,023.341	10.000	10,000.000
WFHRatio2019	629,390	0.110	0.203	0	1
Log(WFHRatio+1)	747,646	0.106	0.224	0.000	0.693
PostCovid	747,646	0.457	0.498	0	1
Firm Type:					
Private	747,646	0.687	0.464	0	1
SOE	747,646	0.047	0.212	0	1
Mixed	747,646	0.203	0.403	0	1
Others	747,646	0.062	0.241	0	1.

(b) Summary Statistics of Firm-city-month Panel Data

VARIABLES	N	mean	sd	min	max
WFHRatio	1202055	0.138	0.324	0.000	1.000
Log(WFHRatio+1)	1202055	0.099	0.227	0.000	0.693
AccumulatedCases(Mar2020)	1202055	225.373	202.596	0.000	581.000
Log(AccumulatedCases/Population2019)	1151569	-4.304	0.729	-7.839	-2.217
Population	967,724	12.481	7.026	0.252	32.054
Urbanization Rate	815,680	0.780	0.115	0.340	0.998
GDP	987,100	1.574	1.169	0.013	3.870
Share of Primary Industry	985,370	0.039	0.048	0.001	0.493
Share of Secondary Industry	985,370	0.349	0.096	0.113	0.653

Table 2: Evidence on the Validity of Sample Construction, Type of firm and Number of employees

Note: This table compares the entire WFH population and the random sample we draw from the population in terms of type of firm and number of employees. Here type of firm refers to the type of the firm releasing the job postings, and number of employees refer to the number of people employed by that firm.

(a) Summary Statistics of Firm-month Panel Data

Type of firm	Sample ratio	Population ratio
Listed firms	5.30%	5.14%
Government-affiliated institutions	0.20%	0.18%
Representative offices	0.09%	0.08%
Hospitals	0.03%	0.03%
Joint ventures	5.24%	5.06%
State-owned enterprises	4.96%	4.87%
Governments	0.01%	0.01%
Wholly foreign owned firms	2.44%	2.38%
Schools	0.14%	0.14%
Law firms	0.04%	0.04%
Private firms	68.69%	68.26%
Social groups	0.06%	0.07%
Joint stock enterprises	9.91%	9.91%
Banks	0.03%	0.08%
Firms from Hong Kong, Macau, and Taiwan	0.00%	0.17%
Others	2.87%	3.58%

(b) Summary Statistics of Firm-city-month Panel Data

Number of employees	Sample ratio	Population ratio
20 and below	7.57%	7.40%
20-99	27.64%	27.16%
100-499	25.39%	26.29%
500-999	8.89%	8.74%
1000-9999	15.07%	14.62%
10000 and above	14.08%	13.88%
Others	1.36%	1.90%

TABLE 3: EVIDENCE ON THE VALIDITY OF SAMPLE CONSTRUCTION, WORK EXPERIENCE REQUIREMENT AND EDUCATION REQUIREMENT

Note: This table compares the entire WFH population and the random sample we draw from the population in terms of work experience requirement and education requirement. Here work experience requirement refers to the number of years previously worked required for the job, and education requirement refers to the minimum education attainment required for that job.

(A) SUMMARY STATISTICS OF FIRM-MONTH PANEL DATA

Work experience requirement	Sample ratio	Population ratio
1 year and below	3.34%	3.35%
1-3 years	21.57%	21.43%
3-5 years	7.93%	7.82%
5-10 years	2.24%	2.21%
10 years and above	0.21%	0.20%
No experience / no requirement	64.71%	65.00%

(B) SUMMARY STATISTICS OF FIRM-CITY-MONTH PANEL DATA

Education requirement	Sample ratio	Population ratio
Junior high school and below	0.23%	0.23%
Secondary specialized school	6.46%	6.48%
Senior high school	2.20%	2.24%
Junior college	38.77%	38.64%
College	24.17%	23.82%
Master's degree	0.54%	0.52%
Doctor's degree	0.02%	0.02%
MBA/EMBA	0.00%	0.00%
No specific requirement	27.61%	28.05%

TABLE 4: DID RESULTS USING PRE-COVID WFH RATIO, FIRM-MONTH PANEL

Note: This table summarizes the results of the following regression:

$$Log(WFHRatio_{fit} + 1) = \alpha + \beta PostCovid_t \times WFHRatio2019_f + \lambda_f + f(t) + \varepsilon_{fit}$$

where $WFHRatio_{fit}$ is the share of WFH job postings amongst all job postings released by firm f in industry i in month t. $WFHRatio2019_f$ is the annual average of each firm's $WFHRatio$ in 2019. $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. λ_f is firm fixed effects, and $f(t)$ is month fixed effects. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHRatio2019	-0.365***	-0.365***	-0.365***	-0.365***	-0.364***	-0.365***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PostCovid	0.038***		0.038***		0.038***	
	(0.001)		(0.001)		(0.001)	
WFHRatio2019	0.643***	0.643***	0.640***	0.640***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	629,390	629,390	629,390	629,390	624,314	624,314
Adjusted R-squared	0.315	0.316	0.316	0.316	0.314	0.314

