China Economic Review 75 (2022) 101832

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

The impact of COVID-19 on employment and income of vocational graduates in China: Evidence from surveys in January and July 2020

Xiao Liang [a,b], Scott Rozelle [c], Hongmei Yi [a,b,*]

[a] *School of Advanced Agricultural Sciences, Peking University, China*
[b] *China Center for Agricultural Policy, Peking University, China*
[c] *Center on China's Economy and Institutions, Stanford University, USA*

ARTICLE INFO

JEL classification:
J21
J22
J24
J31
J63

Keywords:
COVID-19 pandemic
Labor market outcome
Vocational graduates
China

ABSTRACT

The COVID-19 pandemic shocked the economy of China in early 2020. Strict lockdown measures were implemented nationwide to prevent the further spread of the virus. During the lockdown period, many economic activities were affected, which had repercussions for the nation's overall employment. Vocational graduates were among the most affected by the crisis. To estimate the causal effects of COVID-19 on the full-time employment of vocational high school graduates as well as their monthly income and hours worked by week, we exploit variations in the intensity of the pandemic in time and across space using survey data from vocational schools from six provinces in China. The results of the difference-in-differences (DID) estimates indicate that being located in counties with high pandemic intensity significantly reduced both the employment in full-time jobs of vocational graduates as well as their monthly income. Our study's analysis demonstrates that the effects of COVID-19 on the labor market can be attributed to the large-scale contraction of labor demand of the enterprises that were hiring vocational graduates. To cope with this situation, vocational graduates took various measures, including reducing consumption, drawing on their savings, searching for new jobs, taking on part-time jobs, borrowing money, and attending new training programs. In addition, the empirical analysis finds that there were heterogeneous effects with respect to gender, family social capital, the industry in which the vocational graduate was participating, and whether the individual was in a management position.

1. Introduction

COVID-19 shocked global labor markets in 2020, and historic contractions in the labor markets of many countries were reported (Adams-Prassl, Boneva, Golin, & Rauh, 2020; Aum, Lee, & Tim), & Shin, Y., 2021; Coibion, Gorodnichenko, & Weber, 2020; Forsythe, Kahn, Lange, & Wiczer, 2020; Wang et al., 2022). Studies indicate that the increase in infections led to drops in employment and income (Aum et al., 2021; Qian & Fan, 2020). On the labor demand side, enterprises in areas with more infections often faced tighter restrictions in business activities from local government, which, in turn, resulted in a decrease in demand. On the supply side, people in such areas also curtailed their labor supply, often voluntarily, out of fear of infection or due to the need to care for their children.

China was no exception to these conditions. Its labor market was severely disrupted, although, in the case of China, the government

* Corresponding author at: 408B, Wangkezhen Building, Peking University, China.
E-mail address: hmyi.ccap@pku.edu.cn (H. Yi).

https://doi.org/10.1016/j.chieco.2022.101832
Received 23 January 2022; Received in revised form 2 July 2022; Accepted 7 July 2022
Available online 12 July 2022

is known for its rapid response and the implementation of strict measures across the nation after the outbreak. The measures, including strict quarantining, social distancing, and community containment, effectively contained the spread of the pandemic—albeit, during the initial months of the lockdown, economic activity in many sectors was severely affected. For example, 80% of small- and medium-sized enterprises were temporarily closed; such firms are known to generate 80% of employment in China (Dai et al., 2021). Due to this and other actions, China reported a decrease of 6.8% in GDP in the first quarter of 2020 (National Bureau of Statistics of China, 2020a) as well as serious repercussions in employment (Che, Du, & Chan, 2020; Wang et al., 2021; Wang et al., 2021; Wang et al., 2022).

Of all groups who suffered from the pandemic, unemployment among younger workers has been one of the most severe. Before COVID-19, unemployment was higher among the youth compared to other age groups. According to International Labour Organization, the unemployment rate of workers aged 15 to 24 years fluctuated between 16% and 20% during 2010–2019, about three times that of workers aged over 25 years (International Labour Organization, 2021). COVID-19 has increased the age gap in unemployment. Adams-Prassl et al. (2020) found that the young workers in Germany were more likely to lose their job during the pandemic. Montenovo et al. (2020) showed that young workers in the U.S. experienced a decrease of over 20 percentage points in employment after the outbreak, the highest decrease among all age groups. Although there is no rigorous causal analysis, the Urban Survey of Unemployment indicates that employment among the youth might decline more due to the pandemic compared to other groups in China (National Bureau of Statistics of China, 2020b). Specifically, the unemployment rate among the youth aged 16 to 24 years increased from 12% in 2019 (right before the pandemic) to 14% in 2020 (right after the break of the pandemic) while unemployment among the population aged 24 to 59 years increased from 4.6% to 5.1% in the same period.

Despite the fact that vocational graduates are the major source of young workers, the effects of the pandemic on vocational school graduates received little attention. Such an omission is notable, given that vocational education has been taken as one major measure to deal with youth unemployment by many governments (Polidano & Tabasso, 2014) and is also an essential track in the education system in many countries. In the case of upper secondary vocational school (hereafter, vocational high school), 35% of global high school students in 2017 attended vocational high schools (UNESCO, 2017). In China, vocational high school students number >16 million and accounted for 40% of upper secondary high school students in 2020 (Ministry of Education, 2021). Between January 2020 and October 2021, at least five studies have examined the effect of COVID-19 on different education groups, according to a search of the Web of Science. Of these important studies, none separates the impact of the pandemic on labor markets by educational tracks (Adams-Prassl et al., 2020; Cortes & Forsythe, 2020; Jain, Budlender, Zizzamia, & Bassier, 2020; Montenovo et al., 2020; Qian & Fan, 2020).

Besides, a focus on the impact of COVID-19 on vocational high school students is important for three reasons. First, vocational education develops mainly specific job-related skills of students, which means that, in a world of rapid technological and structural change, there is potentially high unemployment and income risks (Hanushek, Schwerdt, Woessmann, & Zhang, 2017). Hence, when the pandemic quickly transformed the ways that people were working (e.g., switching to remote work), vocational students could be more vulnerable to this shock than are graduates of academic high schools due to the lack of required general knowledge. Second, vocational high school students are more likely to come from disadvantaged families that generally have lower levels of income and social capital, which have been shown to help families to deal with the shocks in cases of pandemic responses and other crises (Aguilera, 2002; Franzen & Hangartner, 2006; Jain et al., 2020; Mouw, 2003; Qian & Fan, 2020). Third, because a significant proportion of vocational graduates were working in relatively low-wage industries and occupations before the outbreak of COVID-19, such workers would be more likely to be affected by the pandemic's employment shocks, as low-wage industries and occupations suffered more significant losses during the pandemic (Cortes & Forsythe, 2020).

The overall goal of this study is to explore the effects of COVID-19 on vocational high school graduates in China. To meet this goal, we have four specific objectives. First, we describe the labor market outcomes and work attributes of graduates before and after COVID-19, including (a) the extent of their participation in the labor market as full-time workers; (b) their changes in income; (c) the change in time that the workers spent on work; and (d) work attributes, including contract types, management positions, and industries. Second, we use a difference-in-differences (DID) approach to identify the causal effects of COVID-19 on vocational high school graduates and illustrate the robustness of these estimates using alternative approaches (propensity score matching combined with DID [PSM-DID], subsample analysis, and use of propensity weights). Third, we describe the measures that vocational graduates took to cope with the effects of COVID-19 on their jobs and income. Finally, we explore the heterogeneous effects among different subgroups within the sample.

The results indicate that being in a county with an above-average number of COVID-19 infections significantly reduces the participation rate in full-time jobs of vocational high school graduates and leads to a fall in the levels of their monthly earnings (in the case of those who did not lose their jobs). According to our findings, the contraction of labor demand in the county is the main source of the effects of COVID-19. In addition, there were disparities in the nature of the effects in terms of several different dimensions. For example, being in a high-intensity county had a relatively higher negative effect on the monthly income of male graduates (relative to female graduates). Graduates from families with higher social capital experienced much lower, often negligible, effects on their income from the pandemic as compared to those from families with lower social capital, who experienced considerable effects. Although graduates who worked in the service industry were more likely to lose their full-time jobs due to the pandemic, for those who did not lose their jobs, their incomes did not experience as great a shock as did those of whom had jobs in the non-service sectors. The fall in income was also considerably less for graduates who worked in management positions.

Our study contributes to the literature in three ways. First, this study uses a causal inference approach to identify the pandemic's effects, exploiting variations in time and across space. With such causal inferences, this study adds to the emerging literature on the effects of COVID-19 on labor markets, in general, and China's labor market, in particular. Second, this study contributes to the findings of studies of the heterogeneous effects of COVID-19 by identifying the variation in subgroups that were affected by the shocks. Third, to the best of our knowledge, this study is the first to conduct a survey of vocational high school graduates and evaluate the effects of COVID-19 on their employment, income, and other outcomes. We hope that our study will help to stimulate further discussion and research on vocational students, including how they cope with economic crises, such as those that occurred due to the pandemic.

This study also has one major limitation. We identified the effects of COVID-19 on vocational high school graduates by comparing the effects on graduates who were located in areas with a high pandemic intensity versus those who were in low-intensity areas. Due to data constraints, we could not compare the relative effects of COVID-19 on vocational high school graduates with those on academic high school graduates. That is, we cannot provide a direct conclusion about whether vocational high school graduates are more or less vulnerable than are others in the labor market (e.g., academic high school graduates, workers who never went to high school). We thus hope that more research on this topic will be conducted in the future.

2. Literature review

Previous studies find that assessing the labor market effects of COVID-19 on vocational high school graduates as a separate group is necessary. In general terms, this need is due to the fact that there are significant differences between vocational education and a general, more-academically focused education at the high school level. The fundamental difference lies in the educational goals of the different tracks. Vocational education develops the job-related skills of students and prepares students for jobs/occupations in specific industries. In contrast, a general academic education emphasizes basic academic skills that, in theory, will equip individuals with an ability to learn in the future and enable them to be more easily trainable (Hanushek et al., 2017). Based on this different set of goals, students from vocational and general academic education tracks typically enter different channels of vocations after graduation. Studies indicate that, although vocational graduates sometimes have initial labor market advantages relative to graduates from academic schools, such advantages decrease with age (Gould, Moav, & Weinberg, 2001; Hanushek et al., 2017; Korber & Oesch, 2019; Krueger & Kumar, 2004). Due to the differences in their education as well as their initial labor market experiences, it is highly possible that students who graduated from vocational schools responded to the shock of COVID-19 differently from those students who graduated from academic schools.

The literature also has explored the heterogeneous effects of COVID-19 on labor market outcomes for individuals with different demographics and family backgrounds. A large body of literature concerns the disparities of the effects on individuals with different characteristics, such as gender and education level. Specifically, this literature finds that the labor market outcomes of female workers were systematically more susceptible to the pandemic (Adams-Prassl et al., 2020; Albanesi & Kim, 2021; Alon, Doepke, Olmstead-Rumsey, & Tertilt, 2020; Collins, Landivar, Ruppanner, & Scarborough, 2021; Cortes & Forsythe, 2020; Dang & Nguyen, 2021; Jain et al., 2020; Kikuchi, Kitao, & Mikoshiba, 2020; Montenovo et al., 2020). Gender-based unequal effects on employment and income occur due primarily to the fact that the pandemic had more of an impact on sectors/industries with high female employment (e.g., Albanesi & Kim, 2021; Alon et al., 2020) and, secondarily, to the fact that high levels of infection led to a large-scale closure of schools and daycare centers (e.g., Adams-Prassl et al., 2020; Collins et al., 2021; Montenovo et al., 2020).

