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Pandemics, Global Supply Chains, and Local Labor Demand: Evidence from 100 Million Posted

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Pandemics, Global Supply Chains, and Local Labor Demand: Evidence from 100 Million Posted Jobs in China*

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Abstract

This paper studies how the COVID-19 pandemic has affected labor demand using over 100 million posted jobs on one of the largest online platforms in China. Our data reveals that, due to the effects of the pandemic both in China and abroad, the number of newly posted jobs within the first 13 weeks after the Wuhan lockdown on January 23, 2020 was about one third lower than that of the same lunar calendar weeks in 2018 and 2019. Using econometric methods, we show that, via the global supply chain, COVID-19 cases abroad and in particular pandemic-control policies by foreign governments reduced new job creations in China by 11.7%. We also find that Chinese firms most exposed to international trade outperformed other firms at the beginning of the pandemic but underperformed during recovery as the Novel Coronavirus spread throughout the world.

Key Words: COVID-19, labor demand, global supply chains, trade

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Introduction

The novel coronavirus pandemic (COVID-19) has resulted in an enormous loss of lives around the world. Measures taken by governments to contain the virus have flattened the epidemic curve and slowed the spread of the disease (1, 2, 3) but also have resulted in the loss of hundreds of millions of jobs and thrown the global economy into a deep recession. In an age in which most goods are "Made in the World" (4), there are worries that COVID-19 and pandemic-control policies could generate shock waves, transmitted via global supply chains, and impose economic costs that bypass national borders (5, 6, 7).

Two emerging strands of literature attempt to estimate the economic impact of the COVID-19 pandemic. On the empirical side, studies have shown that new job postings online dropped by about 40% in countries such as the United States (8, 9) and Sweden (10). There also are strong correlations between the drop in job postings and exposure to COVID-19 by state or county in the United States (8, 9). In addition, tradable sectors can better withstand the pandemic (8). On the theoretical side, macroeconomic models have been used to simulate the impact of the pandemic on employment and other outcomes (6, 7, 11). These studies all highlight the possibility of COVID-19 shocks as propagating through the global production network, and neither strand of literature has provided direct evidence on whether and how global supply chains have played a role in transmitting the COVID-19 shocks and policy across borders.

In this paper, we attempt to understand the nexus between COVID-19, government pandemic-control policies, international trade, and Chinas labor market by exploring over 100 million jobs posted on a leading Chinese online employment platform. China, the country where COVID-19 first broke out, also has been the largest trading nation in the world since 2013. In the first quarter of 2020, as COVID-19 cases peaked in China, total Chinese exports fell by 9.3% quarter-on-quarter, the largest fall in a decade.[1] At the same time, according to our data, in the first 14 weeks after the lockdown on January 23, 2020 of Wuhan City—the first epicenter of COVID-19—the number of newly posted jobs dropped by about 31%, or 3.8 million, relative to the same lunar calendar period in 2018 and 2019.[2]

Our empirical model correlates, at the city-week level, the creation of new jobs with exposure to the pandemic in the city, in other parts of China, and to foreign

[1]Source: the Federal Reserve Bank of St. Louis.

[2]The urban unemployment rate went up by about one percentage point to 5.9%, the highest level and largest month-to-month increase of this statistic since it was officially published in January 2018. Source: National Bureau of Statistics of China. This official unemployment rate percentage likely does not fully reflect true unemployment in China because the survey does not cover most of the 300 million migrant workers, who are more likely to be unemployed during the pandemic.

countries through supply chains. Similar to other recent studies (8, 9), we first examine the impact of new COVID-19 cases in the local city on local job creation. Different from these studies, we also separately identify the impact of COVID-19 in other parts of China by using a distance-weighted pandemic exposure measure.

We also test whether the pandemic has an impact on job creation through the global supply chain. To the best of our knowledge, we are the first to exploit cross-city variations in their exposure to the global pandemic and virus-containment policies through their differential trade linkages with other countries. Specifically, we create trade-weighted measures of exposure to the global pandemic by using Chinese Customs data to generate weights and to estimate their effects on job creation in a Chinese city. Thus, the variations come from the change of global pandemic and containment policies over time and a citys exposures to trade with different countries. Further, we follow Campello et al. (8) to test whether the trade sector fares differently from other firms at different stages of the global pandemic. Empirically, we identify trade intermediary firms by examining whether the names of firms contain Chinese terms related to trade.