Table 5: DID Results using Teleworkability, Firm-Month Panel

Note: This table summarizes the results of the following regression:

$$Log(WFHRatio_{fit} + 1) = \alpha + \beta PostCovid_t \times Teleworkability_i + \lambda_f + f(t) + \varepsilon_{fit}$$

where $WFHRatio_{fit}$ is the share of WFH job postings amongst all job postings released by firm f in industry i in month t. $Teleworkability_i$ is the teleworkability index of industry i as given in Dingel & Neiman (2020). $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. λ_f is firm fixed effects, and $f(t)$ is month fixed effects. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*teleworkability	0.013***	0.013***	0.016***	0.016***	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PostCovid	0.025***		0.023***		0.008***	
	(0.002)		(0.002)		(0.001)	
teleworkability	0.028***	0.028***				
	(0.002)	(0.002)				
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	747,646	747,646	747,646	747,646	729,367	729,367
Adjusted R-squared	0.008	0.010	0.015	0.018	0.320	0.320

TABLE 6: ROBUSTNESS CHECK: DID RESULTS USING PRE-COVID WFH RATIO IN DIFFERENT TIME INTERVALS, FIRM-MONTH PANEL

Note: This table summarizes the results of the following regression:

$$Log(WFHRatio_{fit} + 1) = \alpha + \beta PostCovid_t \times WFHRatio2019_i + \lambda_f + f(t) + \varepsilon_{fit}$$

where $WFHRatio_{fit}$ is the share of WFH job postings amongst all job postings released by firm f in industry i in month t. $WFHRatio2019$ is the annual average of each firm's $WFHRatio$ in 2019. $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. λ_f is firm fixed effects, and $f(t)$ is month fixed effects. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1. Panel A limits the time interval to 6 months before and after the pandemic (i.e. July 2019 - December 2019 & April 2020 - September 2020), and Panel B limits the time interval to 12 months before and after the pandemic (i.e. January 2019 - December 2019 & April 2020 - March 2021).

	Panel A: 6 months before & after pandemic					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHratio2019	-0.414***	-0.414***	-0.414***	-0.414***	-0.379***	-0.379***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PostCovid	0.045***		0.045***		0.040***	
	(0.001)		(0.001)		(0.001)	
WFHRatio2019	0.705***	0.705***	0.703***	0.703***		
	(0.001)	(0.001)	(0.001)	(0.001)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	271,991	271,991	271,991	271,991	263,516	263,516
Adjusted R-squared	0.365	0.365	0.365	0.365	0.355	0.355

	Panel B: 12 months before & after pandemic					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHratio2019	-0.420***	-0.420***	-0.420***	-0.421***	-0.395***	-0.395***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
PostCovid	0.045***		0.045***		0.041***	
	(0.001)		(0.001)		(0.001)	
WFHRatio2019	0.703***	0.703***	0.701***	0.701***		
	(0.000)	(0.000)	(0.000)	(0.000)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	521,076	521,076	521,076	521,076	513,483	513,483
Adjusted R-squared	0.368	0.368	0.369	0.369	0.326	0.326

TABLE 7: DDD RESULTS USING BOTH TELEWORKABILITY AND PRE-COVID WFH RATIO, FIRM-MONTH PANEL

Note: This table summarizes the results of the following regression:

$$
\begin{aligned}
Log(WFHRatio_{fit}+1) =& \alpha + \beta PostCovid_t \times WFHRatio2019_f \times Teleworkability_i \\
&+ PostCovid_t \times WFHRatio2019_f \\
&+ PostCovid_t \times Teleworkability_i + \lambda_f + f(t) + \varepsilon_{fit}
\end{aligned}
$$

where $WFHRatio2019_f$ is the annual average of firm i's $WFHRatio$ in 2019. $Teleworkability_i$ is the teleworkability index of industry i as given in Dingel & Neiman (2020). $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
postCovid*teleworkability*WFHratio2019	0.060***	0.060***	0.060***	0.060***	0.055***	0.055***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.020)	(0.020)
postCovid*teleworkability	0.008***	0.008***	0.008***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
postCovid*WFHratio2019	-0.406***	-0.406***	-0.407***	-0.407***	-0.402***	-0.403***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
postCovid	0.033***		0.033***		0.034***	
	(0.001)		(0.001)		(0.001)	
WFHRatio2019	0.643***	0.642***	0.641***	0.641***		
	(0.001)	(0.001)	(0.001)	(0.001)		
teleworkability	0.004***	0.004***				
	(0.000)	(0.000)				
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	629,390	629,390	629,390	629,390	624,314	624,314
Adjusted R-squared	0.316	0.316	0.316	0.316	0.315	0.315