In viewing the impact of COVID-19 on subpopulations with higher versus lower levels of education, different studies had different results. On the one hand, Montenovo et al. (2020) found a polarization effect: High school dropouts and college graduates experienced substantially lower employment declines than did those with more intermediate levels of education. On the other hand, other research found that those with less education were more affected by the crisis (Cortes & Forsythe, 2020; Jain et al., 2020; Kikuchi et al., 2020). Finally, studies found that the COVID-19 pandemic had disproportionately adverse effects on the income and active employment of individuals from families with lower income (Jain et al., 2020; Qian & Fan, 2020).

Beyond the literature that examines heterogeneous effects on individuals based on their own or family characteristics, a number of studies reported heterogeneous effects of COVID-19 with respect to work attributes. In these studies, heterogeneity with respect to remote-work compatibility, the specific industry and occupation, employment type (employed or self-employed), work contracts (permanent or non-permanent employment), and whether the job was management based was examined extensively (Adams-Prassl et al., 2020; Brynjolfsson et al., 2020; Cortes & Forsythe, 2020; Montenovo et al., 2020). For example, Adams-Prassl et al. (2020) reported that workers with higher remote-work compatibility and a permanent contract were less likely to be affected by COVID-19. Montenovo et al. (2020) showed that job loss during the pandemic was larger in occupations that involve more personal contact and less remote-work compatibility, while those who worked in essential industries (e.g., agriculture, forestry, fishing and hunting, health care and social assistance, public administration) experienced lower levels of job loss.

Although research has contributed substantially to our understanding of the impact of COVID-19 on employment and income, the literature has a number of limitations. Most studies used only variations in time to identify the impact of COVID-19. In fact, using this approach amounts to using basic ordinary least squares (OLS) regression analysis to measure associations and not causality. In this sense, most of the literature contains results that may be subject to bias. For example, the reliance on either OLS or statistical description omits the time trend of work-related conditions, such as previous job participation and income. The omission of such information could bring bias to the estimation.

3. Method

3.1. Sampling

The data for our study comes from a survey of graduates of vocational high schools in six provinces of China. The survey sample was chosen in four steps. First, within China, we selected one province each in the North (Hebei Province), Northeast (Liaoning Province), East (Zhejiang Province), South Central (Guangdong Province), Southwest (Chongqing Municipality), and Northwest (Shaanxi Province) regions of China. Second, within each province, we randomly selected six vocational high schools, using the school list from the websites of each province's Education Department and/or Human Resources and Social Security Department. Third, we visited each selected school and asked the school principal to recommend two classes from those registered in 2013 that they thought could best represent their school. Note that, in most circumstances, students in these schools should have graduated from their vocational high schools in 2016. Finally, we collected the roster and student contact information for all students in the selected classes.

Although we initially selected 36 schools/72 classes to be in the sample, there was attrition for several reasons (Fig. 1). Specifically, nine schools did not preserve the student rosters of the selected classes, and seven classes failed to provide the contact information for their students. We thus had to exclude these schools and classes from our sample. In total, there were 1788 students from 47 classes in 26 schools in the sample.[1]

3.2. Data collection

3.2.1. Vocational graduate survey

We conducted two rounds of online surveys in 2020 to collect data from the sample vocational high school graduates. The first online survey was conducted with all graduates on the student rosters for whom there was effective contact information between January 4 and 16, 2020. Fortunately, the timing of the survey placed it immediately before the outbreak of the COVID-19 pandemic and before actions had been taken by any government agency to suppress the outbreak.

In developing the survey, we categorized questions into six distinct blocks: basic demographic characteristics, family background before entering vocational high school, education, employment, social behavior, and social attitudes. In the education block, the items focused on respondents' experiences in vocational high schools. The items concerned whether the respondents had graduated from their vocational schools and whether they had begun to work or had continued their education at a higher level (after graduation).

The employment block of the survey contained items that solicited information on the full-time jobs and unemployment experiences of the respondents. The items concerned their first job upon graduation and their current full-time job. Information also was collected on the industry in which the graduate was working, the type of contract that the respondent had, whether he or she was in a management position, the level of income, and the number of hours worked. This survey block also collected information on the counties where the vocational graduates worked or lived at the time of the survey. During the analysis, such information allowed us to match the COVID-19 intensity data with our survey data and to help identify the causal effects of COVID-19 on vocational graduates.

In July 2020, approximately three months after the most severe quarantine measures had been lifted in most places in China, we conducted a follow-up survey with the vocational school graduates who had completed the first round of the survey. This survey focused mainly on their labor market performance in the summer of 2020. In conducting the survey, when focusing on their employment and income during the time of the survey, we essentially repeated the questions that we had asked about the full-time job that each respondent had had in January. In this way, the questions were designed to enable a comparison between the employment and income of the individuals in the sample before and after the pandemic.

The one new block added to the follow-up survey contained a series of questions about respondents' experiences during the pandemic. We asked graduates whether they thought that they were affected by the pandemic. Specifically, we asked questions such as, "Has COVID-19 affected your work in any way?" and "How did COVID-19 affect your work?" If the graduate said that he or she had been affected by the pandemic in any way, we asked for detailed information about how they coped with it. We asked, for example, questions about their consumption, savings, borrowing, and job search.

As is almost always the case in panel data collection efforts, there was attrition between the two rounds of surveys. In the first survey in January 2020, for the 1788 graduates in the sample, we collected complete information on 1005 graduates, a completion rate of 56%. In the second survey in July 2020 of the 1005 graduates who completed the first survey, we successfully followed up with 626 graduates (62%). The main analysis sample in this study consisted of the graduates who completed the two rounds of surveys.

Due to the relatively high rate of attrition during the two surveys, we undertook an analysis to determine whether there was a difference between the characteristics of the graduates who completed the surveys and those who did not. To do so, we used data from the first round of the survey (in January 2020). The results are reported in Table 1.

According to the analysis, the two groups are statistically different in many aspects. Respondents who completed the two rounds of the surveys tended to change jobs more often between their graduation (in 2016) and January 2020. Those who completed the two surveys also had more experience with periods of unemployment and were engaged less frequently in starting their own (self-employed) business. Significantly, the final sample was more likely to have a monthly salary in the middle-income group (2000–6000 yuan, or 290–870 USD). In contrast, those in the attrition group had a higher probability of being in either the lowest-income group (below 2000 yuan, or below 290 USD) or the highest-income group (above 6000 yuan, or above 870 USD). Given that a number of studies showed that the pandemic disproportionately affected the most vulnerable groups (Cortes & Forsythe, 2020; Jain et al., 2020; Qian & Fan, 2020), it is difficult, with the information generated from the attrition analysis, to judge the direction of possible

[1] Unfortunately, we could not test whether the attrition led to any bias of our estimation because we do not have the data for those schools, classes, and graduates who were not present in our survey in January 2020. If the completeness of student records could serve as a proxy of education quality, we believe that graduates from these absent schools and classes might have been more affected by the pandemic than were those who were present in our study because the literature indicates larger effects of COVID-19 on more disadvantaged groups. This means that downward bias would not affect our main conclusion.

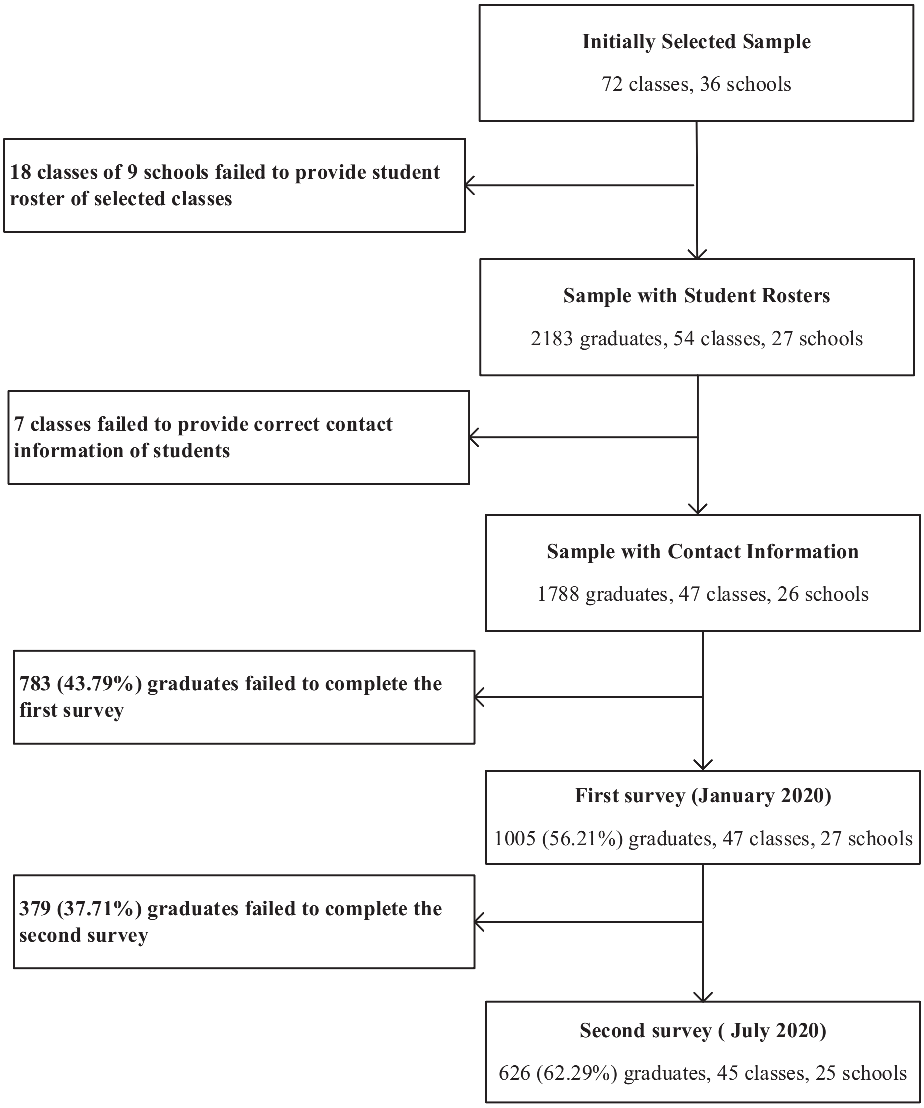

Fig. 1. Data collection procedure.

estimation bias that might be due to attrition. In general, we can say that the empirical results reflect mainly the effect of COVID-19 on the vocational high school graduates who were not in the top or bottom income groups.

3.2.2. Data on COVID-19 intensity

There are two critical dates in the implementation of the COVID-19 containment policy in China (Fig. 2). The first date was January 23, 2020. On this day, the city of Wuhan was shut down to prevent the further spread of the pandemic. Other cities in Hubei province entered lockdown by January 28, 2021. These two events officially confirmed the seriousness of the outbreak of COVID-19.

The second date was April 8, 2020, a little over two months after the initial quarantine announcement. As the epicenter of the pandemic and the area with the greatest impact of the COVID-19 outbreak in China, by this date, Hubei province was able to end its lockdown and to begin the process of returning to normal economic activities. As it turned out, most provinces ended lockdown somewhat earlier. After April 8, 2020, there was no large-scale coronavirus outbreak nationwide in China (Fig. 2). As such, economic activities as well as employment in most areas began to recover (Dai et al., 2021).

Considering that the main spread of COVID-19 and the major shocks that it imposed on the nation's economy and labor markets occurred between January 23 and April 8, we use publicly available data on confirmed cases during this period in the counties where the sample vocational graduates worked and lived in January when the initial outbreak occurred. The data of confirmed cases were (and still are) available from the web pages of Health Commissions in each city. Although the stringency of the quarantines, lockdowns of the cities, and other public health measures effectively restricted human mobility while the government was making an effort to curb

Table 1
Differences between the non-attrition and attrition group in the second survey.