We establish three main findings. First, we find that COVID-19 cases in the local city and other parts of China have large negative impacts on job creation in a Chinese city, and the elasticity of job creation with respect to the latter is slightly larger in magnitude. Our back-of-the-envelope calculation implies that job creation was down by 9.6% due to local city COVID-19 cases but by 10.7% due to cases in other parts of China in the 14 weeks after the Wuhan lockdown. Second, foreign COVID-19 shocks transmitted via global supply chains also reduced job creation in China. This impact came mainly from the decline of export demand due to the policy responses by foreign governments to COVID-19. In the same 14 weeks, foreign COVID-19 shocks reduced job creation in China by another 11.0%, which weakened the recovery of the labor market. Finally, we find, as a piece of direct evidence for the role of international trade in transmitting the COVID-19 shock, that Chinese firms that rely more on international trade outperformed other types of firms in withstanding the COVID-19 shock when the epicenter was in China but underperformed during the recovery as the epicenter moved to the rest of the world.

In addition to the recent economic literature on COVID-19 cited above, our paper also is related to the literature on the propagation of shocks through input-output linkages and global supply chains. The propagation of a local shocks hitting one or few regions by examining natural disasters in the U.S., the SARS epidemic, and the 2011 east Japan earthquake have been, respectively, studied (12), (13), and (14). The COVID-19 pandemic is a global shock and, thus, differs from these local shocks. Like the pandemic itself, which may have multiple waves (15), the COVID-19 shock may hit local economies multiple times via global supply chains.

Understanding the transmission mechanism through domestic and international linkages is crucial for policymaking to, on the one hand, contain the pandemic and, on the other hand, speed up the recovery of the global economy. Domestically, we find that the effect of COVID-19 cases in other parts of China is similar to that in the local city. This suggests that, for large countries with complex domestic supply chains, such as China, the United States, Brazil, and India, a nationally coordinated strategy is important for controlling both the pandemic and economic recovery. With the pandemic under control in China, the impacts of the global pandemic through trade and pandemic-mitigation policies have become more prominent over time. As evident from our data, seven weeks after the Wuhan lockdown, 78.0% of the loss of new jobs was due to foreign pandemic shocks via the global supply chain. According to our data, over the entire 14-week period, foreign shocks accounted for slightly more than a third of the 3.8 million “lost new jobs. These findings suggest that an open economy cannot fully recover unless the pandemic is well under control among all of its major trading partners, and, thus, international coordination in pandemic control is crucial.

Our findings also have implications for Chinas future trade and job creation beyond COVID-19. The current pandemic will likely pass within a year, when vaccines and more effective therapeutics are developed (16, 17, 18). With deteriorating relations between China and the United States as well as other major western countries, however, economic decoupling of China from the rest of the world or a sudden drop in Chinas trade volume is becoming a real possibility. In light of this, the unprecedented COVID-19 pandemic and the subsequent virus mitigating border control policies adopted by foreign governments could serve as a natural “simulation and be used as a rare opportunity to test how an abrupt severing of the global supply chain might affect job creation in China. We find large negative impacts of trade shocks, in particular, of the drop of foreign demand due to border control policies. Economic decoupling of China from the rest of the world will likely cause job losses in China in a similar manner, except that the magnitude of such a shock will likely be much larger (6).

Data and Methods

Data

We use several data sources for our analysis. Our job posting data come from one of the largest online platforms that provide hiring services in China.[3] We ran a

[3] According to *iResearch*, a leading online market research company in China, the platform we scraped our data from has a stable market share before and during the pandemic. Thus, it is unlikely that the loss in their posted job ads is due to a platform-specific downward trend.

web-scraping algorithm that collected job ads posted on the platform from January 1, 2018, to April 30, 2020. For each ad, we know the basic characteristics of the job, including the job location, the number of vacancies, and some information on the firm, including the firm name, size, and industry classification. In total, we collected roughly 20 million job ads, with 104.9 million posted vacancies by more than 700,000 firms during our sample period.[4] We aggregate the post-level job vacancies to the city-week level, which is the unit of our analysis. The data sample covers 334 cities and 122 weeks, and, thus, we have 40,414 city-week observations in total. As shown in Table 1, a city posted an average of about 500 job ads with about 2,541 vacancies on the platform each week.

