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ABSTRACT

China's Labor Market Demand in the Shadow of COVID-19: Evidence from an Online Job Board*

Using data of the largest online job board in China, Zhaopin.com, we examine the impacts of the lockdown policy on the Chinese labor market demand during the coronavirus disease (COVID-19) pandemic. The analyses reveal that the lockdown policy, which was implemented in Wuhan on January 23, 2020, reduced the labor market demand drastically. Specifically, the "Number of Companies" that posted weekly job vacancies, "Number of Positions," and "Number of Employees" to be recruited reduced rapidly by 18.5%, 21.9%, and 30.0%, respectively. Furthermore, this impact of the lockdown policy began to reduce, thus allowing the labor demand to rebound four weeks after the outbreak. The heterogeneity analyses reveal that the industries with high physical proximity and those manufacturing non-essential products/services, as well as small-size firms, were greatly impacted by the policy. No statistical difference was observed between the impacts on the cities that implemented specific control measures and those that did not. This study quantifies the dynamic impacts of China's stringent control measures on the country's labor demand during the pandemic. These findings indicate that the effective management of public health crises in conjunction with economic policies is critical to revitalizing labor markets.

JEL Classification: J23 , J63, I18

Keywords: COVID-19 , lockdown, job vacancy , online job board, labor demand

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1. Introduction

The coronavirus disease (COVID-19) pandemic has tremendously impacted economic developments worldwide, as well as accounted for the loss of many lives. Many governments have adopted nonpharmaceutical interventions (NPIs) to contain the further spread of the pandemic (Hsiang et al., 2020; Maier and Brockmann, 2020). However, these measures, which ranged from social distancing to complete lockdown, have invariably restricted economic activities, thus accounting for the losses of hundreds of millions of jobs and plunging the global economy into a deep recession (Fang et al., 2020a). Thus, it is crucial to monitor the economy during this special season. As a significant component of the macroeconomic market, the labor market requires special attention, particularly in terms of the COVID-19-hit labor force and human capital, which differentiates from previous shocks. Governments rely on quality and rapid information to formulate policies toward supporting severely affected sectors and promoting economic recovery. Online recruitment information embodies real-time labor demands that reflect firms' anticipation of economic activities. Such information is particularly beneficial during a pandemic since the spread of such a pandemic and the implementation of control policies complicate the obtainment of administrative statistics through traditional surveys. Furthermore, a pandemic shock to the economy is a rare event, and policies to respond to historical economic downturns may become inadequate. The data from a recruitment platform are acquired instantly, exhibit richness in information, and are almost free of misreporting (Shen and Taska, 2021); such data can help governments monitor economic conditions and formulate well-timed policies.

China, which is the most populated country in the world and the first to report confirmed cases of COVID-19, implemented a lockdown policy and other stringent measures in response to the outbreak. The Chinese central government locked down the city of Wuhan, which was the epicenter of the pandemic, on January 23, 2020, and all the provincial governments followed suit by announcing large-scale prevention and control measures, such as mandatory quarantine, contact tracing of cases, partial suspension of public transport, cancelation of public events, the closing of schools and entertainment centers, and the establishment of health checkpoints, before January 29, 2020 (Qiu et al., 2020; Tian et al., 2020). Considering that COVID-19 has continued to spread in pockets of the global population for over two years, it is beneficial to elucidate the economic impacts of the NPIs for policymakers. In this study, we employ the data obtained from the largest online job board in China, *Zhaopin.com*, to examine the dynamic impacts of the lockdown on the Chinese labor market demand during the outbreak.

Employing online recruitment data, an emerging body of literature has estimated the economic impacts of the COVID-19 pandemic. However, only a few countries adopted NPIs as stringently as China did. The community-spread cases were first reported in the United States at the end of February 2020. Forsythe et al. (2020) find that the weekly advertisements of new job vacancies collapsed in the second half of March; by late April, it had reduced by >40%. Employing the data from an online job board, Marinescu et al. (2020) find that the posting of new job vacancies rebounded slightly at the end of April. Campello et al. (2020) reveal that the active job postings dropped by ~40% at the beginning of May 2020. Under mild restrictions, the Swedish government recommended voluntary compliance in response to the COVID-19 outbreak. Sweden confirmed the community spread of the virus in the second week of March. Employing the data from the largest online job board in Sweden, Hensvik et al. (2021) find a reduction of 40% in the advertisement of new job vacancies from early March 2020, culminating in a reduction of 15% in available vacancy inventories in mid-April. The Australian government encouraged their people to stay at home while promoting widespread testing and quarantine during the outbreak (Rothwell and Van Drie, 2020). As a representative of a thin labor market, Australia experienced consistent reductions in job postings between early March and the beginning of May 2020 when it reached the lowest dip of 45% (Shen and Taska, 2020).

This study adopts a panel-interrupted time-series model and an event study analysis to estimate the dynamic impacts of China's lockdown policy on the following three measures of the labor market demand employing the data obtained from *Zhaopin.com*: Number of Companies (NC) that post job ads (reflecting enterprises' vitality), Number of Positions (NP) in weekly postings (embodying enterprises' expectations of the economic situation), and Number of Employees (NE) to be recruited (linking to the tightness of the labor market). Compared with the corresponding lunar period, 2019, our analyses reveal that the active weekly postings regarding NC, NP, and NE decreased rapidly by 18.5%, 21.9%, and 30.0%, respectively, during the COVID-19 outbreak, and the average decrease was 5.7%–7.0% per week within the subsequent six weeks. Despite the significant negative impacts that were observed initially, the impacts were reduced, and the labor demand rebounded four weeks after the outbreak. These results indicate that the implementation of the strict lockdown policy allowed China to quickly contain the spread of COVID-19 and resume economic activities within a short period. Our heterogeneity analyses reveal that the lockdown policy exerted very significant impacts on industries with high physical proximity, industries that produce nonessential products and services, and small-size firms. The difference between the results obtained for the cities that implemented specific control measures and those that did not were insignificant.

To the best of our knowledge, this study is the first to comprehensively investigate the dynamic impacts of China's lockdown policy on the Chinese labor market demand during the outbreak. As a representative of countries that adopted stringent NPIs, our findings quantify the impacts on the Chinese labor market and demonstrate the relatively fast revitalization of the labor, following the short-term stringent measures, and this may offer insights to policymakers.

This study is consistent with Fang et al. (2020a), who find that new job advertisements dropped by ~31% in the first 14 weeks after the lockdown in Wuhan. However, their study differs from ours in several aspects. First, Fang et al. (2020a) aim at evaluating the impact of the pandemic on job creation in China through the global supply chain, and thus focusing on a longer period. Conversely, we examine six weeks, following the lockdown in Wuhan, to minimize the influences of the resumption of work and production policies, as proposed by the central government at the end of February. Second, Fang et al. (2020a) utilize a web crawler to obtain daily data of new job postings from *Zhaopin.com* and aggregate them to the city-week level. Conversely, we obtain the data of weekly active job postings from *Zhaopin.com* that employs algorithms to perform de-duplication, thus improving the accuracy of our data. Further, our analyses are based on units at the city-industry level. In addition to NP, we employ NC and NE as the outcomes to comprehensively depict the Chinese labor demand. Another recent study by Mao and Zeng (2022) utilizes monthly NE data between January and September from *Zhaopin.com* to examine the impacts of COVID-19 on the employment of college graduates in China.

The rest of the article is organized as follows: Section 2 introduces the data and estimation methods. Section 3 presents the main estimation results. Section 4 reports the heterogeneity analyses, and Section 5 discusses our results. Section 6 concludes.

2. Data and Estimation Methods

2.1 Data from Zhaopin.com

Zhaopin.com is an online job search engine, which avails recruitment information that is released by employers to job seekers and facilitates job hunting and job information services. Founded in 1994, *Zhaopin.com* has become the largest online recruitment platform in China, covering almost all the occupations available in the urban labor market (except for civil servants in public sectors). A job seeker is only required to submit relevant information online, and the website will automatically generate a standardized resume that will suit any position that interests the job seeker. Owing to its low search cost, *Zhaopin.com* had 230 million individual subscribers at the end of 2020. Among them, 6.3 million were daily active users. Moreover, the large number of individual users, as well as low recruitment costs, has inspired employers to adopt *Zhaopin.com* as a significant recruitment channel. As of the end of 2020, *Zhaopin.com* had served over 6.16 million firms, accounting for 0.6–0.7 million active firms per quarter.

Compared with traditional data on the labor market, online recruitment data are accompanied by advantages, such as timeliness, sensitivity, and authenticity (Shen and Taska, 2021). Dissimilar to the data availed by online job boards, crawling data may suffer from fluctuating qualities or errors due to technological issues.[1] Additionally, some employers may post job ads several times a week or at different locations to increase the number of views. *Zhaopin.com* checks for false information and duplicate postings and deletes them. The daily data crawling from *Zhaopin.com*

[1] First, data crawling is greatly affected by the design of the crawling program. A slight difference in the program can cause a large gap in the data crawling from the same web page. Second, website developers generally set up anti-crawling strategies on their websites, resulting in complications and errors in data crawling. Third, website data are presented through a series of interactive actions in backstage operations and even hidden addresses, which further increase crawling difficulty and reduce data accuracy (this information was obtained through interviews with relevant computer technicians).

might contain false or duplicate information since *Zhaopin.com* requires a minimum of one week to update its database. Therefore, our preference for weekly data from *Zhaopin.com* will favor the accurate analyses of the labor demand.