	Non-attrited	Attrited	Difference
Observations	626	379	
(1) Basic characteristics			
Male (yes = 1)	0.47	0.46	0.01
Age	22.71	22.82	−0.10
Education level			
Upper secondary vocational school or below	0.55	0.59	−0.04
Junior college degree or above	0.45	0.41	0.04
Marital status			
Unmarried without a partner	0.57	0.61	−0.04
Unmarried with a partner	0.36	0.32	0.04
Married	0.07	0.07	−0.01
(2) Middle school and vocational school experiences			
Attending high school entrance examination (yes = 1)	0.81	0.82	−0.01
Vocational school major			
Information Technology	0.20	0.19	0.01
Manufacturing	0.19	0.20	−0.00
Educational Services	0.17	0.17	0.01
Finance, Economics, Commerce & Trade	0.17	0.15	0.03
Medicine, Pharmaceuticals & Health Care	0.10	0.12	−0.02
Communication & Transport	0.09	0.07	0.01
Others	0.07	0.11	−0.04*
Serving as a student leader during vocational school (yes = 1)	0.51	0.44	0.07*
(3) Labor market characteristics			
Number of full-time jobs after graduation	1.94	1.73	0.20*
Ever been unemployed (yes = 1)	0.33	0.25	0.08**
Ever started a business (yes = 1)	0.11	0.14	−0.03
Ever attended vocational training (yes = 1)	0.38	0.35	0.03
Full-time employment in January (yes = 1)	0.67	0.68	−0.01
Service industry (yes = 1)	0.86	0.84	0.02
Monthly income in January			
Below ￥2000	0.11	0.44	−0.33***
￥2000–4000	0.40	0.01	0.39***
￥4000–6000	0.35	0.02	0.33***
Above ￥6000	0.14	0.53	−0.39***
Weekly work hours in January (h)	48.45	48.31	0.15

the spread of the virus (Qiu, Chen, & Shi, 2020), differences in initial outbreaks and in the administration of the quarantine policies resulted in variations in the intensity of the pandemic across geographic space.

3.3. Identification strategy

Because the intensity of the pandemic varied greatly across localities, local governments usually implemented different levels of public health measures, including different levels of intensities of lockdowns and quarantines. As a result, the pandemic had different levels of impact on local economies, including employment and wages. Using these differences in the intensities of the pandemic (across time and geographic regions), we sought to identify the causal effects of COVID-19. To date, most of the studies that examine the impact of the pandemic on employment and wage use only time variation to explore the pandemic's effect (Adams-Prassl et al., 2020; Cortes & Forsythe, 2020; Forsythe et al., 2020; Montenovo et al., 2020). Unfortunately, if studies use only a time variable, the analyses omit potential time trends of employment and income (e.g., the increasing trend of job participation and monthly income) and, as a result, could create bias in the estimated coefficients.

In our analysis, we use DID estimation as our primary approach and implement it in two steps. First, we divide the sample into two groups: treatment and control. The literature indicates that increasing infections are associated with a drop in local employment and income (Aum et al., 2021; Qian & Fan, 2020). In making the assignment to one of the two groups, we identified which of the vocational high school graduates in our sample lived and worked in counties with an above-average number of confirmed cases between January 23 and April 8, 2020 (counties for which the number of newly confirmed cases between January 23 and April 8 was larger than 23). We assigned those individuals who live in high-intensity counties to the treatment group. The others, i.e., graduates who lived and worked in low-intensity counties, were in the control group.

After dividing the sample into a treatment and control group, in the second step, we carry out the estimation using the model defined by the following equation:

$$Outcome_{cit} = \alpha + \beta\, Treatment_{ci} \bullet Post_t + \mu\, Treatment_{ci} + \gamma Post_t + X_{ci}{}' \theta + \varepsilon_{cit}$$

where $Outcome_{cit}$ is one of the outcome variables of graduate i in county c in t^{th} period, including whether they were employed in a full-time job, their monthly income level, and the average number of hours worked during the week. The variable $Treatment_{ci}$ is a dummy

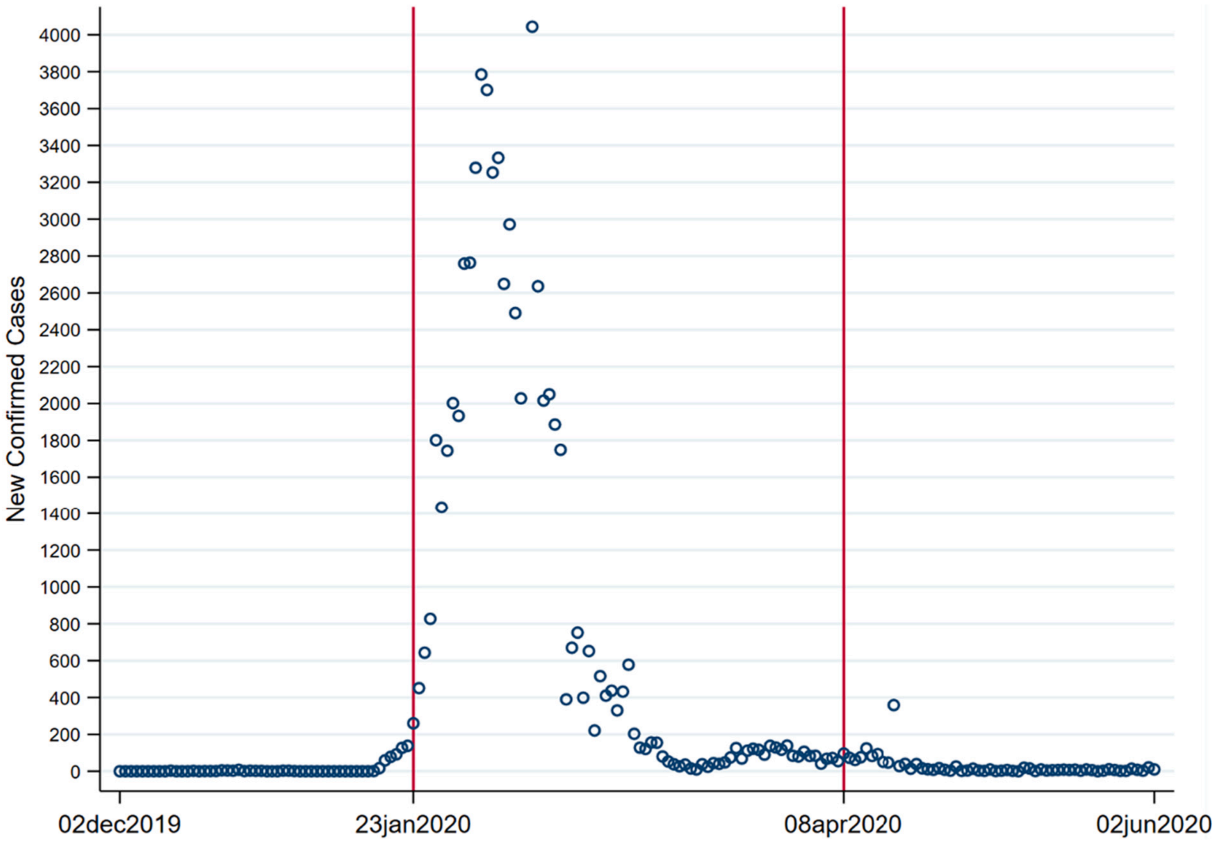

Fig. 2. Number of new confirmed cases in China.
Data Source: China National Health Commission.

variable that indicates whether the sample graduate was located in a high-intensity county in January 2020. The variable $Post_t$ is a dummy variable which equals 0 in January and 1 in July 2020. To increase the efficiency of the estimation, we also control for a set of baseline variables that were collected in the first round of the survey (X_{ci}). The variables in X_{ci} include gender, age, marital status, education level, education level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city. Given this definition of the equation, the estimate of the coefficient β will be interpreted as the causal impact of a graduate's being in (working and living in) a high-intensity county on one of the three outcome variables (*full-time employment*, *monthly income level*, and *weekly work hours*). All standard errors in the following estimates are clustered at the class level. The descriptive statistics of dependent and independent variables used in the analysis are described in Table A1 of the appendix.

The validity of the DID approach relies on a common-trend assumption. In the case of this study, the common-trend assumption means that, in the absence of the COVID-19 pandemic, the trends in employment, income, and hours worked in the treatment and control groups would have remained the same. Unfortunately, due to the limitations of our data (that is, we do not have data from prior to January 2020), we cannot test the assumption. We do, however, subject our analysis to a robustness check using PSM-DID. This approach allows us to adjust for observed systematic differences between the control and treatment groups by using the observations in each group that have common observables as a way to deal with unobserved confounders that are constant over different periods. We test the robustness of estimation results using several PSM methods, including 1:1 matching, 3-nearest neighbor matching, radius matching, kernel matching, and local linear matching. The variables used in propensity score estimation include gender, age, marital status, education level, education level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city. The estimated results of the process producing the propensity scores are reported in Table A2. The distribution of propensity scores is reported in Fig. A2, which shows that the scores of the treatment and control groups have a large proportion of overlap.

We also test the robustness of the results by using subsamples of different class completion rates, which alleviates the bias from attrition, to some extent, in the two rounds of the survey. In classes with higher completion rates, the proportion of graduates in the attrition group is lower. Therefore, the bias from sample attrition becomes minor when we restrict the analysis to the subsample of classes with completion rates higher than a certain threshold, which produces a more accurate estimation of effects. We set the threshold of completion rates at 35% and 55% and estimate the effect of COVID-19 on these two subsamples, respectively. Finally, we compare the results for subsamples and the whole sample.

In addition, we use a propensity cell weighting approach to alleviate attrition bias, which adjusts the estimation based on a model of the response propensity (the probability that the individual will cooperate in the survey request; Heeringa, West, & Berglund, 2017; Little & Rubin, 2019). The propensity cell weighting approach adjusts the attrition or nonresponse bias according to the following steps (Heeringa et al., 2017). First, we predict the response propensity of each graduate in the second-round survey, using the information collected in the first-round survey in January 2020. Second, we divide the data into ten adjustment cells based on deciles of the distribution of the response propensities and compute the mean propensity in each fold. Third, we use the reciprocal of the mean