Our job posting data do not include whether a firm trades with foreign countries. We follow Ahn et al. (20) to identify trade intermediaries by firm names. Specifically, we define firms as *trade intermediaries* if their names contain Chinese characters that mean "importer," "exporter," or "trading companies."[5] Using this method, we define 3.8% of the firms in our sample as trade intermediaries.

Our primary COVID-19 data source is DXY, the largest online platform run by the community of Chinese medical professionals. The platform publishes COVID-19 epidemic data for each Chinese city, and for each foreign country or region, in almost real time.[6] DXY started to publish the data only after the Wuhan lockdown on January 23, 2020. For epidemic data from earlier dates, we use data from the Harvard Dataverse. DXY reports the cumulative number of confirmed cases for each region, from which we calculate the number of newly confirmed cases in each week, which is the focus of our analysis.[7]

We use the Oxford COVID-19 Government Response Tracker (OxCGRT) to obtain data on policies adopted by governments in response to the pandemic. OxCGRT collects comprehensive and consistent worldwide data on policy responses to COVID-19, including containment and closure, testing, and monetary and fiscal policies (22). Given our interest in the global supply chain, we focus on the international aspect of these policies, which include border control measures that can

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Inevitably, online posted jobs are biased toward the urban areas in China. Wang et al. (19) examine the impact of COVID-19 in rural China.

[4]The numbers of vacancies are 44.4 million in 2018, 50.5 million in 2019, and 10.1 million in the first four months of 2020.

[5]The list of Chinese words are "mao4yi4" (trade), "jin4kou4" (import), "chu1kou3" (export), "jin4chu1kou3" (import and export), "ke1mao4" (science and trade), "wai4mao4" (foreign trade), and "wai4jing1" (foreign economic).

[6]DXY is also the primary data source of the online interactive dashboard run by the Center for Systems Science and Engineering at Johns Hopkins University (21). If there are missing data in DXY, we complement it using OxCGRT, which also reports the number of confirmed cases by country.

[7]Results are robust using other COVID-19 measures such as the cumulative number of cases.

generate friction to international trade.[8] The tracker classifies such measures into five levels of stringency, ranging from no measure at all to total border closure.[9] We also use Chinese Customs data, which cover export and import transactions by Chinese firms to measure the trade linkages of each Chinese city with the rest of the world. We aggregate these transactions to calculate, for each city, its imports from and exports to other countries/regions.

To examine how foreign COVID-19 shocks affect job creation in China, we also construct several trade-weighted pandemic and policy response variables. The variable *expCovid* (and, respectively, *impCovid*) is the weighted average of the number of new cases in all countries, for which the weights are a citys relative share of export to (and, respectively, import from) each foreign country in the year 2012, which are the latest customs data available to us.[10] Similarly, the trade-weighted policy response measures $expBorderControl$ and $impBorderControl$ are the border control policies imposed by each foreign country, weighted by a citys relative share of exports to and imports from each country/region, respectively. To measure the exposure of local labor markets to shocks from other domestic cities, we construct a distance-weighted measure of new cases in each domestic city, using the inverse city-pair distance as the weight. All technical definitions of these constructed measures are in the Appendix S1.1. Table 1 presents the summary statistics of the key variables.

Methods

Formally, we study the impact of COVID-19 on job creation by estimating the following equation:

$$\begin{aligned}\ln(jobs_{it}) = {} & a_1 \ln(localCovid_{it}) + a_2 \ln(domCovid_{it}) \\ & + a_3 \ln(expCovid_{it}) + a_4 \ln(impCovid_{it}) \\ & + a_5 expBorderControl_{it} + a_6 impBorderControl_{it} \\ & + M_t + Spring_t + Autumn_t + CityYear_{it} + \epsilon_{it}, \end{aligned} \tag{1}$$

where the subscripts i and t represent city and week, respectively. We define weeks using the lunar calendar, starting from the Chinese New Year, as it coincides with

[8]As a robustness check, we also use a policy index developed by OxCGRT, which captures different policies DIMITRI.

[9]The five levels of border controls are 0 = no measures, 1 = screening, 2 = quarantine arrivals from high-risk regions, 3 = ban on arrivals from some regions, 4 = total border closure. In the appendix, we show that we obtain a similar result by using a general policy stringency index that covers other aspects of containment and closure, including lockdown.