Job posting data have shortcomings. Affected by internet penetration, offline recruitment is not fully incorporated by *Zhaopin.com*. *Zhaopin.com* overrepresents and underrepresents white-collar and blue-collar jobs, respectively, in the urban labor market. Regardless, the data from *Zhaopin.com* can sufficiently reflect the Chinese labor market. The China Institute for Employment Research (CIER) at Renmin University of China, in conjunction with *Zhaopin.com*, generates the CIER index based on the data from *Zhaopin.com* to describe the state of the labor market and monitor the macroeconomic prospect. The CIER index is defined as the ratio of the number of employees to be recruited to the number of job seekers in the labor market (Zeng, 2015). Geng and Mao (2017) demonstrate the dynamic consistency of the CIER index with the purchasing managers' index released by China's National Bureau of Statistics (NBS) between the first quarters of 2011 and 2017. We compare the CIER index to the unemployment rates that are released by NBS between January 2017 and October 2020. Figure 1 shows that the CIER index during this period moved in the opposite direction of the national unemployment rate, as well as the average unemployment rate of 31 cities. Particularly, the CIER index slumped in early 2020, while the unemployment rates increased rapidly. Therefore, the data from *Zhaopin.com* remain consistent with the official data of China's labor market.

2.2. Our Sample and Summary Statistics

We employ active job posting data that have been processed and de-duplicated by *Zhaopin.com*. We focus on three weekly measures of labor market demand, namely NC (the number of active firms that post job ads), NP (the number of active positions, which is widely utilized in the literature on online recruitment information (e.g., Campello et al., 2020; Marinescu et al., 2020)), and NE (the number of employees to be recruited). These three measures comprehensively describe the state of the labor demand and reflect the different levels of the demand. Our data cover 55 major cities, 52 subdivisions of industries, and different sizes of firms in mainland China. The 55 cities are scattered across the east, middle, west, and northeast of China and exhibit different levels of economic development. Appendix Tables A.1 and A.2 present the specific cities and industries covered by our data, respectively. The industries are categorized by *Zhaopin.com*.

Considering that the COVID-19 pandemic broke out during the Chinese New Year (CNY) in 2020, we match the Chinese lunar dates (Chen et al., 2021; Fang et al., 2020a, 2020b; Qiu et al., 2020) between 2019 and 2020 and obtain two symmetric periods covering twelve weeks around CNY. The CNY periods witness large-scale inter-provincial and intra-provincial movements of people. As a large city with over five million people, Wuhan is the transportation hub of the central region of China. Following the implementation of lockdown in Wuhan on January 23, 2020 (two days before the 2020 CNY), all the provinces in mainland China also declared level I responses to major public health emergencies before January 29, 2020. Similarly, most large and medium cities (population of over 1 million people) issued different levels of control policies before February 12, 2020. Our data cover six weeks, following the 2020 CNY because of the policy of the resumption of normal production and business activities proposed by the central government. On February 22, i.e., the Saturday of the fourth week after CNY, the State Council issued the guidelines for epidemic prevention and control measures for the resumption of work and production in enterprises and institutions. On March 4 (the sixth week after CNY), the State Council issued a notice of streamlining approvals and optimizing services to accurately and prudently promote the resumption of work and production by enterprises. When the lockdown in Wuhan was lifted on April 8, 2020, the central government offered a proposal for the first time to comprehensively promote the resumption of work and production.

Considering that the lunar date of 2020 CNY started on January 25, we define the period from December 16, 2019, to January 19, 2020, as the pre-2020 CNY weeks and define the period from January 20 to March 6, 2020, as the post-2020 CNY weeks. Similarly, since the lunar date of 2019 CNY begins on February 5, we define the period between December 31, 2018, to February 3, 2019, as the pre-CNY 2019 weeks and the period from February 4 to March 18, 2019, as the post-CNY 2019 weeks. Therefore, we obtain the panel data of twelve weeks at the city-industry level, covering 2,860 cross-sectional units (55 cities interact with 52 subdivisions of industries).

Table 1 reports the summary statistics of the three outcomes. Columns (1)–(3) and Columns (4)–(6) present the outcomes for 2019 and 2020, respectively. Before 2019 CNY, the average value of log(NE), i.e., 7.536, was larger than those of log(NC) (4.465) and log(NP) (5.880). Further, Columns (3) and (6) present the differences between pre-CNYs and post-CNYs of both years. Contrary to the significant increases in the labor demand in post-CNY 2019, the three outcomes dramatically reduced in post-CNY 2020. Although log(NC), log(NP), and log(NE) increased after 2019 CNY by 13.6%, 17.4%, and 19%, respectively, they decreased after 2020 CNY by 24.9%, 24.7%, and 30.4%, respectively, and the highest decrease was observed in NE.

To visualize the dynamic pattern of weekly recruitment demands over time, Figure 2 shows the plot of the average values of the outcomes per week as hollow circles and solid dots in 2019 and 2020, respectively. We rescale the starting week of CNY to be zero. Contrary to 2019 when the labor demand increased rapidly after CNY, the three outcomes of the labor demands reduced after 2020 CNY, followed by troughs. However, within our observation period, they rebounded four weeks after CNY but not to the levels before 2020 CNY.

2.3 Estimation Methods

We first analyze the impacts of the lockdown policy on recruitment demands via a panel-interrupted time-series approach (Linden, 2015, 2021). We employ week as a continuous-time variable and impose a linear-trend assumption on the outcomes. Employing this approach, we capture the immediate impact of the policy on the labor demand, as well as the average effect over time within the observation period. The following model (1) is employed:

$$y_{i,t} = \alpha_0 + \alpha_1 w_i + \alpha_2 D_{i,t} + \alpha_3 cutoff_{i,t} + \alpha_4 w_i \cdot cutoff_{i,t} + \alpha_5 D_{i,t} \cdot cutoff_{i,t} + \beta D_{i,t} \cdot w_i$$
$$+\gamma D_{i,t} \cdot w_i \cdot cutoff_{i,t} + \varepsilon_{i,t} (1),$$

where the dependent variable, $y_{i,t}$, represents the weekly outcome of a city-industry unit, i, measured by the log of NC, NP, or NE, at week t. t is rescaled as $t = -5, \ldots, -1, 0, 1, \ldots, 6$. The dummy variable, w_i, is defined as 1 and 0 for the 2020 (the treatment group) and 2019 (the control group) units, respectively; thus, α_1 captures the difference in the labor market demands before CNY in both years. The dummy variable, $D_{i,t}$, indicates whether a unit, i, is located before CNY ($D_{i,t}$= 0 if $t = -5, \ldots, -1$) or after ($D_{i,t}$= 1 if $t = 0, 1, \ldots, 6$). Thus, α_2 portrays the immediate effect of CNY on the labor market demand in 2019. $cutoff_{i,t}$ is the scaled variable for measuring the span between the week, t, and CNY. Namely, $cutoff_{i,t}$= 0 if week t is the starting week of CNY, and $cutoff_{i,t}$= 1 if week t is one week after CNY, etc. Thus, α_3 captures the linear time trend of the demand before 2019 CNY. The coefficient of $w_i \cdot cutoff_{i,t}$, α_4, denotes the difference between the time trends of the two years before CNY, while the coefficient of $D_{i,t} \cdot cutoff_{i,t}$, α_5, indicates the effect of CNY on the slope of the time trend in 2019. The coefficients, β and γ, represent our parameters of interest in Model (1). The former measures the immediate effect of the lockdown policy on the labor market demand; it denotes the difference between the average demands after 2020 and 2019 CNYs. The latter captures its effect on the linear time trend because it measures the difference between the slopes of the labor demand after CNY of the two years with reference to the period before 2019 CNY. $\varepsilon_{i,t}$ is the error term. We estimate Model (1) via the ordinary least squares (OLS) and calculate the clustered standard errors at the city level.

The ease of interpretation accounts for an advantage of Model (1); however, the linear trend after 2020 CNY may not capture the true effect of the lockdown policy (see Figure 2). Therefore, we incorporate potential confounders into Model (1) to improve our estimation. First, the outcome variables may be dominated by long-term trends and seasonal patterns owing to the aggregate time-series nature of each city-industry unit. Second, the individual fixed effect at the city-industry level may confound our parameters of interest. Third, we consider the nonlinear time trend of the labor demand, as shown in Figure 2. Therefore, we incorporate additional covariates and employ Model (2) as our main estimation model:

$$y_{i,t} = \alpha_0 + \alpha_1 w_i + \alpha_2 D_{i,t} + \alpha_3 cutoff_{i,t} + \alpha_4 w_i \cdot cutoff_{i,t} + \alpha_5 D_{i,t} \cdot cutoff_{i,t} + \beta D_{i,t} \cdot w_i + \gamma D_{i,t} \cdot w_i \cdot cutoff_{i,t} + harmonics_t + city\_ind_i + f\left(cutoff_{i,t}\right) + \varepsilon_{i,t} \quad (2).$$

$harmonics_t$ includes pairs of the sine and cosine functions of week t with an underlying period reflecting the seasonal cycle (Bhaskaran et al., 2013). $city\_ind_i$ is the city-industry interaction dummy, which is employed to control the city-industry fixed effects. $f\left(cutoff_{i,t}\right)$ represents the polynomial of $cutoff_{i,t}$, including the secondary, tertiary, and quaternary terms of $cutoff_{i,t}$, to capture the flexible functional forms of the time trend.

Finally, we employ an event study model by replacing the continuous-time variable, $cutoff_{i,t}$, with discrete time variables and allowing the time effects to vary per week. The model is specified in the following equation:

$$y_{i,t} = \alpha_0 + \sum_{t=-5}^{-1} \alpha_t T_{i,t} + \sum_{t=1}^{6} \alpha_t T_{i,t} + \sum_{t=-5}^{6} \beta_t w_i T_{i,t} + city\_ind_i + \varepsilon_{i,t} \quad (3)$$

$T_{i,t}$ is an indicator variable for a certain week (it is 1 if $t = cutoff_{i,t}$ and 0 otherwise). α_t captures the week effects in 2019, with the starting week of the 2019 CNY (i.e., $\mathrm{t} = 0$) as the baseline. β_t denotes the difference in the week effects between 2020 and 2019. Thus, the estimates of $\beta_{-5}, \ldots, \beta_{-1}$ inform the assessment of the parallel trend before CNY, and those of $\beta_1, \ldots, \beta_6$ capture the dynamic effects of the lockdown policy after 2020 CNY with reference to the starting week of 2019 CNY. We also control the fixed effects at the city-industry level and calculate the clustered standard errors at the city level.

