Is Working from Home Here to Stay? Evidence from Job Postings and the COVID-19 Shock*

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Abstract

We use proprietary data from a leading online job portal in China to examine the labor demand transition toward working from home (WFH) after the COVID-19 outbreak, a quasi-experiment inducing the short-run WFH take-up. We find that the increase in WFH job postings is persistent in the post-pandemic era and is more prominent among firms with less pre-COVID WFH hiring experience, consistent with the learning hypothesis. Within firms, the increase is larger in cities hit harder by COVID-19. Additionally, the WFH transition is more pronounced for postings with higher wages and stricter requirements and thus has labor market inequality implications.

Keywords: Work from home, job posting, labor demand, COVID-19, pandemic, quasi-experiment

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

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1 Introduction

Working from home (WFH), while shown to reduce commuting costs and improve rather than impede work efficiency (prominently by Bloom et al., 2015), remained an uncommon work arrangement until the outbreak of COVID-19.[1] When lockdown and shelter-in-place policies were put in place to contain the COVID-19 virus, jobs had to be done at home given the restrictions on human mobility and social contact. However, as the pandemic has subsided and commuting restrictions are lifted, will this short-term WFH experience have a lasting impact on corporate hiring?

Our paper aims to answer this question using detailed job posting data from a leading online job posting platform in China, where COVID-19 broke out in January 2020 and was quickly contained in March of the same year. We exploit the outbreak of COVID-19 as a large-scale quasi-experiment that offered a compulsory WFH trial session for firms and workers in cities where mobility was severely inhibited.[2] The job posting data capture firm demand for WFH workers and thus reflect the impact of the COVID-19 shock on future transitions in work arrangements. If the underadoption of WFH prior to COVID-19 is due to barriers[3] that can be overcome during a relatively short period of learning from experience, then these firms should demonstrate a persistent increase in WFH job postings after temporary exposure to WFH arrangements.

We find that the share of WFH jobs in job vacancies has risen sharply since the COVID-19 shock and remains at a higher level, indicating a persistent and long-lasting impact of the

[1] To list a few related studies, Bick et al. (2021) find that 35.2% of the workforce worked completely 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 and Hossain (2020) show that under some specifications, workers in occupations with lower possibility of remote work experienced larger employment losses between March and April 2020.

[2] This role of the COVID-19 pandemic in inducing a WFH experiment has been described in, for instance, Hern (2020); Molino et al. (2020); Kramer and Kramer (2020).

[3] Firms might face barriers to technology adoption for various reasons, including uncertainties regarding the benefits of WFH for specific jobs and firms, a lack of incentives to acquire information about the costs and benefits of WFH, high technological and organizational adjustment costs, and inertia from working habits formed by employees in a traditional working environment (see, e.g., Hall and Khan, 2002; Bloom et al., 2015; Barrero et al., 2021).

COVID-19 shock. Firms' pre-COVID WFH hiring experience has a negative impact on the post-COVID growth in their WFH job share, consistent with the learning theory of WFH adoption. We further exploit geographical variation in the city-level number of confirmed COVID-19 cases to identify the causal impact of the COVID-19 shock on the transition in firm labor demand toward WFH. We find that within firms, establishments in cities with a larger number of confirmed COVID-19 cases during the shock period show a persistently higher ratio of WFH job postings after the COVID-19 shock. We include firm, city, and year-month fixed effects to absorb the impact of time-invariant firm and city characteristics and macroeconomic time trends, including the structural change in consumer demand due to the lockdown. The results are robust to the exclusion of cities at the epicenter of the COVID-19 outbreak in China. Heterogeneity analyses show that the impact is more pronounced for job postings offering higher wages and requiring more educated workers, which could exacerbate labor market inequalities.

Our paper makes a unique contribution to the following five strands of the literature. First, we examine the impact of COVID-19 on WFH by exploiting job vacancy postings, the actual presentation of firms' WFH labor demand. Our paper is most similar in approach to Forsythe et al. (2020), Campello et al. (2020), Fang et al. (2020), and Shuai et al. (2021) in that we use job vacancy data to study the impact of COVID-19 on the labor market. While these papers examine general labor demand, our paper focuses specifically on WFH jobs. Our paper provides extensive evidence that the impact of COVID-19 on remote working will persist. Previous research has focused mainly on survey data regarding working status under established employer-employee relationships.[4] Prominently, Barrero et al. (2021) examine why WFH will stick using survey data on U.S. workers over multiple waves and informal interviews conducted with managers. Bick et al. (2021) document the evolution of commuting

[4] According to Bartik et al. (2020), over 1/3 of firms in the U.S. 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 their WFH arrangement after the crisis ends. Barrero et al. (2021) further show that 20% of full workdays are expected to be supplied from home after the pandemic ends, while this percentage was just 5% prior to the pandemic. More recent analysis can be found in, for instance, Aksoy et al. (2022); Hansen et al. (2022).

behavior in the U.S. based on survey data. Erdsiek (2021) elicits employers' perceptions of WFH both during and after the pandemic using survey responses from over 1,700 managers in Germany. While survey data can offer a timely description of what happened in the past and gauge people's perceptions of the future, our job posting data capture the job types that firms are likely to actually create. In addition, survey data focus on jobs already filled by existing workers, while our job posting data look into vacancies to be filled. Moreover, high-frequency and constantly updated job posting data give us a real-time record of the dynamics of WFH and non-WFH jobs in the pre- and post-COVID-19 periods, which avoids the memory noise inherent in surveys. Thus, our job posting data complement the available survey data in helping us understand this alternative work arrangement in the labor market.

Second, we provide empirical evidence on the impact of the COVID-19 outbreak on WFH using data from a large developing country, adding to the existing studies in the context of advanced economies. The Chinese context is of particular interest and importance in this case because the strictly implemented lockdown policies successfully contained the first and most major wave of the COVID-19 outbreak between January and March 2020. Given that COVID-19 was brought under control within a relatively short period of time and that the economy had returned to normal throughout most of 2020 and 2021, we are able to track corporate hiring behaviors when commuting restrictions are alleviated. Exploiting the large geographical variation in the severity of the first wave of the COVID-19 shock, we further identify its causal impact on WFH job postings. Methodologically, our paper is among the first attempts to study job task and skill requirements using textual analysis of job posting data in the Chinese context[5], while this methodology has been adopted in studies of the U.S. labor market (e.g., Deming and Kahn, 2018; Hershbein and Kahn, 2018).

Third, our paper contributes to the debate on whether and how adverse economic shocks can accelerate adjustments to technological advances, connecting to the literature on how

[5] In previous studies of the Chinese labor market, researchers mainly used worker surveys such as the China Urban Labor Survey (e.g., Lewandowski et al., 2019) to measure the tasks and skills associated with jobs, and job ads have been used to study gender discrimination and matching on education in the Chinese labor market (e.g., Kuhn and Shen, 2013; Shen and Kuhn, 2013; Kuhn et al., 2020).

technology is shaping the future of work. A long theoretical literature, beginning with Schumpeter (1939)'s notion of "creative destruction", suggests that recessions can produce shocks that are sufficiently large to overcome frictions that could inhibit the optimal reallocation of resources in the face of technological change. This argument has been applied to the Great Recession and routine-biased technological change (Hershbein and Kahn, 2018). More recently, Tuzel and Zhang (2021) examines the job creation through investment incentives at the expense of routine-based jobs. The COVID-19 pandemic could have 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. Davis et al. (2021) construct a equilibrium model to study the impact of WFH. Contributing to the ongoing debate over how technology is shaping the future of work, we investigate whether and how the short-term lockdowns during the COVID-19 pandemic induced a work arrangement transition toward WFH, which in turn could permanently alter the demand for different skills in the labor market.

Fourth, our paper deepens the understanding of the cross-sectional heterogeneity in the suitability and effectiveness of WFH. The information contained in job postings (such as tasks, skill requirements, and wages) enables us to explore the adjustment of labor demand to WFH along multiple dimensions. Complementing experimental studies within firms that identify the causal productivity impacts of WFH (e.g., Bloom et al., 2015; Emanuel and Harrington, 2021; Bloom et al., 2022; Choudhury et al., 2022; Gibbs et al., 2022), our paper extends the analysis on WFH to a greater range of firms and jobs. In addition, compared with the literature examining cross-sectional variation in the prevalence of WFH, our panel analysis combined with a quasi-natural experiment adds identification power to our findings.

Last but not least, our paper connects to the literature concerning inequality during the time of the COVID-19 pandemic and notes that the ability to WFH differs systematically by educational attainment(for instance, Albanesi and Kim, 2021; Alon et al., 2020; Goldin, 2022). We find that WFH jobs are more likely to pay higher wages and favor more educated workers, echoing several recent papers. For instance, Mongey and Weinberg (2020) and Bick et al. (2021) find that highly educated, high-income and white individuals are much more likely to shift to remote work; Irlacher and Koch (2021) find a substantial wage premium for workers performing their job from home; Brynjolfsson et al. (2020) find that firms in 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. In addition, Angelucci et al. (2020) show that job losses during the pandemic were up to three times larger for nonremote workers than for remote workers. Other studies have also found that the take-up of WFH during the pandemic may have enhanced inequality (see, for instance, Yancy, 2020; Kawaguchi and Motegi, 2021).

The rest of our paper proceeds as follows: Section 2 introduces the background information on COVID-19 and WFH in China. Section 3 summarizes our data, and Section 4 provides a descriptive analysis. Section 5 shows the results from firm-month panel regressions, while Section 6 presents a firm-city-month DID analysis exploiting geographical variation in the COVID-19 shock. Section 7 concludes the paper.