[10]In the appendix, we also present results using measures that are scaled by total exports or imports divided by GDP for each city. This does not change our results qualitatively.

the week of the Wuhan lockdown (January 23, 2020) and is the start of the Chinese labor market cycle.[11] The dependent variable $jobs_{it}$ is the number of posted jobs in city i at week t. The two variables $localCovid$ and $domCovid$ are the number of newly confirmed cases in the city and other cities in China, respectively, capturing the severity of the pandemic in China. The two trade variables $expCovid_{it}$ and $impCovid_{it}$ are used to estimate the effects of pandemic outbreaks in trading partners on job creation in Chinese cities through export and import channels, respectively. To disentangle pandemic effects from the effects of policies in response to the pandemic, we include the trade weighted policy variables $expBorderControl_{it}$ and $impBorderControl_{it}$. Below, we report the estimation results from variations of Eq. (1) as we gradually include more explanatory variables in the regressions.

All estimated models include the following control variables. We include M_t, dummies of the month to capture the seasonal movements in job creation. In addition, we include $Spring_t$ and $Autumn_t$, dummies for spring and autumn hiring seasons. In Appendix Figure S1, we plot the aggregate number of job postings for each week, which features two major peaks, the spring and autumn hiring seasons in each year. The spring season is usually right after the Spring Festival, and the autumn season typically falls in October or November. We construct these dummies to capture these hot seasons in the job market. $CityYear_{it}$ is a city by year fixed effect which captures city and year shocks specific to the local labor market.

Results

In this section, we present the effects on job creation of domestic COVID-19 cases and those of the global pandemic through the supply chain. For the global supply chain effects, we disentangle direct COVID-19 trade effects from pandemic-mitigation policy effects. We also examine whether trade intermediaries fared differently from other firms.

Overall Job Losses The COVID-19 pandemic had a large impact on job creation in China. Figure 1 presents a plot of the fall in the number of posted jobs for each week, compared to the average of the same lunar calendar week in the years 2018 and 2019.[12] At the trough of the line, which is two weeks after the

[11]Most workers take a vacation of between one to four weeks during the Chinese New Year and start to search for jobs immediately after. Correspondingly, there is normally a spike of job postings right after the Chinese New Year.

[12]The week that follows the Wuhan lockdown is the Spring Festival holiday in China. The Spring Festival is based on the lunar calendar and falls on different dates on the Gregorian calendar in different years. For the years 2018 and 2019, the job posting numbers are those

week that follows the Wuhan lockdown on January 23, 2020, which we refer to as "week zero," the number of posted jobs fell by as many as 1.85 million, or 89% relative to the same lunar period of the previous two years. As the virus subsided in China and hit the rest of the world six weeks later, Chinas labor demand gradually rebounded. It stayed below pre-pandemic levels, however, due partly to foreign COVID-19 shocks. In the 14 weeks after the Wuhan lockdown, the total number of jobs posted on the platform was 8.36 million, down 31.2% from the average level in the same period of 2018 and 2019 (about 12.15 million).

Domestic COVID-19 Cases The results from estimating Eq. (1) show that domestic COVID-19 cases indeed have a large negative effect on job creation. As shown in Table 2, the coefficient on $\ln(localCovid)$ is negative and statistically significant at the 1% level, suggesting that fewer jobs were created as the number of new local COVID-19 cases increased. The magnitude of this effect is large. As seen in column (4), if the number of local newly confirmed cases increases by 1%, job numbers fall by about 0.18%.

The results presented in Table 2 also indicate that the pandemic in other parts of China influences local labor demand. In Columns (2) - (4), the coefficient of the variable that captures the pandemic in other domestic regions $\ln(domCovid)$ is negative and significant at the 1% level. Therefore, if the novel coronavirus hit other domestic regions badly, the local job market will suffer, capturing important domestic cross-city economic linkages. Moreover, comparing the estimated coefficients in a given city, we can see that the magnitude of the effect in other regions is similar to that of the local city. We summarize these results into the following fact.

Fact 1: In a given Chinese city, COVID-19 cases in both the local city and other parts of China have large negative impacts on job creation.

Global Supply Chain The severity of the pandemic abroad also reduced local labor demand through both the direct trade linkage and the pandemic-control policies. In Column (3) of Table 2, we include variables that measure exposure to foreign COVID-19 shocks via export demand ($ln(expCovid)$) and import supply ($ln(impCovid)$) channels. Both trade-weighted measures have negative coefficients and are significant at least at the 10% level. The magnitude of the export-weighted pandemic variable almost doubles that of the import-weighted variable, suggesting that the impact of export demand is relatively more important.