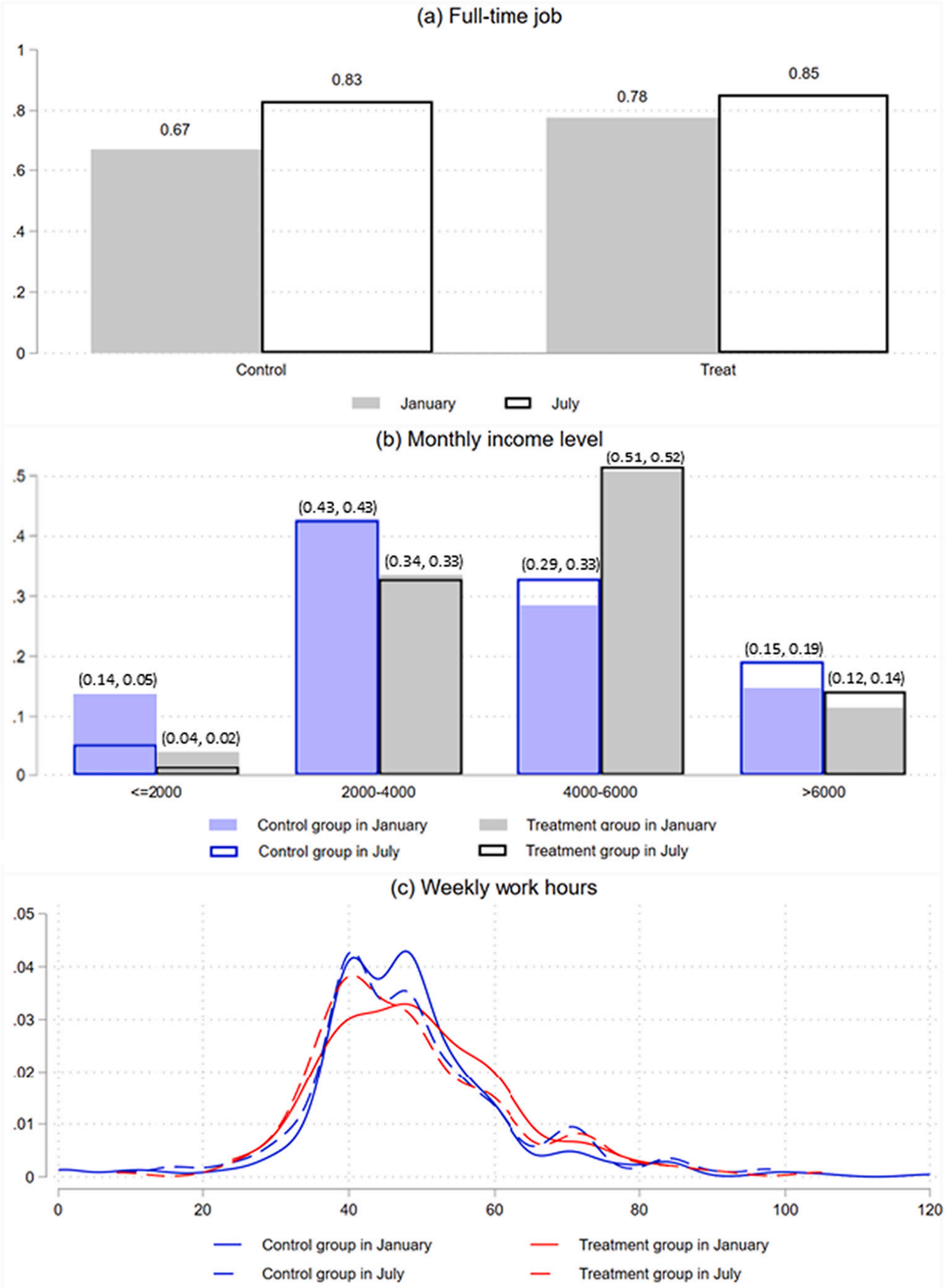

Fig. 3. Labor market outcomes of vocational high school graduates.
Note: The first number in the parenthesis in Panel B represents the share of graduates in the corresponding income group in January 2020, and the second number represents that in July.

response propensity in each cell as a weight for individuals in this cell and carry out the DID estimation. Finally, we compare the weighting estimates with the original estimates.

Because *full-time employment* is a binary variable, and *monthly income* is an ordered discrete variable (the questionnaire contained monthly income questions that involved choosing between different income levels), it is theoretically better to use models for discrete outcome variables, such as probit or logit, than OLS. Although we prefer to use certain models for discrete variables, it remains difficult to explain the implications of coefficients of interactions in the non-linear DID model and heterogeneous analysis, and the coefficient can be of the opposite sign (Ai & Norton, 2003). Thus, we estimate the above models with discrete outcome variables using OLS regressions, as do other studies (Acemoglu, De Feo, & De Luca, 2020). For the sake of robustness, we also used probit and logit models, and the results are reported in Table A3. The estimated coefficients are consistent with OLS regressions in direction and significance.

Also included in the appendix is a demonstration of how we can use different standards (median, lower quartile, and upper quartile of local county confirmed cases) to assign treatment and control groups and to test whether the effects of COVID-19 are robust across different treatment assignments. The results based on three other assignments are reported in Table A4 and show that the effects of COVID-19 on labor market outcomes of vocational high school graduates are robust across different assignments.

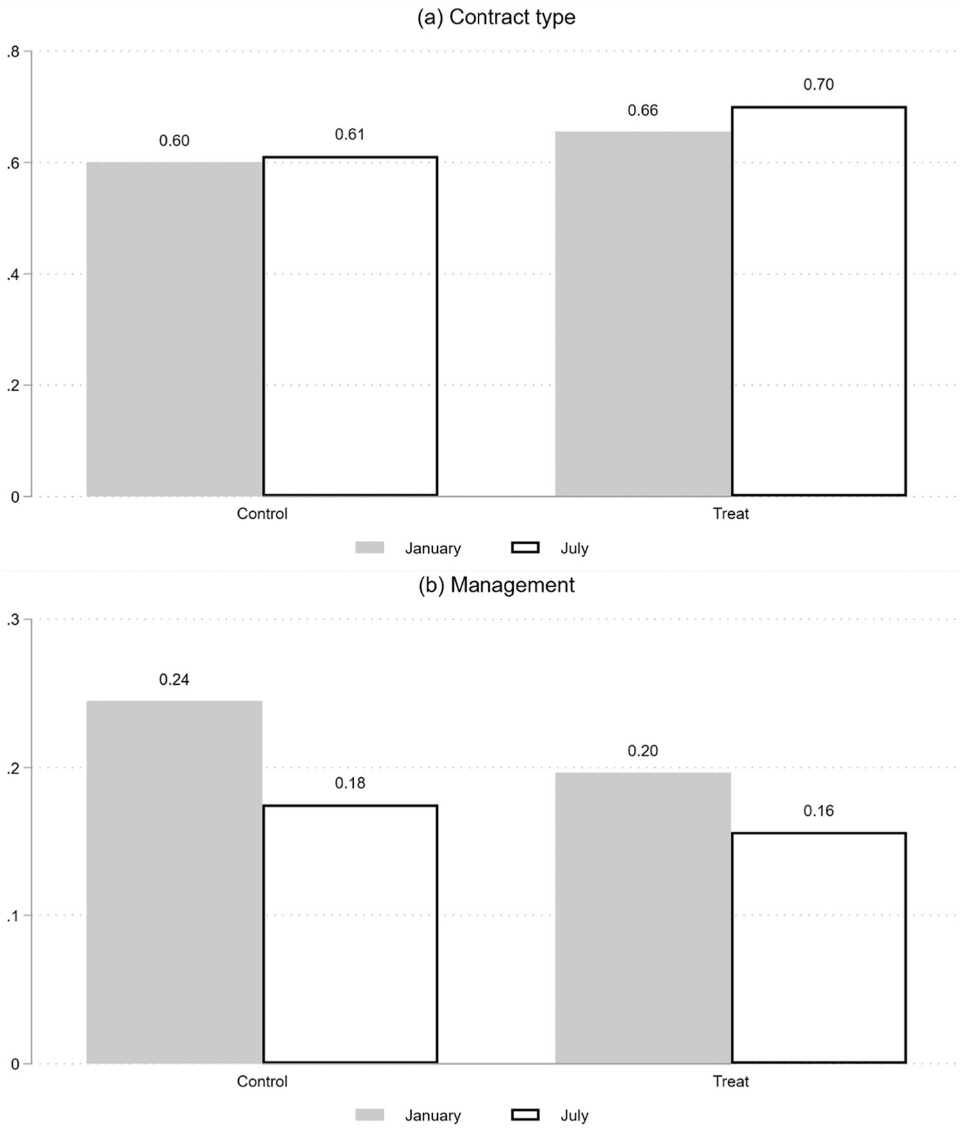

Fig. 4. Full-time employment of vocational high school graduates by contract types and management positions.

4. Results

4.1. Labor market performance and workplace attributes of vocational high school graduates in January and July 2020

We show the labor market outcomes of vocational high school graduates by treatment status in Fig. 3. Overall, the full-time job participation rate of both groups increased from January to July (Panel A, Fig. 3). Specifically, the participation rate of the control group rose from 67% in January 2020 to 83% in July 2020, an increase of 16 percentage points. Meanwhile, it rose from 78% to 85% among the treatment group, an increase of 7 percentage points. The difference in the increase of full-time employment between the two groups is statistically significant ($p < 0.10$).

The low rate of full-time job participation in January occurs as a result of the Spring Festival (January 25 in 2020), a time when people in China often decide to change jobs (Zhaopin.com, 2021). In fact, this propensity to change jobs might be particularly true for vocational high school graduates because many are not permanent employees in their workplaces, as we found in this study. The data from the Ministry of Transport in China suggests that many of these non-permanent employees might have quit their jobs prior to the early January survey date and prepared to return to their hometown for the Spring Festival with the intent of starting a search for a new job soon after the festival (Ministry of Transport of the People's Republic of China, 2020). This increasing trend from January 2020 to July 2020 of the full-time job participation rate supports a DID approach to identify the causal effects of the COVID-19 on labor market outcomes. When using a DID approach, it is possible to account for the influence of any time trend that might be embedded in the data.

The income levels of the sample vocational high school graduates saw an increase (Panel B, Fig. 3). Among the full-time workers, upper-middle income earners (4000–6000 yuan) increased from 29% in January 2020 to 33% in July 2020 in the control group, and from 51% to 52% in the treatment group. Those who earned a high income (above 6000 yuan) in the control group increased by 4 percentage points while those in the treatment group increased by 2 percentage points. However, the increases between the two groups are not statistically different.

The comparison of the distribution of working hours before and after the pandemic showed the change in the number of working hours of graduates in the treatment and control groups (Panel C, Fig. 3). On average, the weekly work hours of the treatment group reduced from 49.2 h to 48.5 h while it increased from 48.1 h to 48.6 h in the control group. However, these changes in the working hours between the two groups are not statistically different.

Fig. 4 presents the work attributes of vocational high school graduates by treatment status. We found that the proportion of permanent employees increased from 60% before the pandemic to 61% after the pandemic in the control group and from 66% to 70%

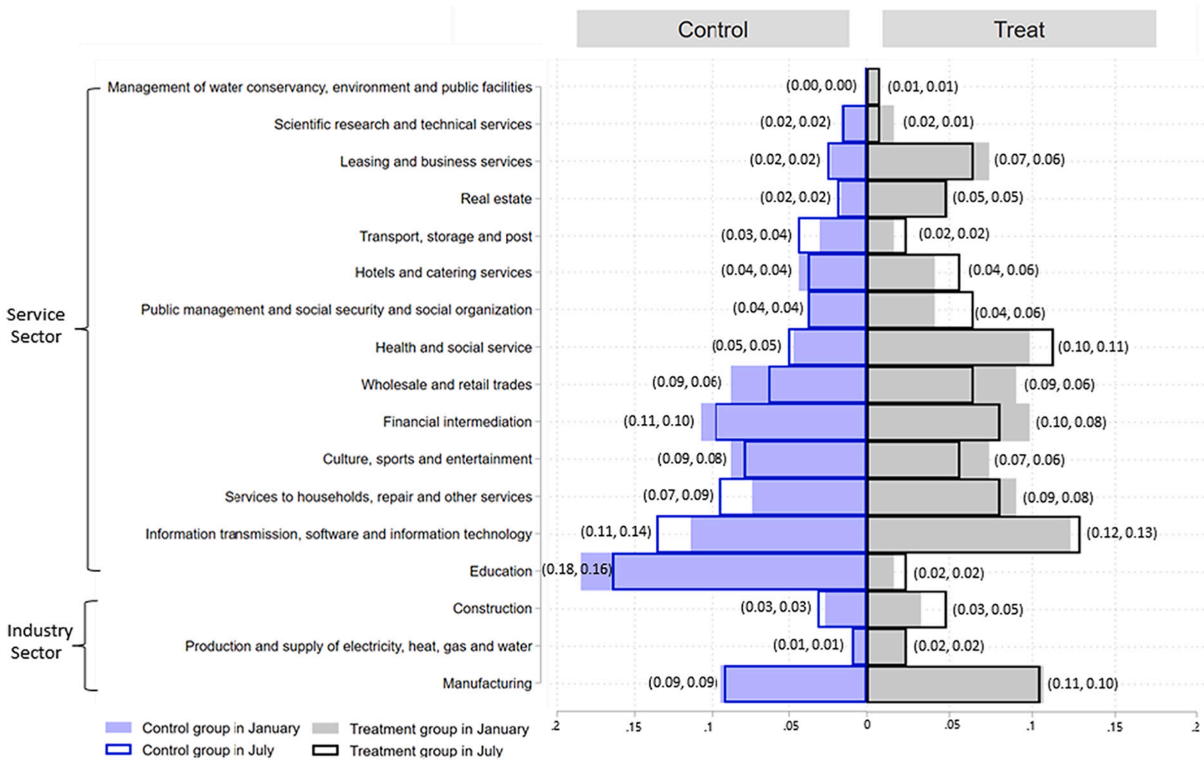

Fig. 5. Full-time employment of vocational high school graduates by industry.
Note: The first number in the parenthesis represents the share of graduates in the corresponding industry group in January 2020, and the second number represents that in July.