2 Background on COVID-19 and WFH in China

China offers some unique opportunities for our study. First, China was hit hard by the initial COVID-19 outbreak. The Chinese government launched a top-down lockdown policy to combat the virus, and it was strictly implemented. Second, the severity of the pandemic and the length of the lockdown periods varied greatly among different cities across the country, enabling us to exploit geographical variation in the presence and intensity of the lockdown treatment and the extent to which firms were forced to adopt WFH arrangements in the short run. Third, the first wave of the pandemic was quickly controlled and was followed by an economic recovery during most months in 2020 and 2021, making this setting ideal for studying the persistent impacts of a relatively short-term but intense shock.

2.1 The COVID-19 Outbreak and Lockdown Policies

The COVID-19 epidemic in China broke out in Wuhan, the capital city of Hubei Province, in mid-January 2020 and quickly spread to the rest of the country. According to the National Health Commission (NHC), as of the end of January, more than 10,000 confirmed cases were reported in all 31 mainland provinces and municipalities in China, with more than 100,000 people under medical observation. To contain the spread of the COVID-19 virus, the Chinese government introduced strict lockdown policies that inhibited human mobility and in-person activities, led by the lockdown of Wuhan on January 22, which shut down all intra- and intercity transportation networks. Other local governments adopted similar lockdown measures in the following week, including closed-off management measures for residential communities, workplaces, and nonessential businesses.

The lockdown policies were effective in curbing the spread of the COVID-19 virus. By mid-February 2020, the epidemic had been brought under control in most parts of the country. On February 27, the number of newly confirmed COVID-19 cases dropped into the single digits for all cities except Wuhan. Local governments began to reduce their emergency response and lift their human mobility restrictions during the last week of February 2020, when the domestic spread of COVID-19 was under control. On March 11, 2020, the total number of newly confirmed COVID-19 cases nationwide dropped into the single digits for the first time after the outbreak. The number remained low during the following week, marking the end of the first wave of the COVID-19 pandemic in mainland China.

Figure 1 presents a visualization of the COVID-19 shock and lockdown policies in China. Panel A of Figure 1 plots the time series of newly confirmed COVID-19 cases reported in mainland China each day, which measures the severity of the COVID-19 shock. The daily number of newly confirmed cases peaked at 15,152 (including corrections from the past) on February 12 and dropped to single digits starting from March 2020, when most cities lifted their lockdown policies. Panel B shows that for the period prior to the Wuhan lockdown on January 23, 2020, the human mobility index for 2020 is comparable to that for 2019, with similar and even higher levels of human movement. The indices both drop during the period around the Spring Festival, when most people stayed at home to hold family reunions and celebrate the start of the traditional new year. While the 2019 index quickly rises during the period after the Spring Festival, the 2020 index plunges even further, netting out the impact of seasonal factors from the implementation of the lockdown policies. The intensity of human mobility slowly recovered to its pre-COVID level during March 2020, when the lockdown policies were lifted. Based on the spread and containment of the COVID-19 epidemic in China, we define January through March 2020 as the lockdown period and the following months as the recovery period.

2.2 WFH during the COVID-19 Lockdown

People in almost all parts of China were subject to mobility restrictions upon the outbreak of COVID-19, limiting their ability to return to their physical workplaces. Meanwhile, the lockdown policies resulted in the closure of brick-and-mortar shops, factories, in-person service industries, traveling and hospitality businesses, and schools while promoting online activities and remote working. Therefore, working from home became the only viable option for corporate operations, and this option was also promoted by the government. 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 epidemic. The local 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".

The demand for WFH surged against the backdrop of lockdown policies preventing and controlling the COVID-19 pandemic. Survey data show that in Wuhan, the epicenter of the pandemic, 55% of employees in the software industry work online by telecommuting. The remote working software market also experienced explosive growth. According to data from WeLink, a remote working platform developed by Huawei, the daily number of new enterprise users on the platform exceeded 15,000 after the Spring Festival holiday in 2020, and the daily number of conferences held was as high as 120,000, with an average daily increase of 50%.[6] WeChat Work, another leading business communication platform in China, served 5.5 million enterprises and 131 million active users by the end of 2020, while these two numbers had been 2.5 million and 60 million back in 2019.

2.3 Returning to Workplaces after the COVID-19 Shock

As the COVID-19 epidemic subsided in China starting in mid-February, returning to work was encouraged in most provinces. Local governments took initiatives to implement differentiated policies depending on their local situations while following the central government's general guidelines. In addition to dynamically lifting lockdown measures based on their concurrent risk level, local governments subsidized firms that recruited employees and those that facilitated the reentry of their employees into their workplaces. For large numbers of migrant workers, gate-to-gate transportation–including specially designated trains–was arranged.[7] On March 4, 2020, the State Council prohibited low-risk counties from postponing employees' resumption of work. Medium- and high-risk areas were encouraged to simplify the procedures required for restarting work.[8]

Starting on March 25, 2020, the lockdown measures in Hubei Province were gradually lifted, with all other provinces having already returned to normal. Although there was pressure from imported COVID-19 cases as the disease became a global pandemic in March 2020, the government stressed the need to resume work and normal life. More emphasis was placed on economic growth to ensure an orderly return to normalcy. China's economy recovered in response to these policies. In the first quarter of 2020, China's GDP fell by 6.9% as a result of the strict lockdown following the COVID-19 outbreak, while in the second and third quarters, China's GDP rebounded, growing at year-on-year rates of 3.1% and 4.8%,

[6]See https://www.ndrc.gov.cn/xwdt/ztzl/jzjj/202008/t20200805_1235576.html?code=&state=123.

[7]See http://www.gov.cn/xinwen/2020-02/19/content_5481020.htm.

[8]See http://www.gov.cn/zhengce/content/2020-03/04/content_5486767.htm.

respectively.[9]

3 Data and Sample Construction

3.1 Data

3.1.1 Job posting data

Our job posting data come from Zhaopin.com (hereafter, Zhaopin), one of the largest online job boards in China.[10] For the purpose of our research, we limit our sample of posting firms to those located in mainland China and focus on job postings active between December 2017 and June 2021, which covers periods both before and after the COVID-19 outbreak.

We use two sets of job posting data to examine the status of WFH job hiring. The first set contains all job postings with alternative work arrangement (AWA) keywords, such as "working from home", "online working", "flexible work schedule" and their variants. The second set of job posting data is a snapshot of general labor demand containing 20 million job ads randomly drawn from the universe of job ads posted between December 2017 and June 2021. The two data sets are connected through unique IDs for the posting firms and job ads, enabling us to track WFH and non-WFH job postings from the same firm. For each job vacancy entry in the database, we obtain the following information: posting date, posting firm, firm size, firm type, main industry, occupation type and subtype, number of workers to be hired, wage range, education requirement (if any), work experience requirement (if any), work location, title, and full text of the job descriptions.

[9] See https://data.stats.gov.cn/english/easyquery.htm?cn=B01&zb=A0103&sj=2020.

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

3.1.2 City-level COVID-19 and macroeconomic data

We obtain daily city-level numbers of newly confirmed COVID-19 cases[11] from the National Health Commission (NHC) of the People's Republic of China via the China Stock Market and Accounting Research Database (CSMAR). To control for other city-level characteristics that may have impacted the severity of COVID-19, we obtain from CSMAR city-level macroeconomic time series such as GDP, population, and the share of the secondary industry in GDP for 367 cities at the prefecture level or above. Time-invariant city characteristics, such as the urbanization level prior to the COVID-19 outbreak, are absorbed by the city fixed effects in our regressions.

3.1.3 Teleworkability data

We characterize each job's suitability for WFH with Dingel and Neiman (2020)'s measure of teleworkability, which classifies the feasibility of WFH for different occupations using responses to the Work Context Questionnaire and Generalized Work Activities Questionnaire from the O*NET database. A higher teleworkability index indicates a larger portion of job tasks that can be completed by WFH and hence predicts higher feasibility of a job being performed remotely. To match the teleworkability index to the Chinese data, we create an industry and occupation crosswalk between the classifications defined by Zhaopin and the NAICS and Standard Occupational Classification (SOC) used in Dingel and Neiman (2020). We compute our measure of teleworkability by mapping the Dingel-Neiman measure of teleworkability to the Chinese occupation and industry categories.[12]

[11]The COVID-19 data distinguish mainland cases from cases transmitted from overseas (including Hong Kong, Macau, Taiwan, and other countries and regions). We use the number of confirmed mainland cases throughout this paper.

[12]For occupation-level teleworkability, we merge the classification of occupations in China with the Dingel-Neiman 6-digit SOC occupation-level teleworkability measure by mapping an occupation in China to the three most relevant 4-digit SOC occupations and then aggregating the 6-digit SOC occupation-level teleworkability measure at the 4-digit level using equal weights. For industry-level teleworkability, we merge the classification of industries in China with the Dingel-Neiman 3-digit NAICS industry-level teleworkability measure by mapping an industry in China to the three most relevant 3-digit NAICS industries and computing the weighted teleworkability.

3.2 Sample Construction

3.2.1 Identifying WFH jobs

We define WFH keywords as "working from home", "working at home", "remote working", "working remotely" and other similar variants of these expressions, including synonyms such as "no need to come to office" and "flexible work location". We also explore keywords associated with other AWAs that offer work flexibility to some extent. One type of job is "online working", which by its nature has the potential to transform into WFH. Another relevant keyword category is "flexible working", which provides flexible working schedules and locations. We identify 6,917,419 WFH and other AWA job postings active between December 2017 and December 2021. We find that many variations of wording do not appear frequently in the job postings and make up only a minor fraction of all AWA keywords; 99% of the job postings fall into the standard keyword categories. Thus, the standard wording should capture the vast majority of relevant job postings.