3. Main Estimation Results

3.1. Results of the Panel-Interrupted Time-Series Analysis

Table 2 presents the estimation results of Model (1) via a balanced panel data obtained from our sample. Column (1) reports the result for NC, which reflects enterprises' vitality. The coefficient of w indicated that the average value of log(NC) before 2020 CNY was larger than that of 2019 by 18.1%. The coefficient of D indicated a rapid increase of 3.7% after 2019 CNY. The coefficient of $D \cdot w$, which was one of our parameters of interest, indicated an immediate decrease of 17.1% in the average log(NC) owing to the lockdown policy. The negative coefficient of $Cutoff$ indicated a downward time trend before 2019 CNY. The positive coefficient of

$D \cdot Cutoff$ represented the positive effect of CNY on the linear trend in 2019. Thus, the slope of the time trend after 2019 CNY was 0.052, indicating the positive linear trend of the labor demand after 2019 CNY. The coefficient of $w \cdot Cutoff$, which was only marginally significant, indicated that the slope of NC before 2020 CNY was slightly smaller than that before 2019 CNY. The coefficient of $D \cdot w \cdot Cutoff$, which was our other parameter of our interest, denoted the difference in the average linear trend of 7.0% per week owing to the lockdown policy. Thus, the slope of the trend after 2020 CNY was −0.019. Namely, NC decreased by 1.9% per week during the six weeks after 2020 CNY.

Column (2) of Table 2 presents the results for NP, which embodies the expectations of enterprises in the market. Although the average level of log(NP) before 2020 CNY was larger than that of 2019 by 7.0%, the difference was statistically insignificant. NP in 2019 CNY increased rapidly by 4.6%. The coefficient of $D \cdot w$ was −0.198, indicating that the lockdown policy rapidly reduced NP by 21.9%. Similar to the results of NC, NP exhibited downward and upward linear trends before and after 2019 CNY, respectively. The slope of the time trend before 2020 CNY was slightly smaller than that before 2019 CNY, and the lockdown policy significantly decreased the slope of NP by an average of 5.7% per week after 2020 CNY. The slope after 2020 CNY indicated an average weekly decrease of 0.9% in NP during the six weeks after 2020 CNY.

Column (3) of Table 2 presents the results of NE to be recruited, which is linked to the labor market tightness. The average log(NE) before 2020 CNY was 11.8% larger than that of 2019. NE in 2019 CNY exhibited a rapid increase of 6.6%. The coefficient of $D \cdot w$ was −0.262, indicating that NE decreased rapidly by 30.0% owing to the lockdown, with more intensified effect than those of NC and NP. Similar to NC and NP, NE exhibited downward and upward time trends before and after 2019 CNY, respectively. The slope of the time trend before 2020 CNY was slightly smaller than that before 2019 CNY. Again, the coefficient of $D \cdot w \cdot Cutoff$ indicated that the lockdown policy decreased the slope of NE by an average of 6.5% per week after 2020 CNY. The slope after 2020 CNY indicated that NE reduced by 0.8% per week during the six weeks after 2020 CNY.

Figure 2 shows the predicted values of the labor demand employing dash lines based on the estimation of Model (1). The three outcomes generally display parallel trends before CNY of both years, with only NP displaying a slight difference in the slope. Although the dash line approximated the upward trend after 2019 CNY, the downward linear trend might not capture the nonlinear variations in the demand after 2020 CNY.

3.2 Main Estimation Results

Figure 3 shows the plots of the residuals in the estimation of Model (2) based on our sample. These residuals barely exhibited evident patterns, indicating that Model (2) effectively controlled the periodicity of the aggregate time-series nature at the city-industry level. Table 3 presents the estimated coefficients of Model (2). The coefficients of w decreased slightly compared with those in Table 2, although they still indicated a larger labor demand before 2020 CNY than they did before 2019 CNY. The coefficients of D increased slightly, denoting the increases in the labor demands after 2019 CNY. The coefficients of $cutoff$ changed substantially owing to the incorporation of its polynomial in Model (2). The slope of the coefficients of $D \cdot cutoff$ increased significantly after 2019 CNY compared with those reported in Table 2, while the coefficients of $w \cdot cutoff$ changed only slightly, indicating approximately parallel trends before the CNYs of both years. Our parameters of interest, the coefficients of $D \cdot w$ and $D \cdot w \cdot cutoff$, remained largely the same as the ones reported in Table 2, indicating that the lockdown policy rapidly reduced log(NC), log(NP), and log(NE) by 17%, 19.7%, and 26.2%, respectively, and averagely by 7.0%, 5.7%, and 6.5%, respectively, per week within the six weeks after 2020 CNY.

3.3 Results of the Event Study Analysis

We plot the estimated coefficients of Model (3) in Figure 4 and report the estimation results in Appendix Table A.3. In 2019, each measure of the labor demand decreased at the starting week of CNY, after which they increased rapidly until the fifth weeks after CNY. Conversely, the estimates of β_t generally displayed a horizontal trend before 2020 CNY except for the slight downward trend of (log)NP. This coincided with the pattern of the estimated coefficients of $w \cdot cutoff$ in Model (2). After 2020 CNY, the labor demand slumped compared with that after 2019 CNY. The estimates of β_t after CNY were substantially larger than the estimated coefficients of $D \cdot w$ and $D \cdot w \cdot cutoff$ in Model (2) because the reference of β_t s was the labor demand at the starting week of 2019 CNY, while those of $D \cdot w$ and $D \cdot w \cdot cutoff$ were the average level and linear trend before 2019 CNY. One week after 2020 CNY, the lockdown policy reduced log(NC), log(NP), and log(NE) by 7.1%, 25.5%, and 26.0%, respectively. However, the impacts began to reduce around four weeks after CNY when the largest decreases in log (NC), log(NP), and log(NE) were 38.5%, 55.0%, and 56.7%, respectively.

In summary, our main estimation results reveal that the lockdown policy decreased NC, NP, and NE (instead of their log values) rapidly by 18.5%, 21.9%, and 30.0%, respectively, as well as on an average of 5.7%–7.0% per week within the six weeks after CNY. The event study analysis indicates that the largest decrease in the labor demand was observed four weeks after the outbreak. Afterward, the impacts began to reduce, and the labor demand rebounded.

4. Heterogeneity Analyses

4.1 Industries

We conduct the heterogeneity analyses for the industries, cities, and firm sizes based on Model (2). Among the 52 subdivisions of industries, Figure 5 shows 22 subdivisions of the smallest and largest coefficients of $D \cdot w$ in Model (2). Regarding the three evaluated outcomes, the industries under a relatively small influence generally included computer software/hardware, financial service, outsourcing service, travel/vacation, education/training/college, healthcare, and other health-related industries. The industries under a relatively large influence included the electronic technology/semiconductor/integrated circuit, media/publishing/film/cultural communication, academic/research, advertising/exhibition/public relation, gifts/toys/arts/crafts/ collectibles/luxury good, production and manufacture, home furnishing/interior design/decoration, and trade/import/export industries.

These results revealed the heterogeneous effects of the lockdown policy among the industries. Several industries, such as the healthcare and other health-related industries, averted strong negative shocks. The outbreak of COVID-19 has undoubtedly caused a rapid increase in the demand for medical products and services. The other set of industries included those with low physical proximity, e.g., the computer software/hardware, outsourcing service, financial service, as well as education/training/college; this set could readily shift to online offices. Contrarily, the industries with high physical proximities, such as film, advertising/exhibition/ public relation, production/manufacture, and home furnishing/interior design/decoration, could barely shift to online offices within the short term. Additionally, the lockdown impacted some industries that produce nonessential products and services, e.g., gifts/toys/arts/crafts/ collectibles/luxury good, as well as transportation-related industries, such as the trade and airline industries.

These findings correspond with those in the literature on other countries. The decreases in job postings were larger for nonessential retails than those for essential retails and healthcare in the United States (Forsythe et al., 2021). Significant decreases in retail trade and small impacts in the health and education sectors were found in Sweden (Hensvik et al., 2021). Dissimilar to the studies that found large decreases for leisure, entertainment, and hospitality industries (Campello et al., 2020; Forsythe et al., 2021; Hensvik et al., 2021), our data reveal that the travel/vacation industry was less affected probably because the CNY holidays were usually reserved for family reunions. Rather than travelling as in other long holidays, people generally returned to their hometowns to visit their parents and relatives.

4.2 Cities

The intensities of control measures are different at the city level. First, Hubei province shut down the borders of all the cities within the province, including Wuhan. Concurrently, Hubei implemented a stringent home isolation policy in which residents were required to stay at home. Second, some cities such as Beijing and Shanghai adopted household outdoor restrictions, which confined or strongly encouraged people to stay at home or in their neighborhoods with limited exceptions. Third, some cities such as Tianjin and Hefei adopted closed management of their communities. In this system, people could not enter or leave such communities freely unless they presented their residence permits. Border shutdown was the strictest among these control measures; the residents of Hubei had to call off most of their economic activities. Under household outdoor restrictions or the closed management of communities, the daily activities of the residents were also restricted. Most local governments implemented these measures in early February (around the third week after 2020 CNY) (Fang et al., 2020b). Contrarily, some cities such as Dalian and Luoyang did not implement specific measures because of the less severity of the epidemic there.

We exclude Wuhan from our heterogeneous analyses of cities. Under the most stringent blockade measure, Wuhan demanded a large amount of labor to guarantee the daily life convenience of its residents. The regression results of Model (2) based on the observations of Wuhan reveal that the labor demand increased during the outbreak. We divide the remaining 54 cities into two categories. The cities that implemented household outdoor restrictions or the closed management of its communities are regarded as cities that implemented control measures. Otherwise, they are regarded as cities that did not. The categorization of the cities in our sample is reported in Appendix Table A.4. Figure 6 shows the estimated coefficients of $D \cdot w$ in Model (2). Generally, we barely observed significant differences between the estimates of the two categories. Both city categories suffered rapid decreases in log(NC). Regarding log(NP) and log(NE), the coefficients of $D \cdot w$ for the cities that implemented control measures exhibited slightly higher probabilities of being significantly negative than those for cities that did not.