in the treatment group (Panel A, Fig. 4). However, the increases in the two groups are not statistically different. Meanwhile, the proportion of graduates who worked in management jobs declined significantly from 24% to 18% among the graduates in the control group ($p < 0.05$). Additionally, it declined from 20% to 16% in the treatment group, though it is not statistically significant. When we examined the changes by sector (Fig. 5), we find that no one was working in agriculture. The graduates who were working in the service sector[2] accounted for 84% in the treatment group and 87% in the control group before the pandemic. After the pandemic, the graduates who were working in service sectors changed to 82% in the treatment group and remained 87% in the control group.[3]

4.2. Main results and robustness tests

Table 2 presents the main results and those of the robustness tests. Row 1 shows DID estimates of the main effects of interest. In both the adjusted and unadjusted models, the probability of having a full-time job for vocational high school graduates who are living and working in high-intensity counties was reduced by 8.7 percentage points (10.7%) when compared to those who were living and working in low-intensity counties. The results also show that, when vocational high school graduates were living and working in high-intensity counties, their levels of monthly income were reduced significantly. Although the point estimates of the DID findings suggest that being located in counties with more confirmed cases reduced the weekly work hours of vocational high school graduates, the measured effect was not statistically significant.

Our robustness analyses found results (Rows 2–9) similar to those of the main DID findings (Row 1), as follows. First, we reanalyze the data and produce alternative estimates of the labor market impacts of being located in a high-intensity county using the PSM-DID approach. The findings indicate that the estimated results from the PSM-DID model, using four different matching methods, consistently show that the initial main DID results are robust. In high-intensity counties, there is a negative impact on full-time job employment and monthly income. In addition, the effects estimated from the PSM-DID model are larger than those of the initial DID results, especially for full-time job employment. The estimated effect size for the full-time job employment rate in PSM-DID model varies from 9.3 to 13.4 percentage points (9.3 percentage points from 1:1 matching, 13.4 from 3-nearest neighbor matching, 9.9 from radius matching, 9.3 from kernel matching, and 12.7 from local linear matching), compared with 8.7 percentage points in the DID estimation. The estimated effect size for the monthly income variable varies from 18.7 to 28.7 percentage points in PSM-DID models (18.7, 23.0, 21.4, 22.6, 28.7, and 23.5 percentage points, respectively, from the different matching methods), compared with 23.1 percentage points in the DID estimation. In contrast, when vocational high school graduates were living and working in a high-intensity county, there was no significant effect on work hours as compared to those in low-intensity counties, which is consistent with original DID estimates.

Second, we find mainly robust results when we look at the DID estimates using specific subsamples of the data. Specifically, when we restrict the sample to classes with completion rates higher than a certain threshold (e.g., 35% and 55%, respectively) to account for potential bias due to the unbalanced attrition of individuals within the class, the direction and statistical significance of the coefficients in alternate estimations for the subsamples are consistent with those for the full sample. Notably, the effect sizes for full-time job employment and monthly income become larger when estimating the model using the subsamples. The estimated effect on employment is 9.2 percentage points when we set the threshold of class completion rate at 35% and 16.3 percentage points when the threshold is 55%, compared with 8.7 percentage points in estimates that use the full sample. In addition, the estimated effect on monthly income is 23.5 percentage points when the threshold is set at 35% and 33.9 percentage points when the threshold is set at 55%. The bigger effect sizes from restricted samples indicate the possibility that the actual effects of COVID-19 on full-time job employment and monthly income are larger than the estimated effects in the original DID settings and that the DID estimates should be considered as the lower bounds of true values due to the downward bias from sample attrition during the two rounds of the survey.

Third, in a final robustness check, we add propensity cell weights to the estimation and produce results similar to those seen in the estimates using PSM-DID model and subsamples. For example, Table 2 (Row 9) shows that the effect size increased to 10.3 percentage points in the employment model and 30.5 percentage points in the income model after reweighting the original estimation. Hence, as shown from Table 2 and discussed above, the results are mainly robust when using any number of different approaches.

In regard to the effect of COVID-19 on the labor market, it is meaningful to compare our findings with those of other studies that focus on different countries and different samples. In our study, the estimated effect of the pandemic on unemployment rates of vocational high school graduates (around 23 years old) ranged between 8.7 and 16.3 percentage points. The findings of the current study are consistent with the findings in the literature, both outside and inside China. There are several studies that report the effects of COVID-19 on young workers' employment, although none, to our knowledge, estimate causal coefficients. For example, Montenovo et al. (2020) found the employment of young workers (ages 21–24) experienced a decrease of 20 percentage points during the

[2] According to the classification in National Bureau of Statistics of China, service sector includes information transmission, software and information technology, services to households, repair and other services, wholesale and retail trades, culture, sports and entertainment, hotels and catering services, leasing and business services, transport, storage and post, real estate, management of water conservancy, environment and public facilities, education, financial intermediation, scientific research and technical services, health and social service, public management and social security and social organization; industry sector includes manufacturing, production and supply of electricity, heat, gas and water, construction, and mining.

[3] Interestingly, as shown in Table A1, the distribution of industry types within which the sample vocational high school graduates worked (as shown in Figure 4) appears to be related to the distribution of the fields associated with the vocational high school majors in the sample (21% of graduates majored in information and communication technology, 20% majored in manufacturing, and 18% majored in educational services).

Table 2
The main effects of local pandemic intensity and robustness tests.

		Full-time employment		Monthly income level		Weekly work hours	
		Without controls (1)	With controls (2)	Without controls (3)	With controls (4)	Without controls (5)	With controls (6)
Main effects							
DID	Treatment*Post	−0.087**	−0.087**	−0.231***	−0.231***	−1.178	−1.178
		(0.035)	(0.035)	(0.073)	(0.075)	(1.678)	(1.729)
	Sample Size	1206	1206	764	764	762	762
Robustness Tests							
(1) PSM-DID							
1:1 matching	Treatment*Post	−0.121***	−0.121***	−0.187**	−0.187**	−0.636	−0.636
		(0.038)	(0.039)	(0.091)	(0.094)	(2.152)	(2.230)
	Sample Size	628	628	428	428	426	426
3-Nearest neighbor matching	Treatment*Post	−0.134***	−0.134***	−0.230**	−0.230**	−1.518	−1.518
		(0.037)	(0.038)	(0.090)	(0.093)	(2.022)	(2.091)
	Sample Size	744	744	500	500	498	498
Radius matching	Treatment*Post	−0.099***	−0.099***	−0.214***	−0.214***	−1.896	−1.896
		(0.035)	(0.036)	(0.077)	(0.080)	(1.939)	(1.998)
	Sample Size	1206	1206	764	764	762	762
Kernel matching	Treatment*Post	−0.093**	−0.093**	−0.226***	−0.226***	−2.093	−2.093
		(0.037)	(0.038)	(0.081)	(0.083)	(2.089)	(2.153)
	Sample Size	1206	1206	764	764	762	762
Local linear regression matching	Treatment*Post	−0.127**	−0.127**	−0.287**	−0.287**	−2.569	−2.569
		(0.053)	(0.055)	(0.125)	(0.130)	(2.691)	(2.802)
	Sample Size	518	518	352	352	350	350
(2) Subsamples							
DID completion>35%	Treatment*Post	−0.092***	−0.092**	−0.235***	−0.235***	1.117	1.117
		(0.035)	(0.036)	(0.082)	(0.085)	(1.616)	(1.670)
	Sample Size	940	940	590	590	588	588
DID completion >55%	Treatment*Post	−0.163***	−0.163***	−0.339***	−0.339***	−0.861	−0.861
		(0.034)	(0.035)	(0.108)	(0.113)	(2.634)	(2.764)
	Sample Size	512	512	332	332	330	330
(3) Propensity weights							
DID with weights	Treatment*Post	−0.103***	−0.103***	−0.305***	−0.305***	−0.540	−0.540
		(0.037)	(0.038)	(0.085)	(0.088)	(2.472)	(2.557)
	Sample Size	1206	1206	764	764	762	762
City fixed effects		No	Yes	No	Yes	No	Yes

(1) Standard errors clustered at the class level appear in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
(2) Control variables include gender, age, marital status, education level, educational level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city.
(3) The variables used in propensity score estimating include gender, age, marital status, education level, education level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, and ever attended vocational training.

pandemic. Cortes and Forsythe (2020) estimated that COVID-19 caused a decline of 18 percentage points in the employment rate of youth (ages 16–25). A survey conducted by Aucejo, French, Araya, and Zafar (2020) on undergraduate students in Arizona State University reported that 29% of students lost the jobs they were working before the pandemic, and 13% lost their internship or job offers. These numbers, for China, appear to be as large as or perhaps even a bit larger than the numbers found in most countries and areas, when taking into account that DID estimates deduct the effects on low pandemic intensity areas, which also were affected by the pandemic and suffered, albeit less than did high-intensity area, as a result of public health measures, such as quarantine and lockdown.

While our estimate cannot be compared with the numbers reported in other studies that also measure the effect of the pandemic on income since we use an ordered measurement of income, similar findings are reported in research on more extensive age cohorts. Similarly, Piyapromdee and Spittal (2020) showed that the income of individuals fell by 13–22% in the U.K. during the pandemic. Almeida et al. (2021) estimated that COVID-19 caused a drop of 9.3% in the households' disposable income in the European Union. Additionally, Qian and Fan (2020)'s study on China found that people who lived in regions with higher pandemic intensity were more likely to experience income loss.

At last, an insignificant effect on weekly work hours might be explained by the trade-off of laying off employees and reducing working hours of each worker for the enterprises. Due to wage rigidity, it can be more difficult for employers to reduce work hours (as well as the wage), compared to dismissing employees (Osuna & García, 2021; Rones, 1981; Schmitt-Grohé & Uribe, 2016). As a result, instead of reducing working hours, we find that employers in our study preferred laying off employees during labor demand contractions.

We also were concerned with the extent to which the effects of COVID-19 on the labor market could be attributed to the drop in labor demand or the decline in labor supply. In July 2020, 98 vocational graduates did not have full-time jobs. We grouped their reasons for this into three categories: voluntary unemployment due to reasons unrelated to COVID-19 (44%), voluntary unemployment due to reasons related to COVID-19 (7%), and involuntary unemployment due to reasons related to the pandemic (49%). Table 3 provides additional information on these categories. Overall, our survey findings show that involuntary unemployment that results from a drop in labor demand accounted for approximately 86% of the total number of those unemployed related to COVID-19. Further, among those who changed their full-time job, 21% reported that their "company had cut jobs or closed down during the pandemic." Hence, the main source of COVID-19's shock to the labor market appears to be the large-scale contraction of labor demand and not voluntary withdrawal from the labor force.

To understand how vocational high school graduates responded to the effects of COVID-19, in the second round of the survey, we asked the vocational high school graduates what measures they took to cope with the COVID-19-related labor market downturns. In July 2020, 298 (49%) vocational graduates reported that their jobs or income were affected by COVID-19. In response to the shock, 37% of our respondents stated that they reduced their consumption, 22% used their savings to cover their expenses, and the remaining respondents reported that they used other tactics. For example, some tried to increase their income by "searching for new jobs" (13%) or "taking part-time jobs" (11%). Some took this opportunity to "attend training or learning programs" (7%). There also was a small share of graduates who had to live by "borrowing" (8%) or "selling assets" (1%).