To avoid double counting due to keyword overlap[13], we define three mutually exclusive job posting groups using the following sequential method: First, we define WFH job postings as job ads containing WFH keywords.[14] Then, we define online job postings as those that contain online working keywords but not WFH keywords. Finally, we define flexible job postings as those containing flexible working keywords but not WFH or online working keywords. We find that among the 5,524,196 AWA job postings, 14.4% belong to the standard WFH category, 40.6% fall into the online working (but not WFH) category, and 44% go to the flexible working (but not WFH or online) category.

[13]We find that there are at most three keywords in the job ad title and at most six keywords in the full text of the job description. On average, each job posting has one keyword in the job ad title and one keyword in the job full text.

[14]Bick et al. (2021) conduct surveys of U.S. workers' commuting behavior to generate a clear interpretation of WFH. While commuting patterns give an unambiguous characterization of WFH, the commuting data rely heavily on survey efforts, which are difficult to expand to a large scale.

3.2.2 Merging with non-WFH job postings

To examine the change in the labor demand structure within each firm, we trace the non-WFH job posting history of all firms with WFH job posting in the 7% sample data. We then combine these non-WFH job posting data with our WFH job posting data through the unique firm IDs. We exclude "one-shot" posting firms, which post job ads for only one month, to filter outlier firms. To remove the disproportionately large impact of the education industry on WFH job postings[15], we exclude firms that are in the educational services industry or that post any education-related job postings from our sample to ensure the generalizability of our analysis.

4 Descriptive Analysis on the Rise of WFH

4.1 Time Trends

We find a substantial and long-lasting impact of the COVID-19 outbreak on WFH job postings. Panel A of Figure 2 shows that WFH job postings quickly doubled during the COVID-19 outbreak and continued to increase when the COVID-19 lockdown policies were lifted beginning in mid-February 2020. The number reached three times its pre-COVID level in October 2020, dropped during the Spring Festival in 2021 and has remained at approximately three times its pre-COVID level since April 2021. The substantial increase in WFH job postings *during* the COVID-19 lockdown is not surprising given that WFH was the only viable work arrangement under the restrictions on human mobility and social contact imposed to contain the spread of the virus. However, it is interesting that we find a persistently higher level of WFH job postings during the period *after* the COVID-19 shock

[15] The educational services industry provides a substantial number of WFH jobs: 54.4% of WFH job postings in the raw data are jobs from this industry or are education-related jobs (such as teachers or tutors) listed under other industries. Hence, changes in the educational industry could lead to substantial volatility in WFH job postings. The tremendous impact of the education industry on WFH analyses is echoed by Dingel and Neiman (2020), whose estimate of the percentage of work that can be done at home decreases by 6 percentage points (from 37% to 31%) if teachers are classified as non-WFH jobs.

when the lockdown policies had been lifted. If WFH were merely a backup work arrangement *substituting* for on-site work during the lockdowns, one would expect a reduction in WFH job postings and a return to their pre-COVID level, which is not the case.

4.1.1 Seasonality

The outbreak of COVID-19 in China coincided with the Spring Festival season, creating seasonal fluctuations in corporate hiring and presenting a confounding factor regarding changes in WFH job ads. One may argue that the slack season around the Chinese Lunar New Year could confound the impact of the COVID-19 shock on WFH job postings. However, in our data spanning December 2017 and June 2021, we do not observe significant changes in WFH job postings during the Spring Festival seasons prior to the outbreak of the COVID-19 virus. As shown in Panel A of Figure 2, prior to the COVID-19 outbreak in China in January 2020, WFH job postings remained at a relatively constant level, ruling out the possibility that the post-COVID increase in WFH job postings is solely due to seasonal factors. In later sections, we include year-month fixed effects in our regressions to further control for seasonal effects.

4.1.2 Comparison with other AWAs

The increase in WFH job postings is unique with respect to the trend in other AWAs. As shown in Panel A of Figure 2, we do not find that the COVID-19 shock had a similar impact on job postings featuring online working and flexible working arrangements. The post-COVID levels of online working and flexible working job postings are approximately the same as their pre-COVID levels. WFH job postings behave very differently from postings in the online working and flexible working job categories, while the latter two demonstrate similar patterns. This uniqueness of WFH job postings is consistent with the fact that restrictions on human mobility were a prominent feature of the policies to combat the COVID-19 pandemic.

4.2 Structural Changes in Corporate Hiring

4.2.1 WFH versus non-WFH job postings

Another possibility is that the increase in WFH job postings is not surprising because "a rising tide lifts all boats": the firms posting these WFH job postings may also have increased their non-WFH job postings. In such a case, the increase in WFH job ads would represent not a transition to WFH in corporate hiring but a proportional change in overall labor demand. We rebut this argument by tracking the job posting history of WFH posting firms and presenting the time trends for both the WFH and the non-WFH job vacancies posted by the same group of firms. As shown in Panel B of Figure 2, firms' WFH and non-WFH job postings followed each other closely prior to the pandemic. We find that non-WFH jobs remained at levels similar to their pre-COVID levels, refuting the hypothesis that firms posting WFH jobs increased their non-WFH job postings at the same time. Rather, our findings indicate a persistent WFH transition in the labor demand structure in corporate hiring.

4.2.2 Firm characteristics

Since the costs of WFH adoption vary across occupations within the same firm, it is likely that occupations responded to the COVID-19 lockdowns differently. We divide firms with WFH postings into three types: (1) seasoned firms that started posting both WFH and non-WFH jobs before the COVID-19 shock, (2) transition firms that had already existed but started posting WFH jobs after the COVID-19 shock, and (3) new firms that started posting both WFH and non-WFH jobs after the COVID-19 shock. Table 3 reports the industry and size distribution of these firms. We find that firms with WFH postings share similar distributional patterns, with the IT and internet industry and small- and medium-sized firms (SMEs) contributing the majority of WFH postings. In terms of the number of job postings, more than half of WFH job vacancies posted after the COVID-19 shock come from new firms, showing that firm entry after the COVID-19 shock has contributed the most to the increase in WFH job postings.

5 WFH Transition in Corporate Hiring: Firm-Level Evidence

This section examines the WFH transition in firm labor demand using firm-month panel data. To test the impact of COVID-19 on firms' job posting behavior, we focus on the within firm transition toward WFH jobs among firms that had already started posting job ads before the COVID-19 outbreak, i.e., seasoned firms and transition firms.

5.1 Summary Statistics

To accentuate the structural transition in post-COVID labor demand, we examine the WFH ratio, defined as the number of WFH job postings divided by all postings from firm f in month t. Since the non-WFH job postings are randomly drawn from the universe of job postings while the WFH job ads represent a full sample, we divide the number of non-WFH job postings by the sampling ratio (7%) to approximate the actual number of non-WFH job ads. That is,

$$WFHRatio_{ft} = \frac{WFH_{ft}}{WFH_{ft} + (nonWFH_{ft}/7\%)} \times 100 \tag{1}$$

Table 1 summarizes the main variables in firm-month-level panels consisting of seasoned firms and transition firms. During the sample period between June 2018 and June 2021, seasoned firms contributed 1.69 WFH job postings and 49.67 non-WFH job postings per firm-month unit, while transition firms contributed 0.97 WFH and 60.24 non-WFH job postings per firm-month unit. The WFH ratios are 23.32% and 10.05% for seasoned and transition firms, respectively. The lower number of WFH job ads and lower WFH ratios among transition firms probably occur because by definition, transition firms posted no

WFH job ads prior to the COVID-19 outbreak, thus leading to zero values over most of the sample period. Hence, it is helpful to separate the pre- and post-COVID periods to obtain a more accurate description of firms' job posting behavior.

5.2 Empirical Methodology

We adopt a difference-in-differences (DID) approach as specified in Equation 2 to analyze the labor demand transition among firms that posted jobs both before and after the COVID-19 shock. By the nature of the DID design, our regression results indicate the change in hiring demand among firms that already had job postings prior to COVID-19, allowing us to separate out the impact of new firm entries.

$$WFHratio_{ft} = \alpha + \beta X_f \times post_t + \gamma_f + \gamma_t + \varepsilon_{ft} \tag{2}$$

where $post_t$ takes on a value of 1 for months after January 2020 and 0 for months before. X_f measures a firm's WFH experience, i.e., whether a firm starts its WFH job hiring after the COVID-19 outbreak ($ftype_f$), the firm's pre-COVID WFH hiring experience ($WFHratio2019_f$), and the firm's WFH hiring experience during the lockdown period ($WFHtrial_f$). A selection problem emerges since the firms that kept hiring may be those that benefited from the changes brought about by the pandemic, such as firms related to online shopping, video gaming, live streaming, and social network websites. Hence, these firms may have increased their overall hiring, driving the increase in WFH job postings as well. To absorb the impact of time-invariant firm characteristics (such as age, size, industry, and management style), we include firm fixed effects γ_f in all regressions. We also include year-month fixed effects γ_t to control for macroeconomic trends and seasonality.