These findings are similar to those of Forsythe et al. (2021), who conclude that the collapse in job postings impacted all the states in the United States regardless of the period of the stay-at-home policies. As already mentioned, all the provincial governments in China announced large-scaled control policies before January 29. In fact, more than 250 prefecture-level cities implemented closed management of communities before February 20, and the local governments of 127 cities imposed household outdoor restrictions (Qiu et al., 2020). Residents were also frequently exposed to social media publicities on the epidemic, as well as the advocacy on preventative measures. Because all levels of governments implemented relatively stringent and uniform measures and the people were highly concerned about public health during the outbreak, the labor demands slumped in both categories of the cities.

4.3 *Firm Size*

For the heterogeneity analysis of firm sizes, we employ another dataset from *Zhaopin.com*, namely the CIC data. CIC data are processed at the interaction levels of city, industry, and firm size. Dissimilar to the data in the above analysis, the CIC data contain 13 large industry categories. The firm size is classified by the number of employees: <20, 20–99, 100–499, 500–999, 1,000–9,999, and >10,000 employees. Thus, each cross-sectional unit represents the recruitment demands of firms in the same category of firm size as an industry in a certain city. We obtained a total of 4,290 cross-sectional units.

Figure 7 shows the estimated coefficients of $D \cdot w$ in Model (2) according to the ascending order of the firm sizes from left to right. Generally, the negative impact of the lockdown on the labor demand reduced as the firm sizes increased. The immediate impacts on log(NC) were between −15% and −10% for firms with fewer than 100 employees and approximately −5% for those with over 100 employees. The negative effects on log(NP) and log(NE) varied from lesser than −25% for microenterprises (with <20 employees) to over −15% for firms with over 500 employees. The larger a firm is, the stronger its ability to withstand the negative shocks to the labor market, and this is consistent with the findings in the United States, where the decrease in active job postings by small public firms substantially exceeded that of large public firms (Campello et al., 2020).

Figure 7 also shows that the negative impacts on NC and NE were non-monotonic in the firm size, and a relatively stable scale effect existed when the firm size was beyond a certain level. During the pandemic, the small-size firms were more likely to be shut down and lay off staff owing to the limited credit constraints (Campello et al., 2020; Bartik et al., 2020a). Among businesses in the United States with fewer than 500 employees, more small firms with fewer than 20 employees were closed and suffered the largest employment reduction compared with larger firms (Bartik et al., 2020a). Businesses with limited liquidities required subsidies or loans that could affect their business decisions, such as laying off employees and staying in business (Bartik et al., 2020a). Furthermore, layoffs and entire shut down mostly accounted for the reduction of the total working hours of small firms with fewer than 100 employees (Bartik et al., 2020b). Contrarily, large-size firms might opt to reduce production or temporarily close to avoid losses. Considering the high cost of dismissal, such firms might reduce the working hours of employees during the pandemic or recall laid-off workers to work after the downturn.

5. Discussion

First, it is challenging to distinguish between the effects of the lockdown policy and those of the COVID-19 outbreak in our context. The stringent measures, including city lockdowns, strict quarantines, and other local public health measures, adopted by the Chinese central and provincial governments significantly decreased the transmission rate of the pandemic (Maier and Brockmann, 2020). The spread of the virus was rapidly contained in mid- February 2020 (Qiu et al., 2020). The lockdown in Wuhan significantly reduced the total infection cases outside Wuhan (Fang et al., 2020b). As shown in Figure 8, the number of newly confirmed cases approached zero in cities other than Wuhan with four weeks after 2020 CNY. Our event study analysis reveals that the dynamic effects of the lockdown began to reduce at that time. The decrease in the number of newly confirmed cases was mainly due to the restricted mobility of the population under the lockdown policy, particularly the outflows from the outbreak hotspots (Qin et al., 2021; Fang et al., 2020b)

Considering that the severity of the pandemic varied across cities and over time, we incorporate the number of newly confirmed cases per week in each city into Model (2) to disentangle the effect of the pandemic. Table 4 demonstrates that the coefficients of this variable were close to zero for the three outcomes and barely exerted economic impacts in our model even though they were statistically significant. Compared with the results in Table 3, the estimated coefficients of $D \cdot w$ and $D \cdot w \cdot cutoff$ remained largely the same in Table 4 probably because of the insufficiency of the city-level variations of the pandemic for our units at the city-industry level (55 cities × 52 subdivisions of industries). More significantly, the spread of the pandemic was effectively contained in other cities except Wuhan owing to the control measures of the governments at all levels.

Second, the event study demonstrates that the negative impacts of the lockdown began to reduce around four weeks after 2020 CNY. One reason is that the number of newly confirmed cases approached zero four weeks after the outbreak, and this conformed to the law of COVID-19 prevention and control. The promotion of the resumption of work and production proposed by the central government since the fourth week after CNY is another reason for the reduced impact of the lockdown policy. As discussed in Section 2.2, the central government issued specific guidelines and measures to help enterprises resume production, thereby stimulating the recovery of the labor demand in our data. On March 13 (Saturday of the sixth week after CNY), the State

Council announced the average start-up rate of enterprises above the designated size (with annual main business income of over 20 million yuan) exceeded 95% in mainland China except in Hubei province; the start-up rates of small and medium-size enterprises reached approximately 60%; and the average return rates of enterprise personnel were approximately 80%.

Third, although the lockdown policy considerably impacted the labor demand, we believe that such stringent measures are necessary in China, at least at the early stage of the outbreak, for the following reasons: first, such measures exert substantially positive effects on protecting people's health and lives (Fang et al., 2020b; Qiu et al., 2020; Tian et al., 2020). Second, although these measures inevitably incur economic losses in the short term, they promote economic revitalization on the long run. Compared with the timeline of the findings in other countries (e.g., Campello et al., 2020; Hensvik et al., 2021; Marinescu et al., 2020; Shen and Taska, 2020), the sign of revitalization in China's labor market appeared earlier (four weeks after the outbreak). According to China's Job Market Prospect Reports released by CIER and *Zhaopin.com*, the monthly NE to be recruited rebounded in February and increased continuously until July; the CIER index increased from the bottom, 1.02, in March to 2.01 in September. NBS reported that urban employment increased by 11.86 million in 2020, thus confirming that the early stringent measures effectively curbed the spread of the virus and subsequently contributed to the revitalization of the labor market. Additionally, with the spread of COVID-19 globally, many countries suffered the impacts of the pandemic after China had controlled it domestically. These countries might be confronted with medical and healthcare product shortages, and this might force them to shift the manufacture of related products to China, thus stimulating the demand revitalization in the Chinese labor market accordingly.

Fourth, considering that COVID-19 continues to spread among global populations, active NPIs can be beneficial in addressing the accompanying challenges. Although strict lockdown is no longer necessary except for the new waves of outbreaks, we recommend the implementation of conditional controls since the threat of the virus to health has declined owing to improved detection efficiency, vaccination, and other medical tools. The Chinese central and provincial governments recently implement a precise prevention and control policy to minimize the incurred economic loss and dynamically clear the confirmed cases. Concurrently, regular measures, such as wearing of masks and the maintenance of social distancing, also help reduce the risk of infection, as confirmed by previous studies (Mitze et al., 2020). These regular measures are particularly essential to China that accounts for a large population and high population densities in urban areas to prevent the overrun on healthcare and medical services.

6. Conclusion

Employing the data obtained from the largest recruitment platform in China, *Zhaopin.com*, we examine the short-term impacts of the lockdown policy on China's labor market demand. We find that NC posting job ads immediately, NP in weekly posting, and NE to be recruited decreased by 18.5%, 21.9%, and 30.0%, respectively. Moreover, their average decrease was 5.7%–7.0% per week within the six weeks after 2020 CNY. Further, we find that the impacts began to reduce, while the labor demand rebounded after four weeks, following CNY. These findings underscore the relevance of employing timely online recruitment information to monitor the economy in the events of unexpected pandemics, such as COVID-19. As far as we know, this study is the first to comprehensively quantify the dynamic impacts of the lockdown policy on the labor demand in China during the outbreak of COVID-19.

During this special period, the Chinese governments at all levels implemented relatively stringent NPIs, including the disclosure of pandemic-related information and the advocacy of preventative measures, to contain the spread of the virus. The slump in the labor demand reflected the public health concern and a strong sensitivity of the labor market to the existing public health crisis. Following the containment of the spread of the virus and the promotion of resumption of work and production, the hiring demand rebounded around four weeks after the outbreak. This finding indicates that effective management of the public health crisis in combination with economic policies is critical to revitalizing the labor market and economy after an unexpected event.

Our heterogeneity analyses would highly benefit policy makers. First, the lockdown policy exerted heterogeneous impacts on industries. Generally, the lockdown largely affected the industries with high physical proximity and those producing non-essential products and services. This enlightens policy makers on the need to avail targeted policies, such as tax reductions, to these industries. Governments could also encourage investments in electronic-type infrastructures for industries with low physical proximity to enable them shift to online offices. Additionally, this finding indicated that the pandemic could spur technological innovation and shift production methods to accelerate the reduction of physical proximity in certain industries. Second, the labor demand in small-size firms was generally more affected than that of large-size firms, indicating that closures and massive layoffs occurred in small businesses than in larger ones. Targeted policies, such as the provision of loans or subsidies, can help small businesses cushion the impacts of the pandemic. Third, no significant difference was observed between the impacts of the lockdown policy on the labor demands of cities that implemented household outdoor restrictions or closure management of communities and those that did not probably because of the relatively stringent measures implemented by the governments, as well as the people's high concern about public health.