TABLE 8: SUB-SAMPLE DID RESULTS, PRIVATE FIRMS VS. SOES, USING PRE-COVID WFH RATIO

Note: This table compares the regression results of private firms with those of state-owned enterprises (SOEs). Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1

	Panel A: Private firms					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHRatio2019	-0.368***	-0.368***	-0.368***	-0.368***	-0.369***	-0.370***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
PostCovid	0.039***		0.040***		0.040***	
	(0.001)		(0.001)		(0.001)	
WFHRatio2019	0.643***	0.643***	0.641***	0.641***		
	(0.002)	(0.002)	(0.002)	(0.002)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	430,262	430,262	430,262	430,262	426,556	426,556
Adjusted R-squared	0.315	0.316	0.316	0.316	0.312	0.312

	Panel B: SOEs					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHRatio2019	-0.363***	-0.366***	-0.363***	-0.366***	-0.349***	-0.351***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.026)	(0.026)
PostCovid	0.032***		0.034***		0.035***	
	(0.003)		(0.003)		(0.003)	
WFHRatio2019	0.650***	0.650***	0.640***	0.640***		
	(0.006)	(0.006)	(0.006)	(0.007)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	29,332	29,332	29,332	29,332	29,136	29,136
Adjusted R-squared	0.311	0.311	0.313	0.313	0.307	0.307

Table 9: Sub-sample DID Results, Private Firms vs. SOEs

Note: This table compares the regression results of private firms with those of state-owned enterprises (SOEs). Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1

			Panel A: Private firms			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*teleworkability	0.013***	0.013***	0.016***	0.016***	-0.002	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
PostCovid	0.026***		0.023***		0.007***	
	(0.002)		(0.002)		(0.002)	
teleworkability	0.024***	0.024***				
	(0.002)	(0.002)				
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	513,914	513,914	513,914	513,914	500,707	500,707
Adjusted R-squared	0.007	0.010	0.014	0.016	0.315	0.315

			Panel B: SOEs			
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*teleworkability	0.007	0.008	0.001	0.002	0.016*	0.017*
	(0.011)	(0.011)	(0.011)	(0.011)	(0.009)	(0.009)
PostCovid	0.013*		0.016**		-0.004	
	(0.008)		(0.008)		(0.007)	
teleworkability	0.050***	0.050***				
	(0.008)	(0.008)				
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	35,407	35,407	35,407	35,407	34,746	34,746
Adjusted R-squared	0.006	0.007	0.029	0.029	0.302	0.302

TABLE 10: HETEROGENEITY ANALYSIS, USING PRE-COVID WFH RATIO

Note: This table summarizes the DDD regression results to compare firms with different average wages and different sizes (proxied by the number of employees), respectively. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1

	Panel A: Average-Wage Heterogeneity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHRatio2019*log(wage)	0.059***	0.060***	0.059***	0.059***	0.044***	0.045***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.009)	(0.009)
PostCovid*WFHratio2019	-0.892***	-0.895***	-0.891***	-0.894***	-0.758***	-0.760***
	(0.103)	(0.103)	(0.103)	(0.103)	(0.082)	(0.082)
PostCovid	0.037***		0.038***		0.037***	
	(0.001)		(0.001)		(0.001)	
WFHratio2019	0.642***	0.642***	0.640***	0.639***		
	(0.001)	(0.001)	(0.001)	(0.001)		
log(wage)	-0.003***	-0.003***	-0.003***	-0.003***	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	622,456	622,456	622,456	622,456	617,315	617,315
Adjusted R-squared	0.317	0.318	0.318	0.318	0.316	0.316