5.3 Regression Results: WFH Hiring Experience

Panel A of Table 2 presents the results of the firm-month panel regressions comparing the ratio of WFH job postings before and after the COVID-19 outbreak. Column (1) shows that there is a statistically significant decrease of 0.812% in the WFH ratios for seasoned firms, while Column (2) shows that for transition firms, the ratio increased by 18.842%, a result that is both economically and statistically significant. Column (3) combines the two groups of firms together and a difference-in-differences regression. The estimated coefficient before the interaction term is positive and statistically significant, meaning that the change in WFH ratios in corporate hiring is 19.746 percentage points larger for transition firms than for seasoned firms. This is consistent with our finding in the descriptive analysis that transition firms experienced a larger increase in their WFH ratios, probably due to the fact that seasoned firms had already achieved their optimal level of WFH ratios before the COVID-19 outbreak. Note that we add year-month fixed effects in Column (3) to control for common trends such as macroeconomic conditions and festival seasons. The significantly positive result indicates that the increase in WFH job postings cannot be explained by either the seasonality in corporate hiring or the Spring Festival effect.[16]

One may argue that the lockdown periods between January and March 2020 are likely to account for the majority of the increase in the WFH job posting ratios and hence that a positive coefficient is not equivalent to a persistent impact. To show that the WFH transition in corporate hiring is not solely driven by the lockdown periods, we exclude the three months of lockdowns from our sample and reestimate the same regression. We find the coefficient becomes even larger and is now statistically significant at the 99% confidence level. Column (4) of Panel A of Table 2 shows that seasoned firms reduced their WFH job ratios by 2.066%, while Column (5) shows that transition firms experience a significant increase of 19.366%

[16] Spring Festival Eve fell on February 4 in 2019 and January 24 in 2020, creating an 11-day difference when we conduct the lunar day comparison. Since the job posting data are monthly data, we believe that it is more accurate to compare the same month without adjusting for the lunar calendar. As a robustness check, we find that the plots depict similar patterns regardless of whether we account for this difference.

in their WFH job ratios. The impact of the COVID-19 shock on the WFH transition in firms' labor demand extends beyond the lockdown period. Column (6) combines the two subsamples of firms and includes year-month fixed effects. We find that the increase in the WFH ratios of the transition firms is 21.616 percentage points larger than that of seasoned firms.

Panels B and C of Table 2 decompose the WFH ratio into the numerator and the denominator to investigate whether firms indeed post more WFH jobs. We add one to the original number of job postings before taking the natural logarithm in order to include months with zero postings. We find that the increase in the WFH ratios of transition firms comes from both an increase in the number of WFH jobs and a decrease in non-WFH job ads, while both numbers shrink for seasoned firms. These coefficients become larger in absolute value after we exclude observations from the lockdown periods, except in Column (4) of Panel C, where seasoned firms are shown to have recovered in terms of some non-WFH job postings after the COVID-19 lockdown.

To test the learning hypothesis at the intensive margin, we look at firms' pre-COVID experience with hiring for WFH jobs, as measured by the annual average of each firm's $WFHRatio$ in 2019 (shown in percentage points), $WFHRatio2019_f$. For transition firms, the value of $WFHRatio2019_f$ is always zero. The coefficient of interest β captures the gap in the post-COVID WFH ratio between more experienced firms and less experienced firms. As shown in Panel A of Table 3, the coefficients on the interaction term are all significantly negative at the 99% confidence level, indicating that firms with previously lower WFH ratios experienced a larger increase in WFH ratios after the COVID-19 lockdown. Specifically, we find that a one-percentage point increase in the pre-COVID WFH ratio of a firm reduces the increase in the WFH ratios by 0.298 percentage points, as shown in Column (1). Column (2) restricts the sample to seasoned firms to separate the intensive margin (seasoned firms with different pre-COVID WFH ratios) from the extensive margin (transition firms with zero pre-COVID WFH ratios). We find that seasoned firms with one-percentage point lower pre-COVID WFH ratios experienced a 0.167 percentage point increase in their WFH ratios after the COVID-19 outbreak. The coefficients become larger if we exclude the lockdown period, as shown in Columns (4) and (5), respectively. The regression results support the learning hypothesis that claims that the COVID-19 shock induced firms to overcome barriers to WFH, leading to a larger WFH transition among firms with lower WFH take-up prior to the COVID-19 shock.

The COVID-19 outbreak provided firms with a learning opportunity through forced WFH trial sessions. If firms found that the benefits of WFH outweighed its costs during the trial periods, then these firms would have continued hiring for WFH jobs even after the lockdown policies were lifted. In contrast, firms that found the opposite should have reduced their WFH job postings immediately after the lifting of the lockdowns, even if they were forced to adopt WFH arrangements during the lockdown periods. Panel B of Table 3 tests the impact of this trial experience, measured by a firm's WFH ratio during the lockdown period, on each firm's WFH labor demand. We find that all coefficients are significantly positive at the 99% confidence level, indicating that firms with higher WFH ratios during the lockdown persisted in posting a larger share of WFH job ads. When we exclude the lockdown period from our sample, the coefficients decrease but are still statistically significant. This result means that while the COVID-19 lockdowns contributed to temporary WFH adoption among firms that reverted back afterwards, the number of firms that persistently transitioned toward WFH jobs in their corporate hiring was considerable.

6 WFH Transition in Corporate Hiring: Firm-City-Level Evidence

The rapid nationwide spread of the virus leaves us little room to exploit variation in treatment timing at the monthly level. However, each city faced a different level of pressure in combating the spread of the virus. Cities therefore varied in terms of the strictness of their lockdown policies, providing geographical variation in the intensity of the COVID-19 shock. We use the cumulative number of COVID-19 cases at the city level as of March 2020 to proxy for the severity of the COVID-19 shock in each city. We estimate the following DID model in the firm-city-month-level panel regression:

$$WFHratio_{fct} = \alpha + \beta Covid_c \times post_t + \gamma_f + \gamma_c + \gamma_t + \eta \mathbf{X}_{ct} + \varepsilon_{fct} \tag{3}$$

where $WFHRatio_{fct}$ is the ratio of WFH job postings posted by firm f in month t in city c. $Covid_c$ is the log value of the cumulative number of COVID-19 cases in city c as of March 2020. $post_t$ takes on a value of 1 for months after January 2020 and 0 for months before. Control variables $\mathbf{X}_{ct}$ include the log values of GDP and the population, the share of the secondary industry in GDP, and a constant. γ_f, γ_c, and γ_t represent the firm, city, and year-month fixed effects, respectively. The fixed effects enable us to control for common factors that affect firms' WFH job postings. For instance, one could argue that the increase in WFH job posting ratios is not due to firms' transitioning toward WFH arrangements but that the social distancing and lockdown policies to combat COVID-19 drove up the demand for online services, hence boosting the growth of certain industries that by nature have a higher ratio of teleworkable positions. To exclude this possibility in interpreting our results, we include firm fixed effects to absorb the industry- or firm-specific impacts of COVID-19 on WFH job hiring. Ideally, we would expect that within the same firm, the increase in the WFH ratio would be higher for branches in cities hit harder by the COVID-19 shock (and thus implementing stricter lockdown policies).

6.1 Baseline DID Results: Ratio of WFH Job Postings

Table 4 presents the results using firm-city-month-level WFH ratios, defined as the number of WFH job postings divided by all postings by firm f in city c in month t. Column (1) presents the baseline regression results with firm-, city-, and year-month-level fixed effects.

The estimated coefficient β is 0.727 and statistically significant at the 99% confidence level, indicating that a one-percentage point increase in the number of confirmed COVID-19 cases increases the postpandemic share of WFH job postings by 0.727 percentage points. To account for time-varying city characteristics, we add city-level macroeconomic indicators in Column (2), including GDP (log value), population (log value), and the share of the secondary industry in GDP. Adding city-level controls decreases the magnitude of the coefficient to 0.694 but does not change its statistical significance. Our baseline results show that the COVID-19 experience induced firms to change their hiring structure in favor of WFH: within the same firm, a branch more adversely affected by the COVID-19 outbreak had a larger increase in the share of WFH jobs that it posted.

Given that Wuhan city was the epicenter of the COVID-19 outbreak in China, one may argue that Wuhan, together with other cities in Hubei Province, could be an outlier that drives our main results. Hence, in Columns (3) and (4), we drop observations from cities in Hubei Province (including Wuhan). Contrary to this argument, the estimated coefficients on $Covid_c \times post_t$ increase to 1.136 (without controls) and 1.085 (with controls) while maintaining their statistical significance. These results indicate that cities outside Hubei Province, which experienced wider variation in the intensity of the COVID-19 shock, experienced a stronger boost to their WFH transition in corporate hiring after the COVID-19 outbreak.

Another possible concern is that the user penetration ratio of the online job board may be limited in small- and medium-sized cities, causing bias in our sample. Since we include firm and city fixed effects in our regression, our "within" estimates focus on corporate hiring changes within a firm-city cell, which helps mitigate the impact of geographical variation in user penetration and thus the coverage of job postings. To further reduce the impact of outlier cities, in Columns (5) and (6), we exclude from our sample all cities within an inland border or on an island province. We find that the results are still significantly positive at the 99% confidence level and that the coefficients are smaller but comparable to those in

Columns (3) and (4); our findings are thus robust to sample city refinement.

6.1.1 Pretrend analysis

One concern regarding the DID approach is that firms that hire fewer WFH jobs 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 toward remote working might have done so had there been no exogenous push. We already include firm fixed effects to control for any time-invariant firm characteristics and month fixed effects to control for common macroeconomic factors to address this problem. We find that the estimates are all robust, ruling out the possibility that the significant results are driven by macro-level trends or time-invariant firm characteristics.

To further account for the seasonality of job postings and ensure that the effects are not caused by trends existing before the pandemic, we estimate the following dynamic model, replacing the post-COVID indicator with year-month dummies to examine the pre-COVID job posting patterns:

$$WFHratio_{fct} = \alpha + \sum_{t \neq T} \beta_t Covid_c \times Month_t + \gamma_f + \gamma_c + \gamma_t + \mathbf{X}_{ct} + \varepsilon_{fct} \quad (4)$$

where $Month_t$ represents the monthly dummies for each month during the sample period with December 2019 being the omitted month T. The coefficients, β_t, with t prior to January 2020, capture the prepandemic time trend in the differences between the treatment and control groups. If these coefficients are not significantly different from zero, we can safely conclude that there is no preexisting trend.