References

Bartik, A., Bertrand, M., Cullen, Z., Glaeser, E., Luca, M., Stanton, C. (2020a). How are Small Businesses Adjusting to COVID-19? Early Evidence from a Survey. *NBER Working Paper* No. 26989.

Bartik, A., Bertrand, M., Lin, F., Rothstein, J. and Unrath, M. (2020b). Measuring the labor Market at the Onset of the COVID-19 Crisis. *NBER Working Paper* No. 27613

Bhaskaran, K., Gasparrini, A., Hajat, S., Smeeth, L. and Armstrong, B. (2013) Time series regression studies in environmental epidemiology. *International Journal of Epidemiology* 2013; 42: 1187-1195.

Campello, M., Kankanhalli, G., &Muthukrishnan, P. (2020).Corporate hiring under COVID-19: Labor market concentration, downskilling, and income inequality. *NBER Working Paper* No. w27208.

Chen, H., Qian, W, and Wen, Q. 2021.The Impact of the COVID-19 Pandemic on Consumption: Learning from High-Frequency Transaction Data. *AEA Papers and Proceedings*, 111: 307-11.

Fang, H., Ge, C., Huang, H., and Li, H. (2020a).Pandemics, Global Supply Chains, and Local Labor Demand: Evidence from 100 Million Posted Jobs in China. *NBER Working Paper* No. 28072.

Fang, H., Wang, L., and Yang, Y. (2020b). Human mobility restrictions and the spread of the novel coronavirus (2019-ncov) in China. *Journal of Public Economics*, 191, 104272.

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

Geng Lin and Mao Yu-fei, Construction of China Employment Market Prosperity Index (CIER) and Employment Situation Analysis Based on CIER—Research Based on Large Data on Network Recruitment. *Journal of Renmin University of China* (in Chinese), 2017(06):24-35

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

Hsiang, S., Allen, D., Annan-Phan, S., Bell, K., Bolliger, I., Chong, T., and Wu, T. (2020). The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature*, 584(7820), 262-267.

Linden, A. (2015). Conducting interrupted time‐series analysis for single and multiple‐group comparisons. *Stata Journal* 15: 480‐500.

Linden, A. (2021). XTITSA: Stata module for performing interrupted time-series analysis for panel data," Statistical Software Components S458903, Boston College Department of Economics, revised 23 Mar 2021.

Maier, B. F., & Brockmann, D. (2020). Effective containment explains subexponential growth in recent confirmed COVID-19 cases in China. *Science*, 368(6492), 742-746.

Mao, Y. and Zeng, X. (2022). The Impact of COVID-19 on College Graduates Employment: Empirical Evidence from Recruitment Website Data (in Chinese), *Academic Research*, 1, 104-110.

Marinescu, E., Skandalis, D., and Zhao, D. (2020), Job Search, Job Posting and Unemployment Insurance During the COVID-19 Crisis. http://dx.doi.org/10.2139/ssrn.3664265

Mitze T, Kosfeld R, Rode J, et al. Face masks considerably reduce COVID-19 cases in Germany. *Proceedings of the National Academy of Sciences*, 2020, 117(51): 32293-32301.

Qiu, Y, Chen, X, and Shi, Wei (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, 33, 1127–1172.

Rothwell, J and Van Drie, H. (2020) The effect of COVID-19 and disease suppression policies on labor markets: A preliminary analysis of the data. *Brookings Report*, April 27, 2020.

Shen, K., &Taska, B. (2020). Measuring the impacts of COVID-19 on job postings in Australia using a reweighting-estimation-transformation approach. *Australian Journal of Labour Economics*, 23(2), 153-172.

Tian H, Liu Y, Li Y, Wu C.-H, Chen B, Kraemer MUG, Li B, Cai J, Xu B, Yang Q, Wang B, Yang P, Cui Y, Song Y, Zheng P, Wang Q, Bjornstad ON, Yang R, Grenfell BT, Pybus OG, Dye C (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China, *Science*. 368, (6491), 638-642.

Zeng, X. (2015). Report on Chinese Employment Strategy Studies 2015 (in Chinese). Renmin University of China Press, Beijing, page 1.

Appendix

Table A.1. Regions of the 55 Cities in Our Data

East Region	Shanghai, Xiamen, Ningbo, Fuzhou, Dongguan, Changzhou, Quanzhou, Qinhuangdao,Zhongshan, Guangzhou, Suzhou, Linyi, Xuzhou, Jinan, Foshan, Huizhou, Jiaxing, Shenzhen, Beijing, Yangzhou, Wenzhou, Nanjing, Wuxi, Weifang, Zhenjiang, Tianjin, Yantai, Hangzhou, Zhuhai, Nantong, Weihai, Shijiazhuang, Qingdao
Middle Region	Hefei, Luoyang, Huai'an, Zhengzhou, Nanchang, Taiyuan, Changsha, Wuhan
West Region	Huhehaote, Xianyang, Xi'an, Guiyang, Baotou, Chengdu, Chongqing, Nanning, Kunming,
Northeastern Region	Shenyang, Harbin, Daqing, Dalian, Changchun,

Table A.2. Categorization of the Industries by *Zhaopin.com*

IT, Communication, Electronics, Internet	Internet, E-Commerce
	Computer Software
	IT Services (Systems, Data, Maintenance)
	Electronic Technology, Semiconductor, Integrated Circuit
	Computer Hardware
	Communication, Telecommunication, Network Equipment
	Communication, Telecommunication Operations, Value-AddedServices
	Online Games
Finance	Fund, Securities, Futures, Investment
	Insurance
	Banking
	Trust, Guarantee, Auction, Pawn
Real Estate, Construction	Real Estate, Architecture, Building Materials, Engineering
	Home Furnishing, Interior Design, Decoration
	Estate Management, Commercial Center
Business Service	Professional Service, Consulting (Accounting, Legal, Human Resources)
	Advertising, Exhibition, Public Relation
	Intermediary Service
	Inspection, Testing, Certification
	Outsourcing Service
Trade, Wholesale, Retail, Leasing	Fast-Moving Consumer Goods (Food, Beverage, Tobacco, Alcohol, Chemicals for Daily Use)
	Consumer Durables (Apparel, Textiles, Leather, Furniture, Home Appliances)
	Trade, Import and Export
	Retail, Wholesale
	Leasing Service
Culture, Sports, Education, Art and Craft	Education, Training, College
	Gift, Toy, Art, Craft, Collectible, Luxury Good
Production, Processing, Manufacturing	Car, Motorcycle
	Large Equipment, Electromechanical Equipment, Heavy Industry
	Processing and Manufacturing (Raw Material Processing, Mold)
	Instrumentation and Industrial Automation
	Printing, Packaging, Papermaking
	Office Supplies & Equipment
	Pharmaceutical, Biological Engineering
	Medical Equipment and Devices
	Aviation, Aerospace Research and Manufacturing
Transportation, Logistics, Warehousing	Transportation
	Logistics, Warehousing
Service Industry	Medical, Nursing, Beauty, Healthcare, Health Service
	Hotel, Restaurant

	Travel, Vacation
Culture, Media, Entertainment, Sports	Media, Publishing, Film, Cultural Communication
	Entertainment, Sports, Leisure
Energy, Mineral, Environmental protection	Energy, Mineral, Mining, Smelting
	Petroleum, Petrochemical, Chemical
	Electricity, Power, Water Conservancy
	Environmental Protection
Government, Nonprofit Organization	Government, Public Utility, Non-Profit Organization
	Academia, Research
Agriculture, Forestry, Pastoral, Fishery, Other	Agriculture, Forestry, Pastoral, Fishery
	Cross-industry Operation
	Other

Table A.3. Results of the Event Study Analysis

Variables Economic interpretations	(1) Log(NC)	(2) Log(NP)	(3) Log(NE)
$\boldsymbol{T_{-5}}$	0.124***	0.123***	0.149***
Difference in level between t= −5 and t=0 in 2019	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{-4}}$	0.111***	0.116***	0.132***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{-3}}$	0.092***	0.103***	0.113***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{-2}}$	0.076***	0.093***	0.086***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{-1}}$	0.049***	0.066***	0.063***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{1}}$	0.141***	0.192***	0.199***
Difference in level between t=1 and t=0 in 2019	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{2}}$	0.223***	0.285***	0.305***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{3}}$	0.267***	0.328***	0.361***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{4}}$	0.299***	0.356***	0.385***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{5}}$	0.337***	0.397***	0.426***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{T_{6}}$	0.332***	0.376***	0.420***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{-5}}$	0.180***	0.077***	0.123***
Difference in level at t= −5 of both years	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{-4}}$	0.183***	0.063***	0.112***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{-3}}$	0.176***	0.045***	0.112***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{-2}}$	0.177***	0.038***	0.104***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{-1}}$	0.176***	0.041***	0.093***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{0}}$	0.147***	0.023***	0.031***
Difference in level at t=0 of both years	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{1}}$	-0.071***	-0.255***	-0.260***
Difference in level at t=1 of both years	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{2}}$	-0.212***	-0.419***	-0.432***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_{3}}$	-0.322***	-0.518***	-0.548***
	(0.004)	(0.006)	(0.012)

$\boldsymbol{w \cdot T_4}$	-0.385***	-0.550***	-0.567***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_5}$	-0.367***	-0.509***	-0.532***
	(0.004)	(0.006)	(0.012)
$\boldsymbol{w \cdot T_6}$	-0.266***	-0.384***	-0.411***
	(0.004)	(0.006)	(0.012)
constant	4.375***	5.781***	7.429***
Level at the week of CNY (t=0) in 2019	(0.003)	(0.005)	(0.008)
City-Industry FE	Y	Y	Y
R^2	0.981	0.948	0.988
N	67186	67186	67186

Note: The numbers in the parentheses are standard errors clustered at the city level. *, **, and *** indicate the statistical significances at the 10%, 5%, and 1% levels, respectively.