	Panel B: Firm Size Heterogeneity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*WFHratio2019*log(FirmSize)	0.008***	0.008***	0.007**	0.007**	-0.000	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
PostCovid*WFHratio2019	-0.405***	-0.405***	-0.401***	-0.401***	-0.362***	-0.362***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
PostCovid	0.038***		0.039***		0.038***	
	(0.001)		(0.001)		(0.001)	
WFHratio2019	0.640***	0.640***	0.638***	0.637***		
	(0.001)	(0.001)	(0.001)	(0.001)		
log(FirmSize)	-0.002***	-0.002***	-0.002***	-0.002***		
	(0.000)	(0.000)	(0.000)	(0.000)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	617,975	617,975	617,975	617,975	612,959	612,959
Adjusted R-squared	0.316	0.316	0.317	0.317	0.314	0.314

TABLE 11: HETEROGENEITY ANALYSIS, USING TELEWORKABILITY

Note: This table summarizes the DDD regression results to compare firms with different average wages and different sizes (proxied by the number of employees), respectively. Standard errors are clustered at the firm level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1

	Panel A: Average-Wage Heterogeneity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*teleworkability*log(wage)	0.004**	0.004*	0.004*	0.003	-0.003*	-0.003*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
PostCovid*teleworkability	-0.027	-0.019	-0.019	-0.011	0.026	0.026
	(0.019)	(0.019)	(0.019)	(0.019)	(0.016)	(0.016)
PostCovid	0.023***		0.021***		0.008***	
	(0.002)		(0.002)		(0.001)	
teleworkability	0.028***	0.028***				
	(0.002)	(0.002)				
log(wage)	-0.005***	-0.006***	-0.006***	-0.007***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	734,875	734,875	734,875	734,875	716,771	716,771
Adjusted R-squared	0.007	0.009	0.014	0.016	0.322	0.322

	Panel B: Firm Size Heterogeneity					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PostCovid*teleworkability*log(FirmSize)	0.007***	0.006***	0.005***	0.005***	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
PostCovid*teleworkability	-0.022***	-0.021***	-0.012***	-0.011***	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
PostCovid	0.026***		0.024***		0.008***	
	(0.002)		(0.002)		(0.001)	
teleworkability	0.026***	0.026***				
	(0.002)	(0.002)				
log(FirmSize)	-0.011***	-0.011***	-0.013***	-0.013***		
	(0.000)	(0.000)	(0.000)	(0.000)		
Month FE		Y		Y		Y
Firm FE					Y	Y
Industry FE			Y	Y		
Observations	732,794	732,794	732,794	732,794	714,846	714,846
Adjusted R-squared	0.015	0.017	0.023	0.026	0.320	0.320

TABLE 12: DID RESULTS USING COVID SHOCK, FIRM-CITY-MONTH PANEL

Note: This table summarizes the results of the following regression:

$$Log(WFHRatio_{fct}+1) = \alpha + \beta PostCovid_t \times CovidShock_c + \eta X_{ct} + \lambda_f + \gamma_c + f(t) + \varepsilon_{fct}$$

where $WFHRatio_{fct}$ is the share of WFH job postings amongst all job postings released by firm f in city c in month t. $CovidShock_c$ is the logarithm of the ratio of the number of confirmed Covid cases in city c by March, 2020 to the population of that city in 2019. $PostCovid_t$ takes value 1 for months after March 2020, and 0 for months before January 2020. X_{ct} is a vector of city-level controls. λ_f is firm fixed effects, γ_c is city fixed effects and $f(t)$ is month fixed effects. Standard errors are clustered at the city level and are presented in the parentheses. We use *** for p<0.01, ** for p<0.05, and * for p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PostCovid*CovidShock	-0.010***	-0.010***	-0.002***	-0.002***	-0.007***	-0.004**	-0.001	-0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
PostCovid	-0.007				-0.006			
	(0.007)				(0.010)			
CovidShock	-0.003*		0.001**		0.003*		0.002***	
	(0.002)		(0.000)		(0.001)		(0.001)	
GDP					-0.006**	-0.002	-0.003**	-0.001
					(0.003)	(0.006)	(0.001)	(0.004)
population					0.000	-0.001	0.000	0.001
					(0.000)	(0.001)	(0.000)	(0.001)
urbanization					0.013	0.070	0.011*	0.005
					(0.030)	(0.063)	(0.006)	(0.031)
Share of primary industry					0.109	0.481**	0.025	0.036
					(0.072)	(0.204)	(0.017)	(0.117)
Share of secondary industry					-0.011	-0.030	-0.035***	-0.019
					(0.019)	(0.041)	(0.005)	(0.021)
City FE		Y		Y		Y		Y
Month FE		Y	Y	Y		Y	Y	Y
Firm FE			Y	Y			Y	Y
Observations	1,151,569	1,151,569	1,135,661	1,135,661	804,096	804,096	790,786	790,786
Adjusted R-squared	0.007	0.012	0.433	0.433	0.003	0.006	0.411	0.411