Panel B of Figure 4 plots the estimated coefficients on the interaction terms between COVID-19 severity and the month dummies. The coefficients are not significantly different from zero until the outbreak of COVID-19 in January 2020. The impact persists for approximately three quarters and then fades away. The regression results rule out the possibility that the differences between the treatment and the control firms existed before the COVID-19 shock. We note that the coefficients fade to zero in the middle of 2020, which shows that the geographical differences in WFH ratios within a firms disappear eventually. However, this pattern does not mean that firms revert back their transition toward WFH in corporate hiring, since Panel A has already shown the opposite. Rather, it means that firm branches in cities with fewer COVID-19 cases are catching up with those that were hit harder by the COVID-19 shock, possibly due to intra-firm spillovers through information sharing of WFH benefits and learning from others' experience, contributing to the persistence of corporate hiring transition toward WFH.

6.1.2 Placebo tests: Timing of the treatment

One counterfactual that could undermine our argument is that the WFH transition in labor demand would have happened even without the push from the COVID-19-related lockdown policies. Another possibility is that our proxy for COVID-19 severity may coincide with some unobservable factors that could also have affected firms' hiring decisions, and thus, the estimated coefficient would capture impacts irrelevant to the COVID-19 shock.

To address this problem, we conduct placebo tests by excluding the sample period after the COVID-19 shock (i.e., after January 2020) and using "false" shock months during the period prior to the actual COVID-19 shock (specifically, January 2019 and July 2019.) Table 5 summarizes our placebo test results. All columns report statistically insignificant estimates, showing no evidence that the WFH transition came prior to the COVID-19 shock or was associated with driving forces independent of the COVID-19 outbreak. Firms shifted their labor demand structure toward WFH only after the COVID-19 shock, and this shift has persisted and is likely to stay as part of the "new normal".

6.2 Decomposition: WFH and Non-WFH Job Postings

When the ratio of WFH job postings increases, it is not clear which part of the ratio drives this growth (although the descriptive graphs have already indicated the direction). Hence, we estimate the DID regressions for the WFH ratio numerator and denominator separately to identify whether the resilience observed for WFH job postings comes from a smaller decrease or a larger increase in WFH jobs than non-WFH jobs. Table 6 reports the firm-city-level regression results for the number of WFH and non-WFH job postings. Consistent with our hypothesis, the coefficients on the interaction term are significantly positive for WFH job postings and negative for non-WFH job postings, meaning that the COVID-19 shock leads to an increase in the number of WFH job postings while reducing the number of non-WFH job postings. Again, the coefficients are robust when we exclude cities in Hubei Province and cities in border provinces. Our results show that the COVID-19 shock did not impact job postings evenly; the effect on WFH job postings is due to a structural change in corporate hiring rather than an overall increase in labor demand.

6.3 Heterogeneity Analysis

To examine the heterogeneity in the effect of the COVID-19 shock on job ads with different characteristics in the firm-city-month panel, we decompose all job postings into three groups based on certain characteristics (e.g., wage, education requirements, Dingel-Neiman measure of teleworkability).[17] We perform the same DID regressions as in the baseline model except that the dependent variables have been replaced.

Table 7 presents the regression results, which demonstrate a significant disparity between high-level and low-level jobs. As shown in Columns (1) and (2) in all three panels, the positive impact of the COVID-19 shock on the WFH ratios is more pronounced among

[17]The direct tertiary classification code leads to vastly different group sizes in Stata since there are only a handful level of characteristics. Hence, to achieve equal group sizes, we divide into quintiles first and then define the 4th and 5th quintiles as the *high* level, the 2nd and 3rd quintiles as the *medium* level, and the first quintile as the *low* level. We then calculate the ratio of WFH job postings with specific characteristics to all job postings made by the same firm-city-month unit.

WFH job postings offering medium or high wages, while it is insignificant for the ratio of low-wage WFH job postings. Columns (3) and (4) present the results from regressions in which the dependent variables are the ratios of WFH job postings requiring an educational background above a certain threshold. Again, the increase in the WFH hiring ratios due to the COVID-19 shock is more pronounced among WFH job postings requiring a college degree or above. The impact on the ratio of WFH job postings targeting workers with a high school diploma or below is statistically insignificant. The results for job requirements in Columns (5) and (6) echo those for wages except that no WFH job postings fall into the "low work experience requirement" category, demonstrating assortative matching between labor income and workers' education and work experience. While the COVID-19 shock increased labor demand for WFH positions, its impact is reflected mainly in WFH jobs offering higher wages and imposing stricter requirements; i.e., it boosted labor demand at the relatively higher end of the job spectrum.

Columns (7) and (8) in Table 7 report the heterogeneity regression results using the occupation-level Dingel-Neiman measure of teleworkability.[18] We find that the estimated coefficient on the interaction term $Covid_c \times post_t$ remains significantly positive for highly teleworkable jobs at the 99% confidence level and insignificant for WFH jobs with medium or low levels of teleworkability. The results indicate that the predictive power of the teleworkability measures à la Dingel and Neiman (2020) is strong in a large developing country such as China[19]. The WFH transition is closely associated with the nature of work.

[18]A prominent paper by Dingel and Neiman (2020) utilizing survey data on the nature of various types of jobs and detailed descriptions thereof finds that 37% of jobs in the U.S. can be performed entirely at home. Bartik et al. (2020) show that the Dingel and Neiman (2020) measure of suitability for remote work does a remarkably good job of predicting industry-level patterns of remote work and that remote work is much more common in industries with better educated and better paid workers.

[19]Teleworkability is likely to differ across countries. For instance, Gottlieb et al. (2020) find that the share of employment suitable for WFH in urban areas is 20% in poor countries and 40% in rich ones. Thus, it remains an empirical question whether the teleworkability index derived from job descriptions in developed countries is applicable to a larger range of countries.

7 Conclusion and Discussion

The COVID-19 outbreak served as a large-scale natural experiment in which short-run take-up of WFH was induced in places where lockdown and shelter-in-place policies were implemented. We exploit the variation in firms' pre-COVID WFH take-up and the geographical variation in the number of COVID-19 cases to identify the impact of the outbreak. Our findings show that firms with less pre-COVID WFH take-up experienced a larger increase in WFH hiring after the COVID-19 lockdown, while within the same firm, the ratio of WFH job postings increased more among establishments in cities hit harder by the COVID-19 shock. Our paper shows that the COVID-19 shock promoted WFH adoption among existing firms, leading to a structural change in firms' labor demand that has persisted in the postpandemic era.

Going beyond the research scope of this paper, another persistent impact of COVID-19 is a structural change in industry and firm composition, with the digital economy booming and brick-and-mortar businesses waning. We find that nearly 60% of post-COVID WFH job postings come from new firms that started posting jobs after January 2020, contributing significantly to the increase in WFH job postings. We leave the analysis of the *composition change* among firms to future research. Additionally, given that the fraction of job postings that allow for WFH is tiny, the WFH transition may have only a limited impact on the economy as a whole in the near future. There is a long but promising way to go for WFH to reach its full potential.

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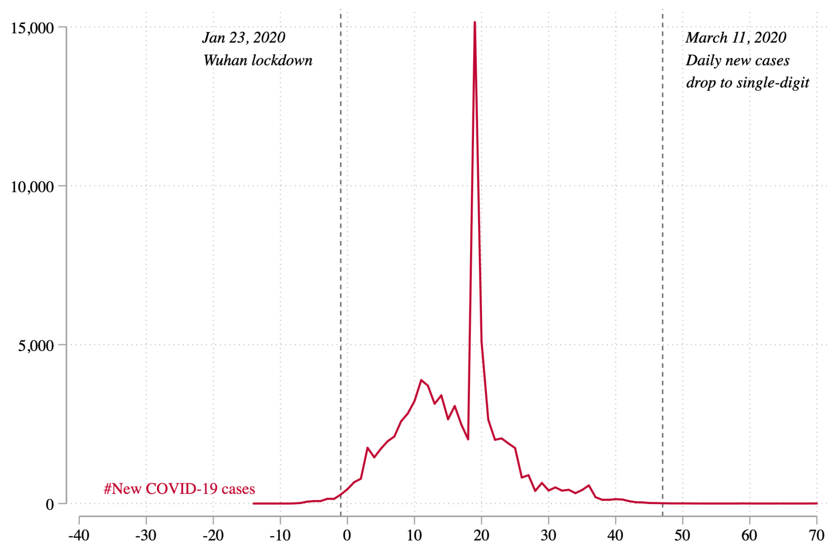
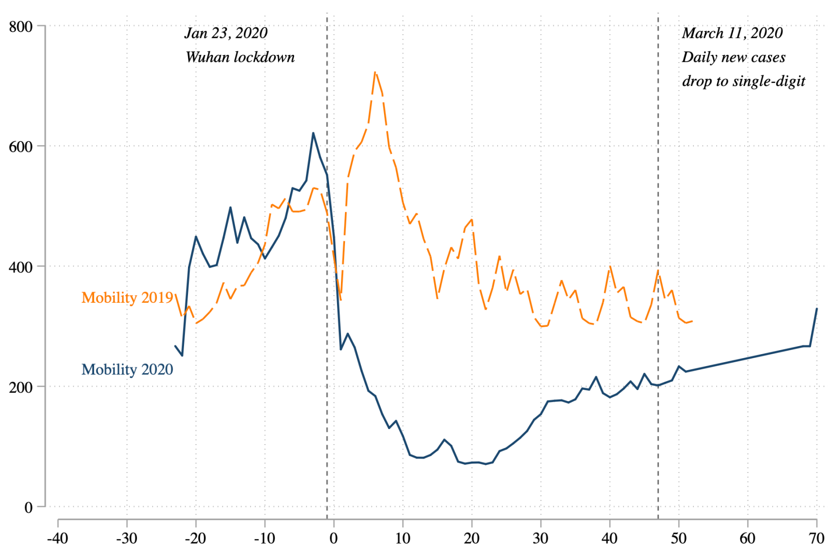
Figure 1: The COVID-19 Outbreak and Reduction in Human Mobility