Table A.4. Control Measures of the 55 Cities

		East Region	Middle Region	West Region	Northeastern Region
Control Measures	Home Isolation Policy	--	Wuhan	--	--
	Household Outdoor Restrictions	Beijing, Changzhou, Dongguan, Foshan, Guangzhou, Huai'an, Huizhou, Jinan, Linyi, Nanjing, Nantong, Qingdao, Shanghai, Shenzhen, Shijiazhuang, Suzhou, Wuxi, Yangzhou, Zhenjiang, Zhuhai	Nanchang, Zhengzhou	Chengdu, Guiyang, Kunming, Nanning, Chongqing	--
	Closed Management of Communities	Fuzhou, Hangzhou, Ningbo, Tianjin, Wenzhou, Xuzhou	Hefei,	Xi'an, Xianyang,	Harbin, Changchun
Without Control Measures		Jiaxing, Qinhuangdao, Quanzhou, Xiamen, Weihai, Weifang, Yantai, Zhongshan	Luoyang, Taiyuan, Changsha	Baotou, Huhehaote	Dalian, Daqing, Shenyang

Tables

Table 1 Summary Statistics of the Labor Demand

	2019			2020		
	(1)	(2)	(3)	(4)	(5)	(6)
	Before CNY	After CNY	Diff.	Before CNY	After CNY	Diff.
log(NC)	4.465	4.602	0.136***	4.645	4.396	-0.249***
	(1.45)	(1.461)		(1.481)	(1.475)	
log(NP)	5.880	6.054	0.174***	5.934	5.687	-0.247***
	(1.706)	(1.706)		(1.692)	(1.694)	
log(NE)	7.536	7.726	0.190***	7.647	7.343	-0.304***
	(1.874)	(1.861)		(1.894)	(1.931)	
Observations	14000	19610	--	13995	19581	--

Note: The difference is calculated by subtracting the value Before CNY from the value After CNY. The numbers in the parentheses are standard deviations. *, **, and *** indicate the statistical significances at the 10%, 5%, and 1% levels, respectively.

Table 2 Results of the Panel-Interrupted Time-Series Analysis

Variables	(1)	(2)	(3)
Economic interpretations (coefficients)	Log(NC)	Log(NP)	Log(NE)
$\boldsymbol{D \cdot w}$	-0.171***	-0.198***	-0.262***
Immediate impact of the lockdown policy (β)	(0.003)	(0.004)	(0.009)
$\boldsymbol{D \cdot w \cdot cutoff}$	-0.070***	-0.057***	-0.065***
Impact of the lockdown policy on the time trend (γ)	(0.001)	(0.002)	(0.004)
$\boldsymbol{w}$	0.181***	0.070	0.118**
Difference in level before CNY of both years (α_1)	(0.039)	(0.045)	(0.050)
$\boldsymbol{D}$	0.037***	0.046***	0.066***
Difference in level due to CNY in 2019 (α_2)	(0.002)	(0.002)	(0.005)
$\boldsymbol{cutoff}$	-0.019***	-0.014***	-0.022***
Time trend before 2019 CNY (α_3)	(0.001)	(0.001)	(0.002)
$\boldsymbol{w \cdot cutoff}$	-0.001*	-0.010***	-0.007**
Difference in slope before CNY of both years (α_4)	(0.001)	(0.001)	(0.003)
$\boldsymbol{D \cdot cutoff}$	0.071***	0.071***	0.086***
Difference in slope due to CNY in 2019 (α_5)	(0.001)	(0.001)	(0.003)
Trend after 2019 CNY	0.052***	0.057***	0.064***
($\alpha_3 + \alpha_5$)	(0.001)	(0.001)	(0.002)
Trend after 2020 CNY	-0.019***	-0.009***	-0.008***
($\alpha_3 + \alpha_4 + \alpha_5 + \gamma$)	(0.001)	(0.001)	(0.002)
Difference in slope after CNY of both years	-0.071***	-0.066***	-0.071***
($\alpha_4 + \gamma$)	(0.001)	(0.001)	(0.002)
Constants	4.513***	5.922***	7.595***
Average level before 2019 CNY (α_0)	(0.027)	(0.032)	(0.035)
N	66984	66984	66984

Note: The numbers in the parentheses are the robust standard errors. *, **, and *** indicate the statistical significances at the 10%, 5%, and 1% levels, respectively.

Table 3 Main Estimation Results of Model (2)

Variables	(1)	(2)	(3)
Economic interpretations (coefficients)	Log(NC)	Log(NP)	Log(NE)
$\boldsymbol{D \cdot w}$	-0.170***	-0.197***	-0.262***
Immediate impact of the lockdown policy (β)	(0.005)	(0.006)	(0.009)
$\boldsymbol{D \cdot w \cdot cutoff}$	-0.070***	-0.057***	-0.065***
Impact of the lockdown policy on the time trend (γ)	(0.003)	(0.003)	(0.005)
$\boldsymbol{w}$	0.174***	0.024**	0.089***
Difference in level before CNY of both years (α_1)	(0.006)	(0.011)	(0.018)
$\boldsymbol{D}$	0.057***	0.084***	0.095***
Difference in level due to CNY in 2019 (α_2)	(0.004)	(0.005)	(0.008)
$\boldsymbol{cutoff}$	-3.925*	-3.128	22.385**
(α_3)	(2.261)	(3.085)	(9.745)
$\boldsymbol{w \cdot cutoff}$	-0.001*	-0.010***	-0.007**
(α_4)	(0.001)	(0.001)	(0.003)
$\boldsymbol{D \cdot cutoff}$	0.115***	0.187***	0.178***
(α_5)	(0.006)	(0.009)	(0.015)
$\boldsymbol{f(cutoff)}$	Y	Y	Y
city-industry FE	Y	Y	Y
harmonics	Y	Y	Y
R^2	0.988	0.980	0.947
N	67186	67186	67186

Note: The numbers in the parentheses are the standard errors clustered at the city level. *, **, and *** indicate the statistical significances at the 10%, 5%, and 1% levels, respectively.

Table 4 Incorporation of the Number of Newly Confirmed Cases into Model (2)

Variables	(1)	(2)	(3)
Economic interpretations (coefficients)	Log(NC)	Log(NP)	Log(NE)
$\boldsymbol{D \cdot w}$	-0.171***	-0.198***	-0.263***
Immediate impact of the lockdown policy (β)	(0.005)	(0.005)	(0.009)
$\boldsymbol{D \cdot w \cdot cutoff}$	-0.069***	-0.056***	-0.064***
Impact of the lockdown policy on the time trend (γ)	(0.003)	(0.003)	(0.004)
$\boldsymbol{w}$	0.174***	0.024**	0.089***
Difference in level before CNY of both years (α_1)	(0.006)	(0.011)	(0.018)
$\boldsymbol{D}$	0.058***	0.085***	0.095***
Difference in level due to CNY in 2019 (α_2)	(0.004)	(0.005)	(0.008)
$\boldsymbol{cutoff}$	-3.761	-2.881	22.601**
(α_3)	(2.262)	(3.092)	(9.742)
$\boldsymbol{w \cdot cutoff}$	-0.001*	-0.010***	-0.007**
(α_4)	(0.001)	(0.001)	(0.003)
$\boldsymbol{D \cdot cutoff}$	0.115***	0.187***	0.177***
(α_5)	(0.006)	(0.009)	(0.015)
newly confirmed cases	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
$\boldsymbol{f(cutoff)}$	Y	Y	Y
city-industry FE	Y	Y	Y
harmonics	Y	Y	Y
R^2	0.988	0.947	0.980
N	67186	67186	67186

Note: The numbers in the parentheses are the standard errors clustered at the city level. *, **, and *** indicate the statistical significances at the 10%, 5%, and 1% levels, respectively.

Figures

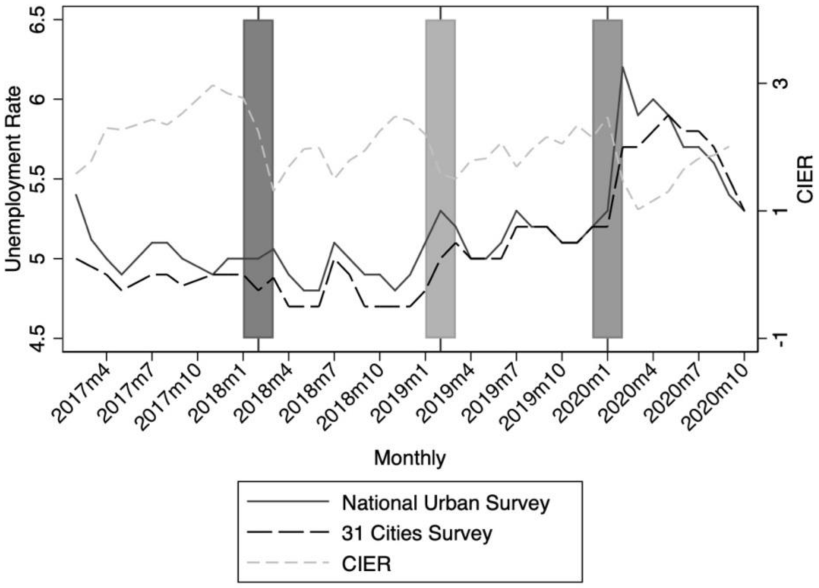


Figure 1: Historical Monthly Change in the Labor Market: Unemployment Rates and CIER

Notes: the unemployment rate data were obtained from the National Bureau of Statistics, and the CIER data were obtained from the China Institute for Employment Research at the Renmin University of China and *Zhaopin.com*.