The variation among all trade-weighted pandemic and mitigation policy variables suggests that border-control policies through the foreign export demand

posted during the three months after the Spring Festival in each year.

channel have the largest impact on job creation in China. In Column (4), we further include variables that capture the exposure to foreign policies created in response to COVID-19. We find that the trade-weighted pandemic variables themselves become small and statistically insignificant. Although the import-weighed policy variable is also small and insignificant, the export-weighted policy variable ($expBorderControl$) is large and statistically significant with a magnitude similar to those of the domestic pandemic variables. These results suggest that the impact of the pandemic abroad on local labor demand in Chinese cities is mainly a result of foreign government policy responses to COVID-19. We summarize the findings into the following fact.

Fact 2: Global supply chains transmitted foreign COVID-19 shocks and reduced job creation in China mostly via policy responses to the pandemic on export demand.

Economic Magnitude of the Effects We use our estimated model (Column (4)) to disentangle the loss in job creation from each of the pandemic shocks: local COVID-19, COVID-19 in other domestic cities, foreign COVID-19 shocks on export and import, and foreign policy shocks on export and import. For each week, we compute the implied reduction in the number of jobs according to the estimated coefficients and the observed shock. We then compute the share of the reduction in job creation attributable to each shock by dividing the implied job posting reduction from each shock (calculated from the estimated coefficients) by the total implied reduction. As can be seen in Figure 2, when the epicenter was in China (Weeks -2 to 6), the negative impact on job creation in a given city was due mostly to COVID-19 shocks in the local city and other domestic cities.[13] As the pandemic was on the wane in China and surged in the rest of the world (Weeks 7 to 13), the impact of foreign policy responses on export demand loomed large and became the primary shocks on Chinese local labor demand (78.0% of the total impact). Out of the 3.79 million new jobs lost in the entire 14-week period of our study, the contributions to job losses from each source in a given city are 31.0% (1.16 million jobs) from the local city, 34.0% (1.30 million jobs) from other Chinese cities, and another 35.0% (1.33 million jobs) from foreign countries, including the effects of both the pandemic itself and policy responses.

Trading Firms In this subsection, we examine whether the pandemic and related trade policies affect trade intermediaries differently from other firms. Trade intermediaries are arguably more exposed to international trade because their main

[13]We define the epicenter to be in China when the total number of confirmed cases in China was higher than the rest of the world.

business is to be middlemen between foreign buyers/sellers and domestic firms.[14] As documented by Ahn et al. (20), trade intermediaries handled 22% of Chinese exports and 18% of imports in 2005.

Empirically, we first split firms in a city into two groups, trade intermediaries and other firms, and then aggregate the job postings by group for each city and each week. We estimate a slightly varied version of Eq. (1), with a dummy variable that indicates whether it is a trade intermediary group and its interactions with the trade and policy variables. The results reported in Table 3 show that both the pandemic and related policies abroad hurt trade intermediaries more than other firms. In Columns (1)(4), we report only the interaction terms between the trade intermediary dummy and other variables. The interaction terms are all negative and significant, meaning that foreign COVID-19 shocks have a larger impact on the labor demand of trade intermediaries than other firms.

We also can examine the impacts of the global supply chain at different times throughout the COVID-19 outbreak. We expect trade intermediaries to be less exposed to COVID-19 than other firms when the pandemic first broke out in China and domestic demand was depressed. When the epicenter moved to the rest of the world and foreign governments started to impose pandemic mitigation policies, however, trade intermediaries in China would be expected to suffer more than do other firms that rely less on the foreign market. To test this, we estimate the change of job postings for both trade intermediary and other firms for each week since the outbreak. The change is relative to the normal level in the previous two years.[15] We plot the implied percentage reduction in job loss for both types of firms in Figure 3.

As we can see from the figure, before the Wuhan lockdown, the labor demands of trade intermediaries and other firms followed parallel trends.[16] At the beginning of the outbreak (Weeks 0 to 2), the number of jobs posted by trade intermediaries fell by a lesser degree than other firms (60% versus 80%). Trade intermediaries, however, underperformed compared to other firms when the virus started to hit the rest of the world; in particular, trade intermediaries missed the large recovery spike of other firms that occurred in Week 9. Overall, job postings by trade

[14] Firms that export directly typically sell both at home and abroad, but exports capture only a small share of total sales. According to Bernard et al. (23), 18% of U.S. manufacturing firms exported in 2002, but exports made up 14% of total sales.