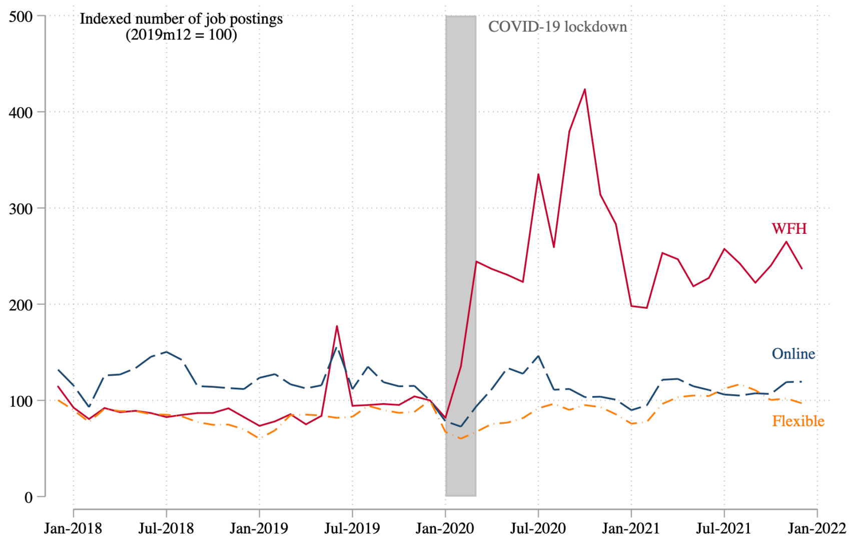
(a) Daily number of new confirmed COVID-19 cases



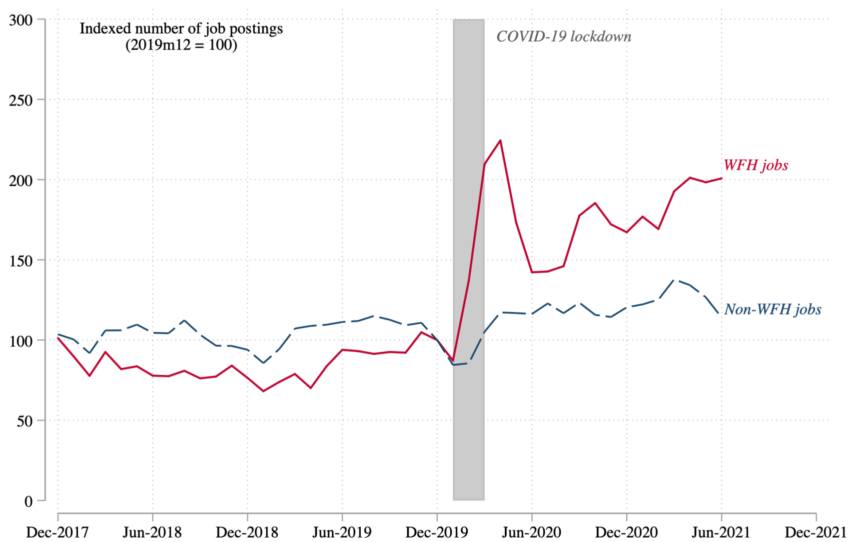
(b) Human mobility index around Spring Festival Eve

Note: This figure shows the daily time series of new confirmed COVID-19 cases in mainland China (Panel A) and the human mobility indices in 2019 and 2020 (Panel B). We use the lunar calendar date to control for the seasonal effect of the Spring Festival. The benchmark date (t=0) refers to Spring Festival Eve, which fell on February 4 in 2019 and on January 24 in 2020, one day after the Wuhan lockdown. The COVID-19 cases data is downloaded from CSMAR. The human mobility index measures the number of people with inter- or intra-city movements compared to the resident population and is obtained from the Baidu Qianxi database.

Figure 2: The Rise of Working from Home (WFH) Job Postings



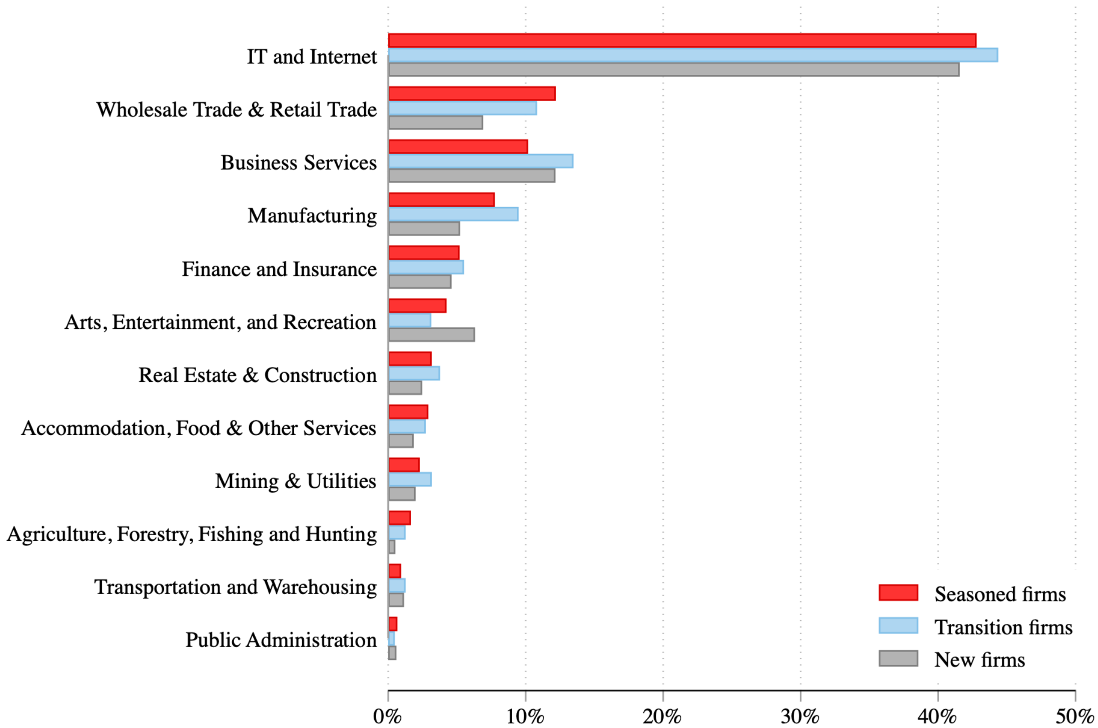
(a) WFH and Other AWA Job Postings



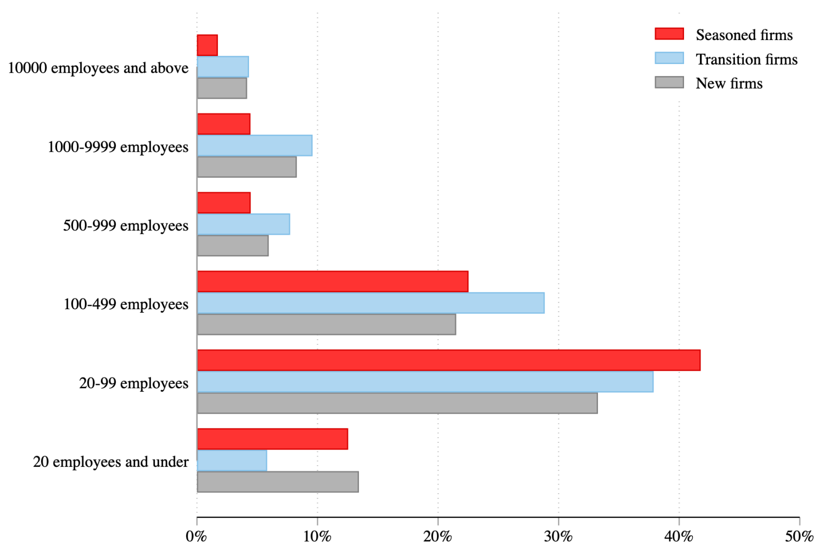
(b) WFH and Non-WFH Job Postings by Same Firms

Note: This figure shows time trends of active WFH job postings in mainland China. Panel A demonstrated monthly job postings of three mutually exclusive AWA categories: job ads allowing for WFH (*WFH*), those providing online work but not WFH (*online*), and those providing flexible work schedule but not WFH nor online (*flexible*). Panel B plots the number of WFH (red solid line) and non-WFH (navy dashed line) job ads posted by the same group of firms with at least one WFH job posting between December 2017 and June 2021. In both panels, we set the benchmark for each time series as its pre-COVID level in December 2019 and exclude job postings from firms in the education industry and firms that posted education-related jobs. The grey bar dates the COVID-19 shock period between January 2020 and March 2020. The data comes from job vacancies posted on Zhaopin.com between December 2017 and December 2021.