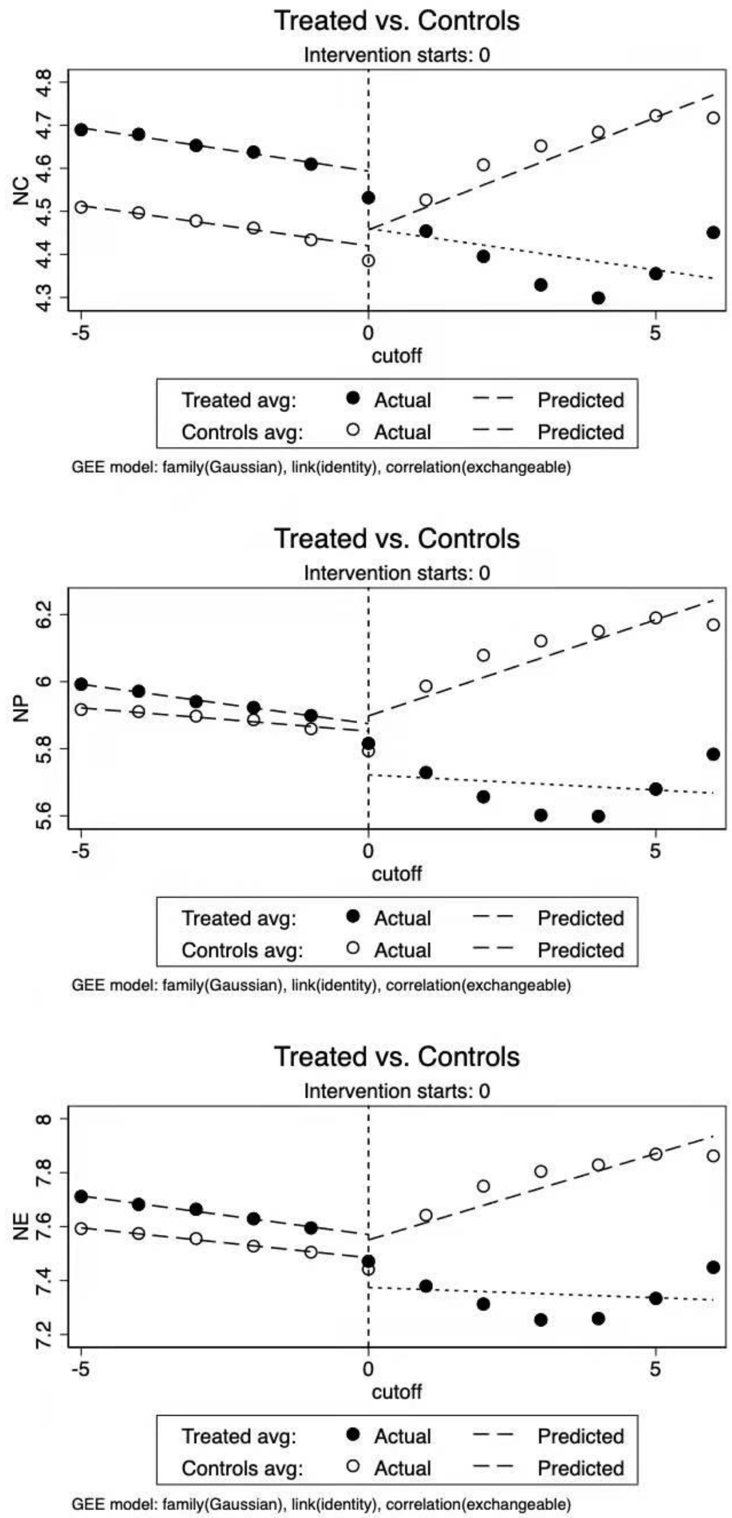


Figure 2: Average Weekly Labor Demand and the Prediction of the Panel-Interrupted Time-Series Model

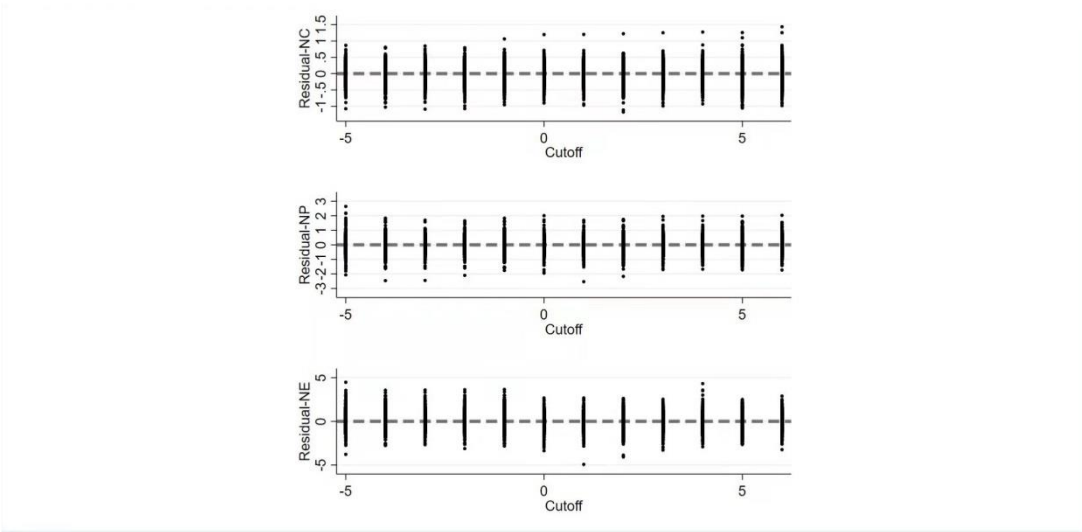


Figure 3 Residuals in the Estimation of Model (2)