4.3. Heterogeneity effects of COVID-19

In this section, we focus on the potential heterogeneity in the estimated effects. Based on the literature, we present a heterogeneity analysis of how living and working in a high pandemic intensity county affected labor market outcomes in terms of (a) gender, (b) parental education, (c) the type of industry in which the vocational high school graduate worked, (d) the respondent's contract type, and (e) whether the individual was a manager.

Panel A of Table 4 shows the heterogeneous effects by the gender of the vocational high school student. The estimated coefficient of interest is not statistically significant in Columns (1) and (3), which indicates that the effects on jobs and work hours are not heterogeneous across male and female vocational high school graduates who are living and working in high-intensity and low-intensity counties. The results in Column (2), however, suggest that living and working in a high-intensity county mainly reduced the monthly income of male vocational high school graduates, relative to female vocational high school graduates. These results are different from those of other studies (e.g., Adams-Prassl et al., 2020; Albanesi & Kim, 2021; Alon et al., 2020; Collins et al., 2021; Cortes & Forsythe, 2020; Dang & Nguyen, 2021; Jain et al., 2020; Kikuchi et al., 2020; Montenovo et al., 2020). These studies found that females are more likely than males to lose their jobs due to the pandemic. There are two possible reasons for the difference between our heterogeneous effects and those in other studies. One reason might be the age of our sample cohort. In the literature, the main reason for the disparities in the effects of COVID-19 by gender is increasing child care needs due to the closure of schools and daycare centers. In the other studies, because the average age of the samples is older, and because females are typically the main caregiver in the family, the females in the other studies experienced a larger negative labor market effect (Alon et al., 2020). In our study, the average age of graduates was 22.7 years, 93% were unmarried, 95% had no children, and women in this age cohort face less pressure in regard to child care.

The other reason might be that COVID-19 affects sectors with a higher share of male employment more strongly, in our sample. Table 5 presents the average monthly income of different industries in January 2020 and July 2020 and the difference between them. In the three industries in which average monthly income decreased during this period, the share of male vocational graduates was 70.6%. In the eight industries whose monthly income increases were below the mean value, the share of males was 67.0%, while the

Table 3
Reasons for unemployment in the full-time jobs.

Type	Reason	Percent	Treatment group	Control group
Voluntary unemployment related to COVID-19		7.14	0.00	9.33
1	I am unwilling to work due to the fear of the health risks under the pandemic.	7.14	0.00	9.33
Involuntary unemployment related to COVID-19		48.97	39.13	52.00
2	My company had cut jobs or closed down during the pandemic, and I have not found jobs yet.	12.24	21.74	9.33
3	I planned to change jobs after the spring festival and have not found jobs yet.	36.73	17.39	42.67
Voluntary unemployment unrelated to COVID-19		43.88	60.87	38.66
4	I do not need to work.	13.27	13.04	13.33
5	I am not able to work due to diseases or pregnancy.	5.10	4.35	5.33
6	I am preparing for job qualifications (civil service qualification examination, teachers' qualification examination, and induction training program).	11.22	21.74	8.00
7	Others.	14.29	21.74	12.00
Total		100.00	100.00	100.00

Note: Others include "I want to change my job for personal reasons and am searching for a job", "I have just graduated and am looking for a job" and etc.

Table 4
The heterogeneous effect of local COVID-19 intensity.

	(1)	(2)	(3)
	Full-time employment	Monthly income level	Weekly work hours
Panel A. Gender			
Treatment*Post	−0.122***	−0.030	−0.604
	(0.036)	(0.076)	(1.855)
Treatment*Post*Male	0.059	−0.334***	−0.951
	(0.050)	(0.103)	(2.491)
Male (yes = 1)	−0.075***	0.504***	1.843
	(0.024)	(0.099)	(1.622)
Sample size	1206	764	762
Panel B. Education level of parents			
Treatment*Post	−0.096***	−0.310***	−1.884
	(0.033)	(0.083)	(2.119)
Treatment*Post*At least one parent with senior high school or above education	0.030	0.230**	2.062
	(0.053)	(0.113)	(1.907)
At least one parent with senior high school or above education (yes = 1)	0.040	−0.021	−2.832*
	(0.029)	(0.081)	(1.469)
Sample size	1206	764	762
Panel C. Industry			
Treatment*Post	0.048	−0.405***	3.016
	(0.040)	(0.124)	(4.769)
Treatment*Post*Service industry	−0.056*	0.210*	−5.060
	(0.031)	(0.121)	(5.232)
Service industry (yes = 1)	0.013	−0.085	−0.116
	(0.021)	(0.137)	(2.173)
Sample size	840	764	762
Panel D. Contract			
Treatment*Post	−0.011	−0.185*	−2.232
	(0.047)	(0.102)	(2.775)
Treatment*Post*Permanent employee	0.018	−0.070	1.602
	(0.063)	(0.088)	(3.500)
Permanent employee (yes = 1)	0.014	0.143*	2.031
	(0.016)	(0.086)	(1.271)
Sample size	840	764	762
Panel E. Management			
Treatment*Post	0.017	−0.302***	−1.834
	(0.035)	(0.086)	(1.731)
Treatment*Post*Management job	−0.086	0.391***	3.641
	(0.110)	(0.135)	(4.385)
Management job (yes = 1)	−0.014	0.161**	0.547
	(0.018)	(0.077)	(1.826)
Sample size	840	764	762
City fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes

(1) Standard errors clustered at the class level appear in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
(2) Control variables include gender, age, marital status, education level, education level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city.

number was 39.4% in the seven industries with above-average monthly income increases. This indicates that industries with higher male employment shares were affected more strongly, similar to what usually occurs in an employment crisis, at least in income.

Panel B of Table 4 provides the heterogeneous effects by level of parental education. Graduates with at least one parent who had at least a senior high school level of education (which can also be understood as vocational high school graduates from families with higher levels of social capital) suffered fewer (had more negligible negative) effects on their monthly incomes when living in high-intensity counties. This finding is similar to that of other studies of how higher and lower levels of social capital in the family help to attenuate the impact of negative factors. Research shows that people from families with higher social capital are better at handling shocks (Aguilera, 2002; Franzen & Hangartner, 2006; Mouw, 2003), and the results in Panel B further add evidence to this point of view.

Panel C of Table 4 shows the heterogeneous effects across different industries. Compared with graduates who worked in the

Table 5
The average income and share of male employment in different industry.

Industry	January 2020		July 2020		Difference (yuan)	Share of male employment
	N	Average monthly income (yuan)	N	Average monthly income (yuan)		
Production and supply of electric power, gas and water	6	5000.00	6	4666.67	−333.33	1.00
Construction industry	12	4333.33	16	4125.00	−208.33	0.58
Neighborhood services and other service industry	33	4333.33	40	4250.00	−83.33	0.70
Scientific research, technical service and geologic examination industry	7	5285.71	6	5333.33	47.62	0.57
Traffic, storage and mail business	11	4636.36	17	4882.35	245.99	0.55
Leasehold and business service industry	16	4250.00	16	4500.00	250.00	0.25
Manufacturing Industry	41	4414.63	42	4666.67	252.03	0.85
Sanitation, social security and social welfare industry	26	3538.46	30	3800.00	261.54	0.19
Wholesale and retail trade	37	4405.41	28	4714.29	308.88	0.59
Information transfer, computer service and software industry	49	4714.29	59	5067.80	353.51	0.61
Finance industry	44	4136.36	41	4560.98	424.61	0.25
Accommodation and food industry	18	3555.56	19	4052.63	497.08	0.50
Public administration and social organization	16	3750.00	20	4300.00	550.00	0.81
Realty business	11	4090.91	12	4666.67	575.76	0.73
Education	57	2578.95	55	3181.82	602.87	0.09
Cultural, physical and entertainment industry	35	4142.86	32	4750.00	607.14	0.40
Water conservancy, environment and public institution management	1	3000.00	1	5000.00	2000.00	1.00
Total	420	4033.33	440	4382.18	348.85	0.48

industrial sector, those who worked in the service industry were more likely, by 5.6 percentage points, to lose their full-time jobs when they were living and working in high-intensity counties. Such a result also is consistent with the literature (e.g., Montenovo et al., 2020). According to Montenovo et al. (2020)., job losses are more considerable in jobs such as those in the service sector that involve face-to-face contact and higher health risks. Interestingly, for those who kept their jobs in the service industry during the pandemic, income decreased less, by 23 percentage points, than for those who work in the industrial sector. Similar findings have emerged in other studies. Within the service sector, low-wage occupations suffered the most from COVID-induced impacts (Cortes & Forsythe, 2020). Occupations such as servers or store clerks involve a higher frequency of face-to-face contact and cannot be accomplished remotely. Thus, these low-wage service-sector jobs have borne the brunt of the pandemic. In contrast, in high-wage occupations, even in the service sector (e.g., information transfer, computer services, software), typically involve less risky contact with other people and are more compatible with a remote working environment. According to the literature, the pandemic's negative labor market effects on these types of jobs and the levels of income of those in these fields are relatively small (Adams-Prassl et al., 2020; Dingel & Neiman, 2020; Montenovo et al., 2020).

Panel D of Table 4 presents the heterogeneous effects across different contract types, that is, between those vocational high school graduates who are permanent employees and those who are non-permanent. Previous studies indicated that non-permanent employees were affected more by pandemic-related shocks compared to permanent employees (Kikuchi et al., 2020). In our study, however, the heterogeneous effects were not statistically significant. This might be explained by the high instability of jobs among vocational high school graduates, despite the type of contract. From the perspective of the labor supply side, the data shows that, among those who changed their full-time job between the two surveys, "I planned to change jobs after the Spring Festival" accounted for 59% of vocational high school graduates who had a permanent job up until that time and 57% in the non-permanent group. These results are similar to those of a survey of migrant workers in China (Tsinghua University, 2013). Several studies have found that workers who switched to a new job tended to have higher re-employment wages (Cortes, 2016; Schmidpeter & Winter-Ebmer, 2021). In sum, these findings may indicate that an employee's contract has little binding force for this group. From the perspective of the demand side, previous studies suggest that permanent employees do not necessarily perform better than do non-permanent ones, and, thus, employers might be neutral in regard to the type of contract that their employees have when employers are considering whether to lay off employees (Muralidharan & Sundararaman, 2013).

Panel E of Table 4 provides the heterogeneous effects between management and non-management jobs. We find that the effects of the pandemic are similar on vocational high school graduates who had a managerial position and those who did not. However, they earned more than others as a result of the pandemic. There are two possible explanations. First, graduates who were managers were more likely to shift to working from home and, thus, experienced less shock from COVID-19. Such a finding is similar to that in the literature that graduates in management jobs experience less income loss due to the pandemic (Brynjolfsson et al., 2020). Second, graduates with a managerial position are usually required to take on the task of prevention of COVID-19 in addition to the regular tasks and thus received additional compensation (Xu et al., 2020).

5. Conclusion

The COVID-19 pandemic was a shock to the global economy. To prevent the further spread of COVID-19, lockdown measures were implemented nationwide for weeks in China, especially in Hubei province. During the lockdown period, economic activities were paused, which had repercussions for the labor market. Although the respondents in the study—vocational high school graduates—account for a sizeable share of the labor force vulnerable to such shocks, these graduates have received less research attention than they should have.