Figure 3: Industry and Size Distribution of WFH Posting Firms



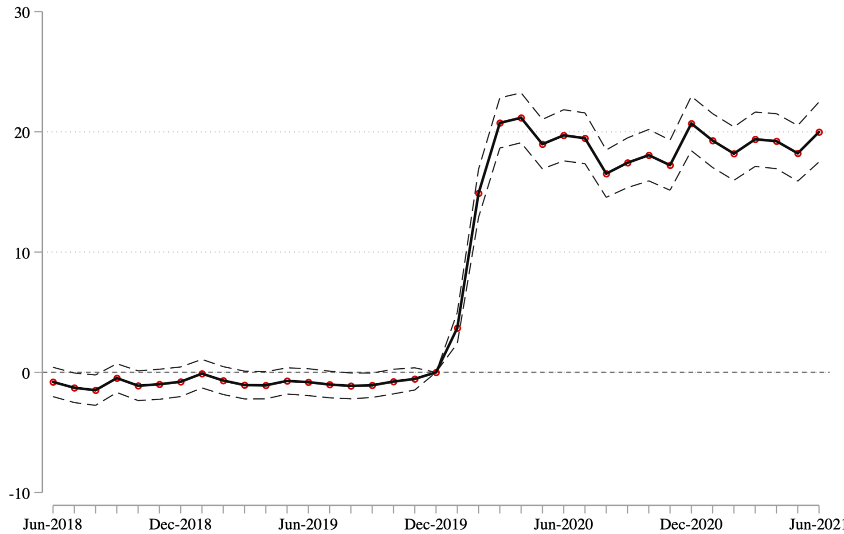
(a) Industry distribution



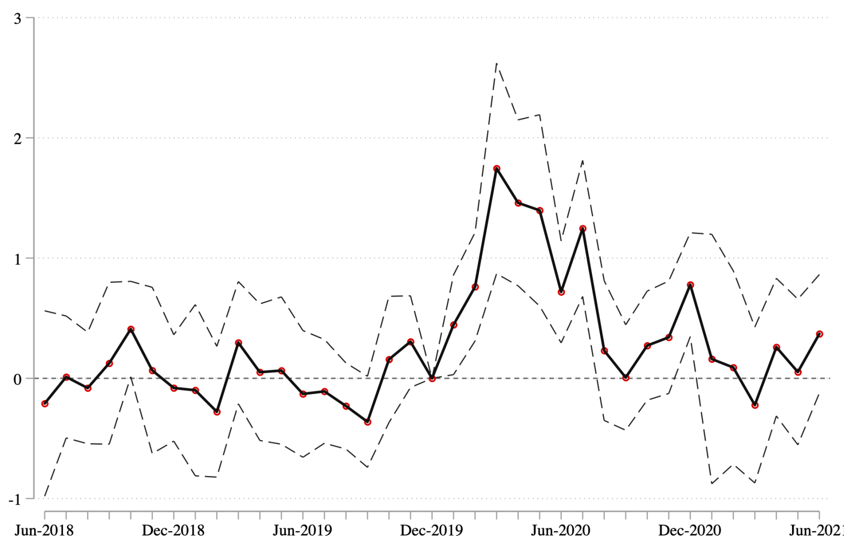
(b) Size distribution

Note: This figure demonstrates the differences in industry (Panel A) and size (Panel B) distribution of WFH posting firms, respectively. We categorize three groups of WFH firms: (1) Seasoned firms (red bars) which already started WFH job hiring before the COVID-19 outbreak; (2) Transition firms (blue bars) which already existed but started WFH job hiring only after the COVID-19 outbreak; and (3) New firms (grey bars) which started hiring only after the COVID-19 outbreak in January 2020. The grey bar dates the COVID-19 shock period between January 2020 and March 2020. The data comes from job vacancies posted on Zhaopin.com between June 2018 and June 2021.

Figure 4: Pretrend Analysis and the Persistence of WFH



(a) Firm-Month Regression



(b) Firm-City-Month Regression

Note: This figure plots the estimated coefficients of the following firm-month and firm-city-month regressions, respectively:

$$WFHratio_{ft} = \alpha + \sum_{t \neq T} \beta_t Month_t + \gamma_f + \varepsilon_{ft} \quad \text{(Panel A)}$$

$$WFHratio_{fct} = \alpha + \sum_{t \neq T} \beta_t Covid_c \times Month_t + \gamma_f + \gamma_c + \gamma_t + \mathbf{X}_{ct} + \varepsilon_{fct} \quad \text{(Panel B)}$$

where $Month_t$ represents the monthly dummy for each month during the sample period including January to March 2020, the COVID-19 lockdown period in China. We define December 2019 as the reference month T.

Table 1: Summary Statistics: Firm-Month Level

Note: This table summarizes the key features of the firm-month-level data for seasoned and transition firms in the period of June 2018 and June 2021. $WFHRatio_{ft}$ is the ratio of WFH job postings posted by firm f in month t. $post_t$ takes value 1 for months after January 2020 and 0 for months before. $size_f$ is firms' size proxied by the self-reported number of workers in firm f. We choose the maximum value if a firm reports different numbers during the sample period.

	Panel A: Sample firms							
	count	mean	sd	min	p10	p50	p90	max
n_wfh	89698	1.29	7.91	0.00	0.00	0.00	2.00	502.00
n_nonwfh	89698	33.53	62.99	0.00	0.00	14.29	71.43	2857.14
n_all	89698	34.82	63.69	1.00	1.00	15.29	72.43	2857.14
WFHratio	89698	23.30	40.68	0.00	0.00	0.00	100.00	100.00
WFHratio2019	89698	9.86	24.49	0.00	0.00	0.00	25.93	100.00
wfhtrial	89698	10.61	27.54	0.00	0.00	0.00	28.40	100.00
	Panel B: Seasoned firms (ftype = 0)							
	count	mean	sd	min	p10	p50	p90	max
n_wfh	56737	1.70	9.43	0.00	0.00	1.00	3.00	502.00
n_nonwfh	56737	28.91	51.46	0.00	0.00	14.29	71.43	1614.29
n_all	56737	30.61	52.60	1.00	1.00	14.29	71.43	1709.29
WFHratio	56737	30.53	44.23	0.00	0.00	1.72	100.00	100.00
WFHratio2019	56737	15.59	29.31	0.00	0.00	2.72	63.64	100.00
wfhtrial	56737	13.54	30.74	0.00	0.00	0.00	100.00	100.00
	Panel C: Transition firms (ftype = 1)							
	count	mean	sd	min	p10	p50	p90	max
n_wfh	32961	0.58	4.04	0.00	0.00	0.00	1.00	378.00
n_nonwfh	32961	41.47	78.37	0.00	14.29	14.29	85.71	2857.14
n_all	32961	42.05	78.71	1.00	14.29	20.29	85.71	2857.14
WFHratio	32961	10.86	29.87	0.00	0.00	0.00	58.33	100.00
WFHratio2019	32961	0.00	0.00	0.00	0.00	0.00	0.00	0.00
wfhtrial	32961	5.56	19.93	0.00	0.00	0.00	6.54	100.00

Table 2: DID Regressions, By Firm Type

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

$$Y_{ft} = \alpha + \beta ftype_f \times post_t + \gamma_f + \gamma_t + \varepsilon_{ft}$$

Panel A presents the results where Y_{ft} is $WFHratio_{ft}$, the ratio of WFH job postings in all job ads posted by the same firm f in month t, Panel B replaces Y_{ft} with $ln(1+WFHnumber)$, the log number of WFH job ads posted by firm f in month t, and Panel C replaces Y_{ft} with $ln(1+NonWFHnumber)$, the log number of non-WFH job ads posted by firm f in month t. $ftype_f$ indicates whether a firm starts its WFH job hiring before (=0) or after (=1) the COVID-19 outbreak in 2020. $post_t$ takes a value of 1 for months after January 2020 and 0 for months before. γ_f and γ_t are firm and year-month fixed effects, respectively, which are controlled in all columns. We include the constant in all regressions. 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.

	Includ. lockdown period			Exclud. lockdown period		
	(1)	(2)	(3)	(4)	(5)	(6)
	Ftype = 0	Ftype = 1	Full sample	Ftype = 0	Ftype = 1	Full sample
Panel A: Y = Ratio of WFH Job Postings						
post	-0.812*	18.842***		-2.066***	19.366***	
	(0.477)	(0.518)		(0.523)	(0.561)	
ftype_post			19.746***			21.616***
			(0.701)			(0.767)
N	61,326	36,499	97,825	56,459	32,895	89,354
Adj. R^2	0.482	0.319	0.478	0.481	0.339	0.483
Panel B: Y = Number of WFH Job Postings						
post	-0.045***	0.394***		-0.065***	0.412***	
	(0.012)	(0.010)		(0.014)	(0.011)	
ftype_post			0.438***			0.480***
			(0.015)			(0.017)
N	61,326	36,499	97,825	56,459	32,895	89,354
Adj. R^2	0.559	0.374	0.545	0.549	0.414	0.547
Panel C: Y = Number of Non-WFH Job Postings						
post	-0.095***	-0.538***		-0.059***	-0.539***	
	(0.017)	(0.019)		(0.019)	(0.021)	
ftype_post			-0.450***			-0.488***
			(0.025)			(0.028)
N	61,326	36,499	97,825	56,459	32,895	89,354
Adj. R^2	0.555	0.471	0.555	0.555	0.481	0.559
Panels A, B and C						
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Month F.E.	N	N	Y	N	N	Y

Table 3: DID Regressions: WFH Hiring Experience

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

$$WFHratio_{ft} = \alpha + \beta WFHexp_f \times post_t + \gamma_f + \gamma_t + \varepsilon_{ft}$$

Panel A examines firms' pre-COVID WFH hiring experience measured by $WFHratio2019_f$, the ratio of WFH job postings in all job ads posted by the same firm f 2019. Panel B examines firms' WFH hiring experience during the lockdown period measured by $WFHtrial_f$, the ratio of WFH job postings in all job ads posted by the same firm f during the lockdown period (2020m1-2020m3). $post_t$ takes a value of 1 for months after January 2020 and 0 for months before. γ_f and γ_t are firm and year-month fixed effects, respectively, which are controlled in all columns. We include a constant in all regressions. 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.