[15] See Eq. S5 in the appendix.

[16] We formally tested the difference between trade intermediaries and other firms by estimating a difference-in-differences model. The coefficients that capture the difference between the two types of firms over time are shown in Figure S2. Instead of looking at the difference week-by-week, we have also done a robustness check which divides the sample into 3 periods: pre-pandemic, epicenter in China, and epicenter outside China; then, we compare the performance of trade intermediaries versus other firms. We also use an alternative method to identify trade intermediaries. Overall, we find similar patterns. The results are in appendix S4.

intermediaries remained 60% lower than pre-pandemic levels, while job postings by other firms gradually outperformed trade intermediaries. To summarize, we present the following fact.

Fact 3: Trade intermediaries, which were more exposed to foreign COVID-19 shocks, outperformed other firms when the epicenter was in China but underperformed as the epicenter moved out of China.

Conclusion

Using big data collected from 100 million posted jobs in China, we empirically demonstrate that the effect of the COVID-19 pandemic can be transmitted along global supply chains. We show that, via the global supply chain, COVID-19 cases abroad and, in particular, pandemic-control policies by foreign governments reduced new job creation in China by 11.0%. We also find that Chinese firms most exposed to international trade outperformed other firms at the beginning of the pandemic but underperformed during the recovery as the novel coronavirus spread throughout the world. Our findings regarding the importance of global supply chains in the transmission of the COVID-19 shock across national borders suggest the importance of global cooperation in the fight against the pandemic and the spread of the novel coronavirus. As long as the pandemic is still raging in some parts of the world, there is a chance for a second or even third wave of infections in some parts of the world. As such, our results suggest that, for the global economy to recover as quickly as possible from the deep pandemic-induced recession, countries need to work together due to the close linkages of global production. Recoveries in other countries will serve as a force that pulls the rest of the world out of the recession, whereas "beggar-thy-neighbor" policies will only prolong the recession.

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Tables

Table 1: Summary Statistics: City Weekly Data

Variable	Definition	Mean	Std. Dev.	Min	Max
jobs	number of jobs	2541.2	19921.8	0	1,347,803
n	number of ads	499.3	2798.3	0	120,562
localCovid	number of confirmed new COVID-19 cases in the local city	1.98	136.2	-32	22,877
domCovid	number of confirmed new COVID-19 cases in other domestic cities weighted by distance	2.38	16.7	-.115	912.9
expCovid	number of confirmed new COVID-19 cases in export destinations weighted by export share	1284. 8	7032.3	-170.6	137,381.2
impCovid	number of confirmed new COVID-19 cases in source countries weighted by import share	1212.8	7934.2	-201.5	220,644
expBorderControl	COVID-19 policy shocks in export destinations weighted by export share	0.29	0.853	0	4
impBorderControl	COVID-19 policy shocks in import source countries weighted by import share	0.28	0.852	0	4
Spring	Spring Festival Dummy	0.025	0.155	0	1
Autumn	Autumn Hiring Season Dummy	0.016	0.127	0	1

Notes. Observations = 40,748. The sample covers 334 cities (including four provincial-level cities: Beijing, Shanghai, Tianjin, and Chongqing) and 122 weeks of data from January 1, 2018, to April 30, 2020. The COVID shocks are measured in terms of the number of new cases for each region and each week. For details concerning the construction of COVID-19 variables, see Appendix S1.1.

Table 2: COVID-19 shocks and local job creation

Dependant variable	ln(number of jobs)			
	(1)	(2)	(3)	(4)
ln(localCovid)	-0.313***	-0.172***	-0.188***	-0.179***
	(0.0392)	(0.0359)	(0.0388)	(0.0367)
ln(domCovid)		-0.142***	-0.203***	-0.175***
		(0.0195)	(0.0217)	(0.0209)
ln(expCovid)			-0.0544***	-0.0110
			(0.0161)	(0.0197)
ln(impCovid)			-0.0290*	-0.00555
			(0.0150)	(0.0175)
expBorderControl				-0.175**
				(0.0676)
impBorderControl				-0.0318
				(0.0316)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.822	0.823	0.824	0.824
No. of observations	40641	40641	40641	40641

Note. The control variables are time dummies that capture major hiring seasons in spring and autumn. The definitions of the variables are shown in Table 1. To address the issue of zeros in the data, we do an $ln(1+x)$ transformation for variables with zeros. The models are estimated using the Stata *reghdfe* package developed by Correia (24). The number of observations is different from those in Table 1 because *reghdfe* drops singletons. The numbers in the parentheses are robust standard errors, clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05, and 0.01, respectively.