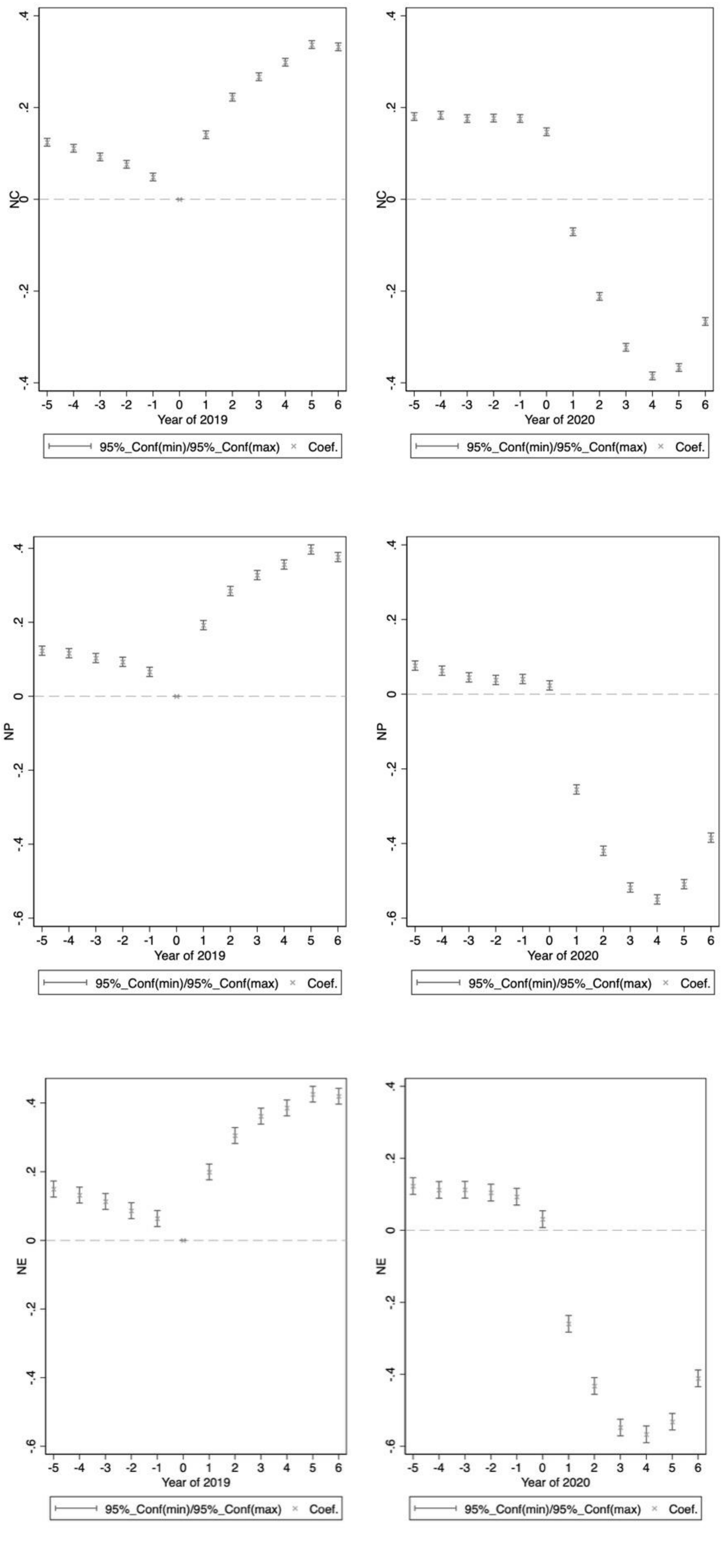


Figure 4 Estimated Coefficients of the Event Study Model

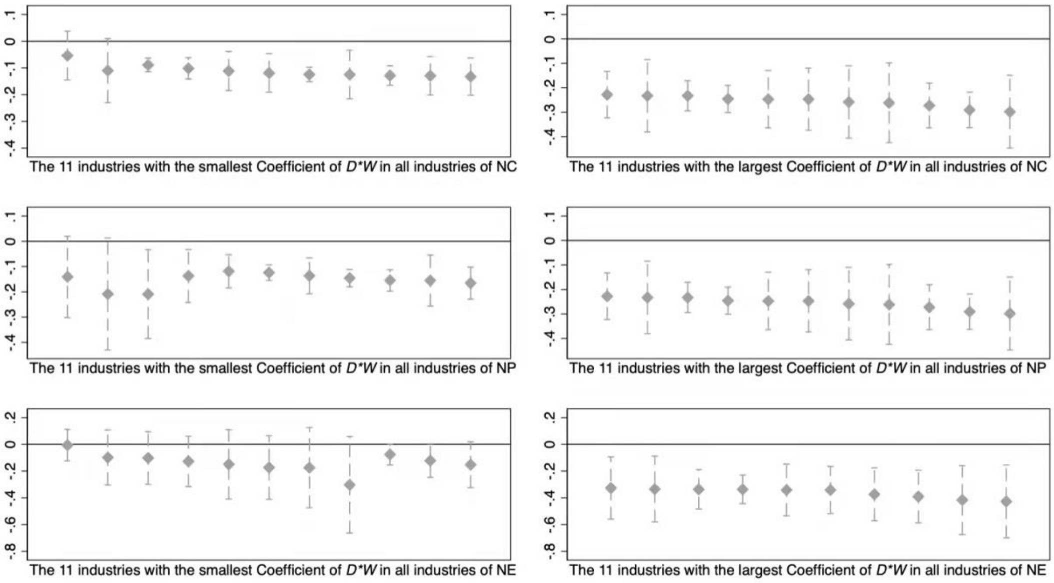


Figure 5 Estimated Coefficients of $D \cdot w$ in Model (2) for Industries

Notes: 11 industries with the *smallest* coefficients for log(NC) in the following ascending order: “Cross-Industry Operation,” “Government/Public Utilities/Non-Profit Organizations,” “Pharmaceutical/Biological Engineering,” “Fund/Securities/Futures/Investment,” “Travel/Vacation,” “Insurance,” “Fast-Moving Consumer Good,” “Outsourcing Services,” “Computer Software,” “Computer Hardware,” “Banking.” For log(NP) in order: “Cross-industry Operation,” “Online Game,” “Outsourcing Services,” “Travel/Vacation,” “Fund/Securities/Futures/Investment,” “Pharmaceutical/Biological Engineering,” “Computer Software,” “Education/Training/College,” Real Estate/Construction/Building Materials/Engineering,” “Insurance,” “Medical/Nursing/Beauty/Healthcare/Health Services.” For log(NE) in order: “Pharmaceutical/Biological Engineering,” “Entertainment/Sports/Leisure,” “Travel/Vacation,” “Insurance,” Trust/Guarantee/Auction/Pawn,” “Cross-industry Operation,” “Government/Public Utilities/Non-Profit Organizations,” “Outsourcing Services,” “Education/Training/College,” “Medical Equipment and Devices,” “Logistics/Warehousing.”

11 industries with the *largest* coefficients for log(NC) in ascending order: “Processing/Manufacturing,” “Energy/Mineral/Extraction/Smelting,” “Trade/Import/Export,” “Transportation,” “Academic/Research,” “Printing/Packaging,” “Electronic Technology/Semiconductor/Integrated Circuit,” “Online Games,” “Home/Interior Design/Decoration,” “Advertising/Exhibition/Public Relations,” “Aviation/Aerospace Research/Manufacturing.” For log(NP) in order: “Media/Publishing/Film/Cultural Communication,” “Intermediary Services,” “Processing and Manufacturing,” “Trade/Import/Export,” “Printing/Packaging/Papermaking,’ “Leasing Services,” “Office Supplies/Equipment,” “Academic/Research,” “Advertising/Exhibition/Public Relations,” “Home/Interior Design/Decorative Decoration,” “Gifts/Toys/Arts Crafts/Collectibles/Luxury Good.” For log(NE) in order: “Communication/Telecommunications Operations/ Value-Added Services,” “Gifts/Toys/Arts Crafts/Collectibles/Luxury Good,” “Estate Management/ Commercial Center,” “Trade/Import/Export,” “Transportation,” “Electricity/Power/Water Conservancy,” “Electronic Technology/Semiconductor/Integrated Circuit,” “Media/Publishing/Film/Cultural Communication,” “Office Supplies/Equipment,” “Aviation/Aerospace Research/Manufacturing,” “Online Games.”

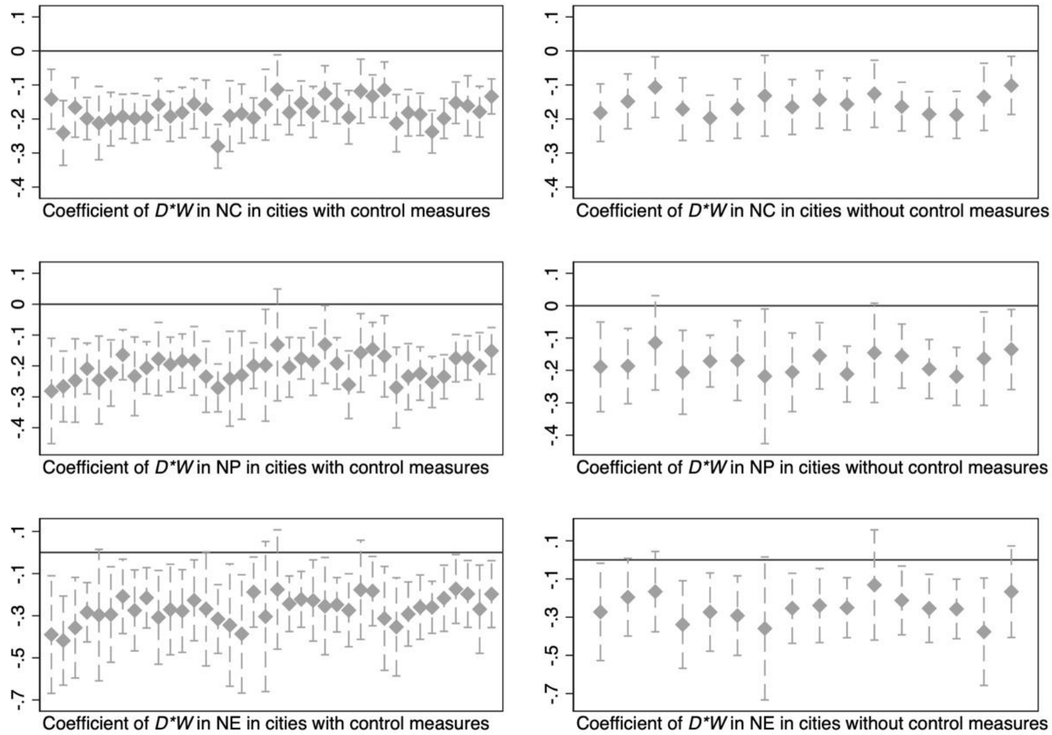


Figure 6 Estimated Coefficients of $D \cdot w$ in Model (2) for Cities

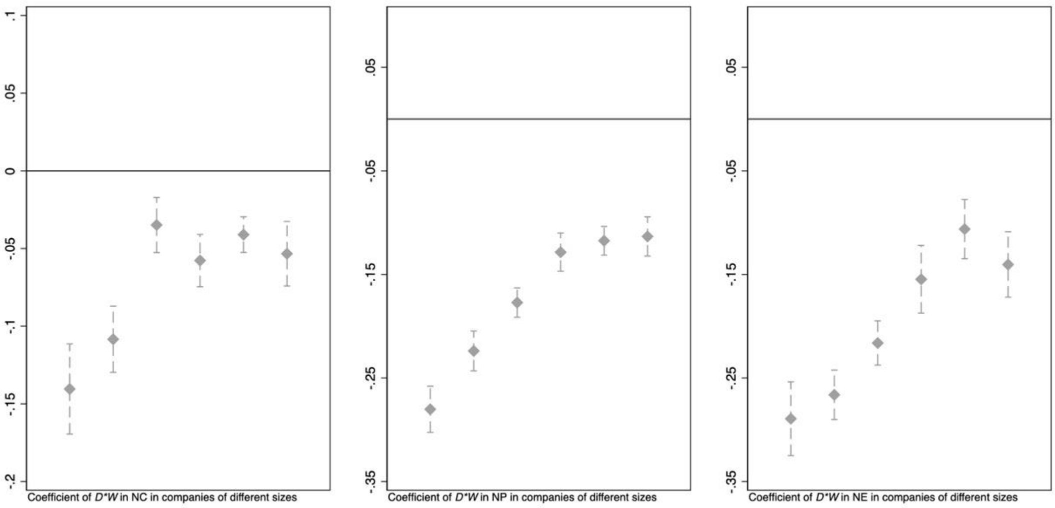
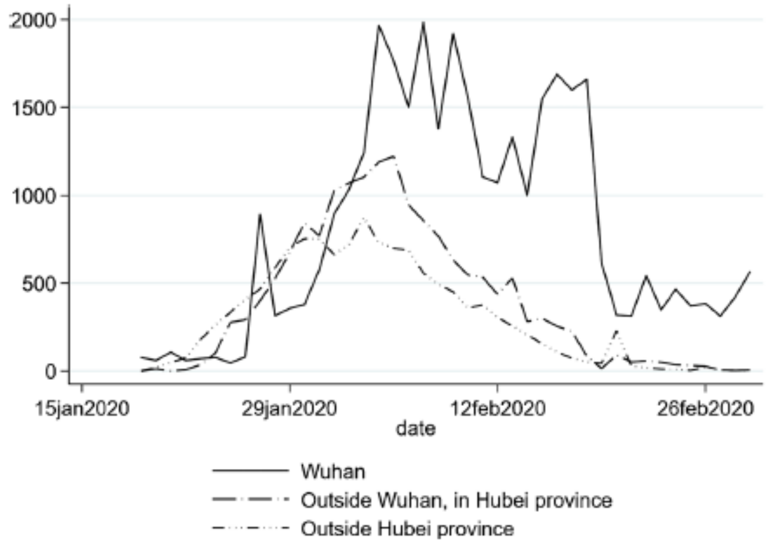


Figure 7 Estimated Coefficients of $D \cdot w$ in Model (2) for Firms of Different Size



Source: Qiu et al. (2020)

Figure 8 Number of Daily Newly Confirmed Cases in Mainland China and Number of the Revised Cases in Hubei Province