	Y = Ratio of WFH Job Postings					
	Includ. lockdown period			Exclud. lockdown period		
	(1) Full sample	(2) Ftype = 0	(3) Ftype = 1	(4) Full sample	(5) Ftype = 0	(6) Ftype = 1
Panel A: Pre-COVID WFH Hiring Experience						
WFHratio2019 × post	-0.298***	-0.167***	.	-0.347***	-0.185***	.
	(0.017)	(0.018)	.	(0.022)	(0.021)	.
Firm FE	Y	Y	.	Y	Y	.
Year-Month FE	Y	Y	.	Y	Y	.
N	97,825	61,326	.	89,354	56,459	.
Adj. R^2	0.472	0.486	.	0.475	0.484	.
Panel B: WFH Hiring Experience during Lockdowns						
wfhtrial × post	0.196***	0.211***	0.526***	0.042**	0.097***	0.284***
	(0.014)	(0.015)	(0.030)	(0.017)	(0.018)	(0.035)
Firm F.E.	Y	Y	Y	Y	Y	Y
Year-Month F.E.	Y	Y	Y	Y	Y	Y
N	97,825	61,326	36,499	89,354	56,459	32,895
Adj. R^2	0.471	0.489	0.353	0.470	0.483	0.346

Table 4: DID Regressions using Geographical Variation of the COVID-19 Shock

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

$$WFHratio_{fct} = \alpha + \beta Covid_c \times post_t + \gamma_f + \gamma_c + \gamma_t + \eta \mathbf{X}_{ct} + \varepsilon_{fct}$$

where $WFHratio_{fct}$ is the ratio of WFH job postings in all job ads posted by the same firm f in month t in city c. $Covid_c$ is the log value of accumulated COVID-19 cases in city c as of March 2020. $post_t$ takes value 1 for months after January 2020 and 0 for months before. γ_f, γ_c, and γ_t are firm, city, and year-month fixed effects, respectively, which are controlled in all columns. Control variables $\mathbf{X}_{ct}$ include the log values of GDP *lngdp*, the log values of population *lnpopulation*, and the share of the secondary industry in GDP *gdp_2*, which are controlled in even columns. We include the constant in all regressions. We exclude the lockdown period in all panels. 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.

	Y: Ratio of WFH Job Postings, Firm-City-Month Level					
	Full sample		Excld. Hubei		Excld. Hubei and far	
	(1)	(2)	(3)	(4)	(5)	(6)
Covid × post	0.727***	0.694***	1.136***	1.085***	1.065***	1.015**
	(0.131)	(0.158)	(0.374)	(0.404)	(0.397)	(0.424)
lngdp		-3.495		-4.956		-5.577
		(3.871)		(4.218)		(4.277)
lnpopulation		-7.474***		-5.587*		-5.260*
		(2.853)		(3.075)		(3.169)
gdp_2		-0.747		-2.196		-1.450
		(6.002)		(6.868)		(6.760)
Firm F.E.	Y	Y	Y	Y	Y	Y
City F.E.	Y	Y	Y	Y	Y	Y
Year-Month F.E.	Y	Y	Y	Y	Y	Y
N	194,242	180,762	189,640	176,285	187,515	174,567
Adj. R^2	0.592	0.589	0.590	0.587	0.588	0.585

Table 5: Placebo Tests with False Shock Months

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

$$WFHratio_{fct} = \alpha + \beta Covid_c \times post_t^{false} + \gamma_f + \gamma_c + \gamma_t + \eta \mathbf{X}_{ct} + \varepsilon_{fct}$$

where $WFHratio_{fct}$ is the ratio of WFH job postings in all job ads posted by the same firm f in month t in city c. $Covid_c$ is the log value of accumulated COVID-19 cases in city c as of March 2020. $post_t^{false}$ represents the "false" treatment months, which takes value 1 for months after January 2019 and 0 for months before in Panel A and takes value 1 for months after July 2019 and 0 for months before in Panel B. We exclude N in months starting from January 2020 in the placebo tests. γ_f, γ_c, and γ_t are firm, city, and year-month fixed effects, respectively, which are controlled in all columns. Control variables $\mathbf{X}_{ct}$ include the log values of GDP *lngdp*, the log values of population *lnpopulation*, and the share of the secondary industry in GDP *gdp_2*, which are controlled in even columns. We include the constant in all regressions. 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.

	Y: Ratio of WFH Job Postings, Firm-City-Month Level					
	Full sample		Excl. Hubei		Excl. Hubei and far	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: False COVID-19 Month in January 2019						
Covid × Post2019m1	-0.007	-0.004	-0.076	-0.083	-0.057	-0.088
	(0.147)	(0.152)	(0.153)	(0.155)	(0.153)	(0.158)
N	158,803	150,435	155,613	147,257	154,300	146,104
Adj. R^2	0.604	0.603	0.603	0.602	0.601	0.600
Panel B: False COVID-19 Month in July 2019						
Covid × Post2019m7	0.065	0.078	0.055	0.050	0.045	0.027
	(0.118)	(0.129)	(0.143)	(0.150)	(0.146)	(0.153)
N	158,803	150,435	155,613	147,257	154,300	146,104
Adj. R^2	0.604	0.603	0.603	0.602	0.601	0.600
Panels A and B						
Controls		Y		Y		Y
Firm F.E.	Y	Y	Y	Y	Y	Y
City F.E.	Y	Y	Y	Y	Y	Y
Year-Month F.E.	Y	Y	Y	Y	Y	Y

Table 6: DID Regressions, Number of WFH and Non-WFH Job Postings

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

$$Y_{fct} = \alpha + \beta Covid_c \times post_t + \gamma_f + \gamma_c + \gamma_t + \eta \mathbf{X}_{ct} + \varepsilon_{fct} \quad (5)$$

Panel A presents the results where Y_{fct} is $ln(1 + WFHnumber)$, the log number of WFH job postings in month t in city c. Panel B presents the results where Y_{fct} is $ln(1 + NonWFHnumber)$, the log number of non-WFH job postings in month t in city c. $Covid_c$ is the log value of accumulated COVID-19 cases in city c as of March 2020. $post_t$ takes value 1 for months after January 2020 and 0 for months before. γ_f, γ_c, and γ_t are firm, city, and year-month fixed effects, respectively, which are controlled in all columns. Control variables $\mathbf{X}_{ct}$ include the log values of GDP *lngdp*, the log values of population *lnpopulation*, and the share of the secondary industry in GDP *gdp_2*, which are controlled in even columns. We include the constant in all regressions. We exclude the lockdown period in all panels. 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.

	Full sample		Excl. Hubei		Excl. Hubei and far	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of WFH Job Postings						
Covid × post	0.011***	0.010***	0.018***	0.018***	0.017***	0.017***
	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)	(0.006)
N	194,242	180,762	189,640	176,285	187,515	174,567
Adj. R^2	0.553	0.556	0.553	0.556	0.552	0.555
Panel B: Number of Non-WFH Job Postings						
Covid × post	-0.028***	-0.027***	-0.040***	-0.039***	-0.038***	-0.037***
	(0.005)	(0.005)	(0.009)	(0.010)	(0.010)	(0.010)
N	194,242	180,762	189,640	176,285	187,515	174,567
Adj. R^2	0.584	0.581	0.582	0.579	0.580	0.577
Panels A and B						
Controls		Y		Y		Y
Firm F.E.	Y	Y	Y	Y	Y	Y
City F.E.	Y	Y	Y	Y	Y	Y
Year-Month F.E.	Y	Y	Y	Y	Y	Y

Table 7: Heterogeneous Impact on WFH Job Postings

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

$$Y_{fct} = \alpha + \beta Covid_c \times post_t + \gamma_f + \gamma_c + \gamma_t + \eta \mathbf{X}_{ct} + \varepsilon_{fct}$$

Panel A, B, and C examine the ratio of WFH job postings with high-, medium, and low-level of certain characteristics posted by firm f in month t in city c, respectively. Specifically, we divide all job postings into quintiles based on wages, education requirements, work experience requirements, and occupation-level teleworkability. The top two quintiles belong to the high level, the middle two quintiles the medium level, and the bottom quintile the low level. $Covid_c$ is the log value of accumulated COVID-19 cases in city c as of March 2020. $post_t$ takes a value of 1 for months after January 2020 and 0 for months before. γ_f, γ_c, and γ_t are firm, city, and year-month fixed effects, respectively, which are controlled in all columns. Control variables $\mathbf{X}_{ct}$ include the log values of GDP *lngdp*, the log values of population *lnpopulation*, and the share of the secondary industry in GDP *gdp_2*, which are controlled in even columns. We include the constant in all regressions. We exclude the lockdown period in all panels. 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.

	Wage		Education		Work Exp.		Teleworkability	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Y = Ratio of WFH job postings with **high** levels								
Covid × post	0.458***	0.423***	0.588***	0.627***	0.447***	0.404***	0.922***	0.906***
	(0.097)	(0.099)	(0.185)	(0.178)	(0.115)	(0.109)	(0.167)	(0.148)
N	187,515	174,567	187,515	174,567	187,515	174,567	187,515	174,567
Adj. R^2	0.572	0.578	0.595	0.601	0.587	0.589	0.568	0.569
Panel B: Y = Ratio of WFH job postings with **medium** levels								
Covid × post	0.706***	0.736***	0.527**	0.461*	0.357*	0.354*	0.127	0.150
	(0.205)	(0.213)	(0.235)	(0.238)	(0.197)	(0.214)	(0.385)	(0.380)
N	187,515	174,567	187,515	174,567	187,515	174,567	187,515	174,567
Adj. R^2	0.543	0.541	0.560	0.555	0.545	0.546	0.648	0.648
Panel C: Y = Ratio of WFH job postings offering **low** levels								
Covid × post	-0.168	-0.122	0.188*	0.171			0.030	-0.029
	(0.232)	(0.232)	(0.106)	(0.131)			(0.099)	(0.125)
N	187,515	174,567	187,515	174,567			187,515	174,567
Adj. R^2	0.576	0.577	0.596	0.599			0.557	0.555
Panels A, B, and C								
Controls		Y		Y		Y		Y
Firm F.E.	Y	Y	Y	Y	Y	Y	Y	Y
City F.E.	Y	Y	Y	Y	Y	Y	Y	Y
Year-Month F.E.	Y	Y	Y	Y	Y	Y	Y	Y