Seeking to address this gap, this study examined the causal effects of labor market outcomes among vocational high school graduates who were living and working in counties with high-intensity levels of pandemic infections, relative to their counterparts in low-intensity counties. Labor market outcomes included whether respondents maintained their full-time jobs, monthly income levels, and weekly work hours. The data used in the study come from a two-period panel survey of vocational schools in six provinces in China. Using a DID inference approach to identify causal effects, the analysis found that being located in a high-intensity county had significantly negative effects on full-time job participation of vocational high school graduates (8.7 percentage points lower) as well as their monthly income (23.1 percentage points). The use of robustness checks that utilize PSM-DID models as well as selected subsamples and weighted estimation approaches showed that the main estimated effects are robust to a number of different methodologies. In comparing our results to those of the literature, we find that the estimated effect sizes on job loss of young workers are close to those of studies conducted in the U.S. (Aucejo et al., 2020; Cortes & Forsythe, 2020; Montenovo et al., 2020). The analysis also identified the reasons that numbers for full-time employment fell for the vocational high school graduates in the high-intensity counties. The findings suggest that the primary problem was the large-scale contraction of labor demand, which is much important than supply-side explanations.

This study also explored the heterogeneity of pandemic intensity effects and found that living and working in a high-intensity county has a larger negative effect on the employment of vocational high school graduates who work in the service industry. In addition, there are larger negative impacts for the income of male graduates, graduates from families with lower social capital, vocational high school graduates who work in the industrial sector, and those who work in non-management jobs. The findings are important and suggest that policymakers need to pay more attention to vocational high school graduates and workers in the young age cohorts who work in lower-skilled jobs in the labor market.

The overall findings of the study suggest that COVID-19 had a significant negative effect on vocational high school graduates, although the effects varied between groups. Moreover, the large-scale contraction of labor demand from enterprises is the major reason for the damage to both employment and income. To address the negative consequences of a pandemic on youth employment, first and most important, the government could extend pro-employment policies to encourage the enterprises to maintain stable employment with flexible working time instead of laying off employees. For example, a tax- and fee-cut policy and short-time financial support for small- and medium-sized enterprises and individually run businesses (which account for 80% of employment in China) could be provided to prevent a sudden and large-scale contraction of labor demand. Additionally, unemployment insurance could be expanded to cover vulnerable groups who lost jobs in the pandemic. In particular, a conditional cash transfer, which requires unemployed people to receive high-quality vocational training, could give youth access to resources to help them get through the shock and prepare for a new job. In addition to providing evidence-based policy recommendations, we hope that this study will stimulate further research on vocational students, especially in regard to how they respond to and cope with a crisis, such as the COVID-19 pandemic.

Declaration of Competing Interest

Hongmei Yi is supported by the Excellent Young Scientist Fund of the National Natural Science Foundation of China (No. 71922001). Xiao Liang and Scott Rozelle have no conflicts of interest to declare.

Appendix

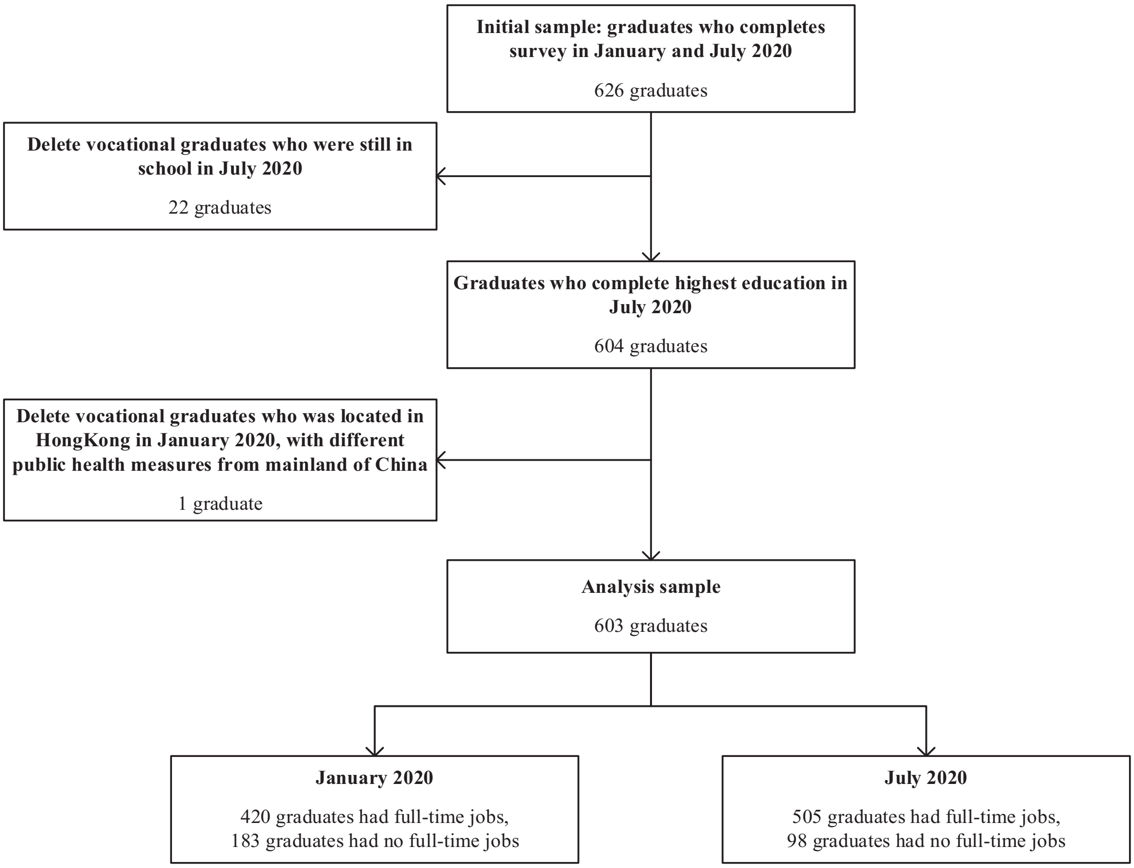

Fig. A1. Analysis sample description.

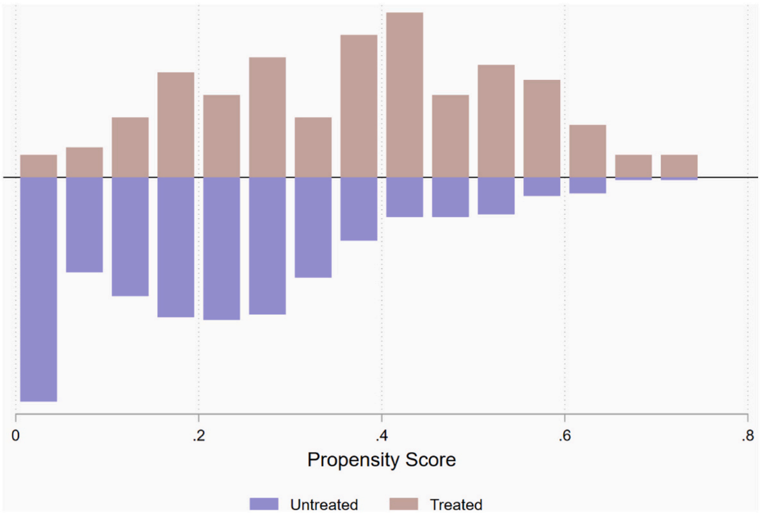

Fig. A2. Histogram of propensity score.

Table A1
Descriptive statistics of variables.

	N	Mean	SD	Min	Max
Panel A. Dependent Variables					
Full-time employment (yes = 1)	1206	0.77	0.42	0	1

(continued on next page)

Table A1 (*continued*)

	N	Mean	SD	Min	Max
Monthly income level					
Below ¥2000	925	0.07	0.26	0	1
¥2000–4000	925	0.40	0.49	0	1
¥4000–6000	925	0.37	0.48	0	1
Above ¥6000	925	0.16	0.37	0	1
Weekly work hours (h)	923	48.52	13.87	0	120
Panel B. Independent Variables					
(1) Interest variables					
COVID-19 confirmed cases	603	19.91	42.55	0	836
Treatment Group (yes = 1)	603	0.26	0.44	0	1
(2) Basic characteristics					
Male (yes = 1)	603	0.48	0.50	0	1
Age	603	22.72	0.98	19	28
Junior college degree or above (yes = 1)	603	0.45	0.50	0	1
At least one parent with senior high school or above education (yes = 1)	603	0.33	0.47	0	1
Marital status					
Unmarried without a partner	603	0.57	0.50	0	1
Unmarried with a partner	603	0.36	0.48	0	1
Married	603	0.07	0.25	0	1
(3) Middle school and vocational school experiences					
Attending high school entrance examination (yes = 1)	603	0.81	0.39	0	1
Vocational school major					
Information Technology	603	0.21	0.40	0	1
Manufacturing	603	0.20	0.40	0	1
Educational Services	603	0.18	0.38	0	1
Finance, Economics, Commerce & Trade	603	0.17	0.38	0	1
Medicine, Pharmaceuticals & Health Care	603	0.09	0.29	0	1
Communication & Transport	603	0.09	0.28	0	1
Others	603	0.07	0.26	0	1
Serving as a student leader during vocational school (yes = 1)	603	0.51	0.50	0	1
(4) Labor market characteristics					
The number of full-time jobs after graduation	603	1.98	1.54	0	7
Ever been unemployed (yes = 1)	603	0.34	0.47	0	1
Ever started a business (yes = 1)	603	0.11	0.31	0	1
Ever attended vocational training (yes = 1)	603	0.39	0.49	0	1
(5) City characteristics					
Per capita GDP of local city (1000 yuan)	603	101.40	39.74	23	203

Table A2
Propensity score estimation using logistic regression.

	Treatment Group (yes = 1)
Male (yes = 1)	0.321
	(0.254)
Age	−0.170**
	(0.110)
Marital status	(−0.335)
Unmarried with a partner	0.219
	(0.102)
Married	0.513
	(0.465)
Junior college degree or above (yes = 1)	0.218*
	(−0.155)
At least one parent with high school or above education (yes = 1)	0.222
	(0.809)
Attending high school entrance examination (yes = 1)	0.319**
	(−1.108)
Vocational school major	(0.397)
Information Technique	0.028***
	(0.450)
Manufacturing	−0.904**
	(0.367)
Educational services	0.166***
	(0.458)
Finance, Economics, Commerce & Trade	−2.993***
	(0.652)
Medicine, Pharmaceuticals & Health Care	−0.971
	(0.414)

(*continued on next page*)

Table A2 (*continued*)

	Treatment Group (yes = 1)
Others	−0.053
	(0.213)
Serving as a student leader during vocational school (yes = 1)	0.106
	(0.067)
The number of full-time jobs after graduation	−0.531
	(0.230)
Ever been unemployed (yes = 1)	0.775***
	(0.321)
Ever started a business (yes = 1)	−0.421**
	(0.228)
Ever attended vocational training (yes = 1)	2.829**
	(2.605)
Sample size	603

(1) *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2) The results of probit and logit regression report the original value of estimated coefficients.

Table A3

Main effects of local pandemic intensity on the job and income using discrete outcome model.

		Full-time employment		Monthly income level	
		without controls	with controls	without controls	with controls
OLS	Treatment*Post	−0.087**	−0.087**	−0.231***	−0.231***
		(0.035)	(0.035)	(0.073)	(0.075)
	Sample Size	1206	1206	764	764
Probit	Treatment*Post	−0.237*	−0.324**	−0.315***	−0.386***
		(0.128)	(0.141)	(0.092)	(0.107)
	Sample Size	1206	1148	764	764
Logit	Treatment*Post	−0.385*	−0.496*	−0.519***	−0.640***
		(0.231)	(0.273)	(0.161)	(0.191)
	Sample Size	1206	1148	764	764
City fixed effects		No	Yes	No	Yes

(1) Standard errors clustered at the class level appear in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2) Control variables include gender, age, marital status, education level, educational level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city.

(3) The results of probit and logit regression report the original value of estimated coefficients. Specifically, we run probit regression and logit regression on the full-time employment, and run ordered probit regression and ordered logit regression on the monthly income level.

Table A4

Main effects of local pandemic intensity based on three different assignments of treatment.

	Full-time employment		Monthly income level		Weekly work hours	
	without controls	with controls	without controls	with controls	without controls	with controls
Treatment by the lower quartile (2)						
Treatment*Post	−0.107**	−0.107**	−0.032	−0.032	−0.325	−0.325
	(0.043)	(0.045)	(0.063)	(0.065)	(1.780)	(1.842)
Sample Size	1206	1206	764	764	762	762
Treatment by the median (5)						
Treatment*Post	−0.081**	−0.081*	−0.092	−0.092	−0.786	−0.786
	(0.041)	(0.042)	(0.066)	(0.069)	(1.472)	(1.523)
Sample Size	1206	1206	764	764	762	762
Treatment by the upper quartile (17)						
Treatment*Post	−0.112***	−0.112***	−0.150**	−0.150*	−0.395	−0.395
	(0.039)	(0.040)	(0.076)	(0.079)	(1.520)	(1.573)
Sample Size	1206	1206	764	764	762	762
City fixed effects	No	Yes	No	Yes	No	Yes

(1) Standard errors clustered at the class level appear in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(2) Control variables include gender, age, marital status, education level, educational level of parents, attending high school entrance examination, vocational school major, serving as a student leader during vocational school, the number of full-time jobs after graduation, ever been unemployed, ever started a business, ever attended vocational training, and the GDP of the local city.

References

Acemoglu, D., De Feo, G., & De Luca, G. D. (2020). Weak states: Causes and consequences of the Sicilian Mafia. *The Review of Economic Studies, 87*(2), 537–581.

Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. *Journal of Public Economics, 189*, Article 104245. https://doi.org/10.1016/j.jpubeco.2020.104245

Aguilera, M. B. (2002). The impact of social capital on labor force participation: Evidence from the 2000 social capital benchmark survey. *Social Science Quarterly, 83*(3), 853–874. https://doi.org/10.1111/1540-6237.00118

Ai, C., & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters, 80*(1), 123–129.

Albanesi, S., & Kim, J. (2021). *The gendered impact of the COVID-19 recession on the US labor market (no. w28505; p. w28505)*. National Bureau of Economic Research. https://doi.org/10.3386/w28505

Almeida, V., Barrios, S., Christl, M., De Poli, S., Tumino, A., & van der Wielen, W. (2021). The impact of COVID-19 on households ́ income in the EU. *The Journal of Economic Inequality, 19*(3), 413–431. https://doi.org/10.1007/s10888-021-09485-8

Alon, T., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). *The impact of COVID-19 on gender equality (no. w26947; p. w26947)*. National Bureau of Economic Research. https://doi.org/10.3386/w26947

Aucejo, E. M., French, J., Araya, M. P. U., & Zafar, B. (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *Journal of Public Economics, 191*, Article 104271.

Aum, S., Lee, S. Y., & (Tim), & Shin, Y.. (2021). Inequality of fear and self-quarantine: Is there a trade-off between GDP and public health? *Journal of Public Economics, 194*, Article 104354. https://doi.org/10.1016/j.jpubeco.2020.104354

Brynjolfsson, E., Horton, J., Ozimek, A., Rock, D., Sharma, G., & TuYe, H.-Y. (2020). *COVID-19 and remote work: An early look at US data (no. w27344; p. w27344)*. National Bureau of Economic Research. https://doi.org/10.3386/w27344

Che, L., Du, H., & Chan, K. W. (2020). Unequal pain: A sketch of the impact of the Covid-19 pandemic on migrants' employment in China. *Eurasian Geography and Economics, 61*(4–5), 448–463. https://doi.org/10.1080/15387216.2020.1791726

Coibion, O., Gorodnichenko, Y., & Weber, M. (2020). *Labor Markets during the Covid-19 Crisis: A Preliminary View. 17*.

Collins, C., Landivar, L. C., Ruppanner, L., & Scarborough, W. J. (2021). COVID-19 and the gender gap in work hours. *Gender, Work and Organization, 28*(S1), 101–112. https://doi.org/10.1111/gwao.12506

Cortes, G. M. (2016). Where have the middle-wage workers gone? A study of polarization using panel data. *Journal of Labor Economics, 34*(1), 63–105.

Cortes, G. M., & Forsythe, E. (2020). *The heterogeneous labor market impacts of the Covid-19 pandemic*. Available at SSRN 3634715.

Dai, R., Feng, H., Hu, J., Jin, Q., Li, H., Wang, R., Wang, R., Xu, L., & Zhang, X. (2021). The impact of COVID-19 on small and medium-sized enterprises (SMEs): Evidence from two-wave phone surveys in China. *China Economic Review, 67*, Article 101607. https://doi.org/10.1016/j.chieco.2021.101607

Dang, H.-A. H., & Nguyen, C. V. (2021). Gender inequality during the COVID-19 pandemic: Income, expenditure, savings, and job loss. *World Development, 140*, Article 105296.

Dingel, J. I., & Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics, 189*, Article 104235. https://doi.org/10.1016/j.jpubeco.2020.104235

Forsythe, E., Kahn, L. B., Lange, F., & Wiczer, D. (2020). Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims. *Journal of Public Economics, 189*, Article 104238. https://doi.org/10.1016/j.jpubeco.2020.104238

Franzen, A., & Hangartner, D. (2006). Social networks and labour market outcomes: The non-monetary benefits of social capital. *European Sociological Review, 22*(4), 353–368.

Gould, E. D., Moav, O., & Weinberg, B. A. (2001). Precautionary demand for education, inequality, and technological Progress. *Journal of Economic Growth, 6*(4), 285–315. https://doi.org/10.1023/A:1012782212348

Hanushek, E. A., Schwerdt, G., Woessmann, L., & Zhang, L. (2017). General education, vocational education, and labor-market outcomes over the lifecycle. *Journal of Human Resources, 52*(1), 48–87.

Heeringa, S. G., West, B. T., & Berglund, P. A. (2017). *Applied survey data analysis*. Chapman and hall/CRC.

International Labour Organization. (2021). *Unemployment rate by sex and age—ILO modelled estimates*. ILOSTAT database. https://ilostat.ilo.org/data/.

Jain, R., Budlender, J., Zizzamia, R., & Bassier, I. (2020). *The labor market and poverty impacts of covid-19 in South Africa*. UCT: SALDRU. http://hdl.handle.net/11090/980.

Kikuchi, S., Kitao, S., & Mikoshiba, M. (2020). Who suffers from the COVID-19 shocks? Labor market heterogeneity and welfare consequences in Japan. *Covid Economics, 40*, 76–114.

Korber, M., & Oesch, D. (2019). Vocational versus general education: Employment and earnings over the life course in Switzerland. *Advances in Life Course Research, 40*, 1–13. https://doi.org/10.1016/j.alcr.2019.03.003

Krueger, D., & Kumar, K. B. (2004). US–Europe differences in technology-driven growth: Quantifying the role of education. *Journal of Monetary Economics, 51*(1), 161–190. https://doi.org/10.1016/j.jmoneco.2003.07.005

Little, R. J. A., & Rubin, D. B. (2019). *Statistical analysis with missing data*. John Wiley & Sons.

Ministry of Education. (2021). 2020 National Statistical Bulletin on The Development of Education. http://www.moe.gov.cn/jyb_sjzl/sjzl_fztjgb/202108/t20210827_555004.html.

Ministry of Transport of the People''s Republic of China. (2020). A total of 1.48 billion trips were made during the Spring Festival travel peak in 2020, dropping by 50% from the same period last year. https://www.mot.gov.cn/zhuanti/2020chunyun_ZT/gongzuobushu/202002/t20200220_3417523.html.

Montenovo, L., Jiang, X., Rojas, F. L., Schmutte, I., Simon, K., Weinberg, B., & Wing, C. (2020). *Determinants of disparities in Covid-19 job losses (no. w27132; p. w27132)*. National Bureau of economic research. https://doi.org/10.3386/w27132

Mouw, T. (2003). Social capital and finding a job: Do contacts matter? *American Sociological Review*, 868–898.

Muralidharan, K., & Sundararaman, V. (2013). *Contract teachers: Experimental evidence from India (working paper no. 19440; working paper series)*. National Bureau of Economic Research. https://doi.org/10.3386/w19440

National Bureau of Statistics of China. (2020a). https://data.stats.gov.cn/search.htm?s=GDP.

National Bureau of Statistics of China. (2020b). *The Urban Survey of Unemployment*.

Osuna, V., & García, P. J. I. (2021). Temporary layoffs, short-time work and COVID-19: The case of a dual labour market. *Applied Economic Analysis*. https://doi.org/10.1108/AEA-06-2021-0118. ahead-of-print(ahead-of-print).

Piyapromdee, S., & Spittal, P. (2020). The income and consumption effects of COVID-19 and the role of public policy. *Fiscal Studies, 41*(4), 805–827. https://doi.org/10.1111/1475-5890.12252

Polidano, C., & Tabasso, D. (2014). Making it real: The benefits of workplace learning in upper-secondary vocational education and training courses. *Economics of Education Review, 42*, 130–146. https://doi.org/10.1016/j.econedurev.2014.06.003

Qian, Y., & Fan, W. (2020). Who loses income during the COVID-19 outbreak? Evidence from China. *Research in Social Stratification and Mobility, 68*, Article 100522. https://doi.org/10.1016/j.rssm.2020.100522

Qiu, Y., Chen, X., & Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics, 33*(4), 1127–1172.

Rones, P. L. (1981). Response to recession: Reduce hours or jobs. *Monthly Labor Review, 104*, 3.

Schmidpeter, B., & Winter-Ebmer, R. (2021). Automation, unemployment, and the role of labor market training. *European Economic Review, 137*, Article 103808. https://doi.org/10.1016/j.euroecorev.2021.103808

Schmitt-Grohé, S., & Uribe, M. (2016). Downward nominal wage rigidity, currency pegs, and involuntary unemployment. *Journal of Political Economy, 124*(5), 1466–1514. https://doi.org/10.1086/688175

Tsinghua University. (2013). Temporary employment: A study on the employment trend of migrant workers. In *Tsinghua Sociology Review* (pp. 1–41). Social Sciences Academic Press.
UNESCO. (2017). UIS Statistics. http://data.uis.unesco.org/.
Wang, H., Dill, S., Zhou, H., Ma, Y., Xue, H., Sylvia, S., … Rozelle, S. (2021). Health, economic, and social implications of COVID-19 for China's rural population. *Agricultural Economics, 52*(3), 495–504. https://doi.org/10.1111/agec.12630
Wang, H., Dill, S.-E., Zhou, H., Ma, Y., Xue, H., Loyalka, P., … Rozelle, S. (2022). Off the COVID-19 epicentre: The impact of quarantine controls on employment, education and health in China's rural communities. *The China Quarterly, 249*, 183–209.
Wang, H., Zhang, M., Li, R., Zhong, O., Johnstone, H., Zhou, H., Xue, H., Sylvia, S., Boswell, M., Loyalka, P., & Rozelle, S. (2021). Tracking the effects of COVID-19 in rural China over time. *International Journal for Equity in Health, 20*(1), 35. https://doi.org/10.1186/s12939-020-01369-z
Xu, T.-L., Ao, M.-Y., Zhou, X., Zhu, W.-F., Nie, H.-Y., Fang, J.-H., … Chen, X.-F. (2020). China's practice to prevent and control COVID-19 in the context of large population movement. *Infectious Diseases of Poverty, 09*(04), 121–134. https://doi.org/10.1186/s40249-020-00716-0
Zhaopin.com. (2021). *2021 spring recruitment market weekly report*. Zhaopin.com.