Table 3: Foreign COVID shocks: trade intermediaries versus other firms

Dependant variable	ln(number of jobs)			
	(1)	(2)	(3)	(4)
ln(expCovid) × intermediary	-0.0484***			
	(0.00784)			
ln(impCovid) × intermediary		-0.0526***		
		(0.00663)		
expBorderControl × intermediary			-0.0790***	
			(0.0177)	
impBorderControl × intermediary				-0.0923***
				(0.0214)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.839	0.839	0.839	0.839
No. of observations	80628	80628	80628	80628

Notes. This table uses data that aggregate job postings, by trade intermediaries and other firms, for each city and week. The controls include the dummy for trade intermediary, *ln(localCovid)*, *ln(domCovid)*, *ln(expCovid)*, *ln(impCovid)*, *expBorderControl*, *impBorderControl*, dummies for the Spring Festival, and the autumn hiring seasons. Table 1 provides the definition for these variables. To address the issue of zeros in the data, we do an ln(1 + x) transformation for variables with zeros. The models are estimated using the Stata *reghdfe* package developed by Correia (24), which drops singletons during estimation. The numbers in the parentheses are robust standard errors, clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05, and 0.01, respectively.

Figures

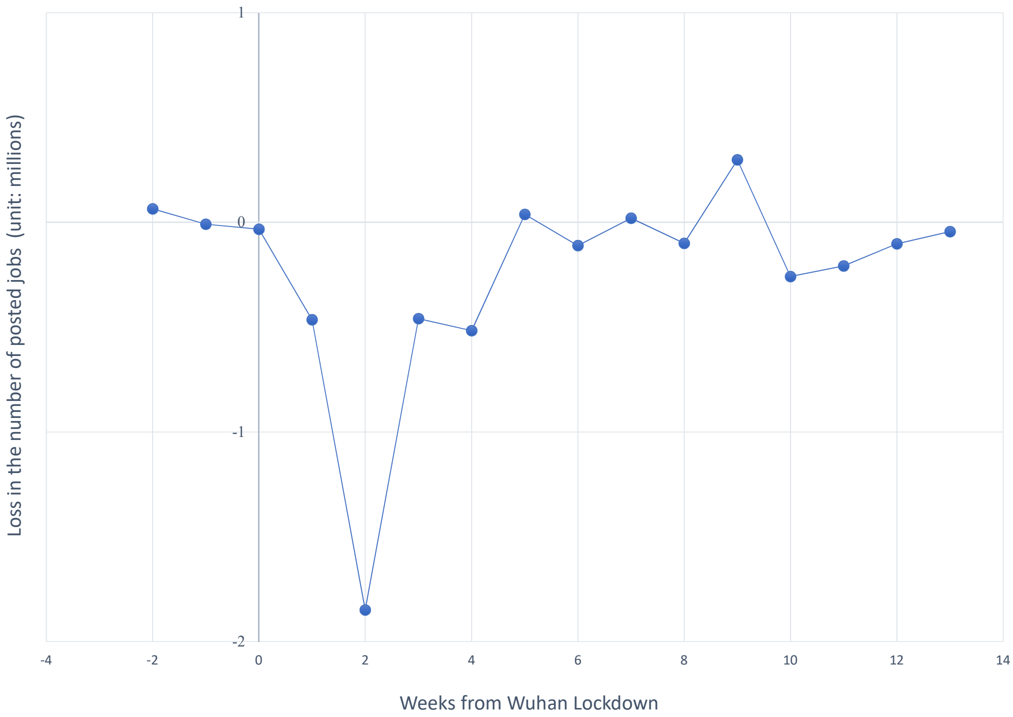


Figure 1: Loss in the number of posted jobs

Notes. This figure is a plot of the weekly loss in the number of posted jobs on the platform during the COVID-19 outbreak in China compared to the average of the years 2018 and 2019. To ensure that the weeks are comparable across years, we align the data to the lunar calendar and set Week 0 of 2018 and 2019 to the week of the Spring Festival. From Weeks 0 to 13, the cumulative job loss was 3.79 million, representing a 31.2% loss in local labor demand.

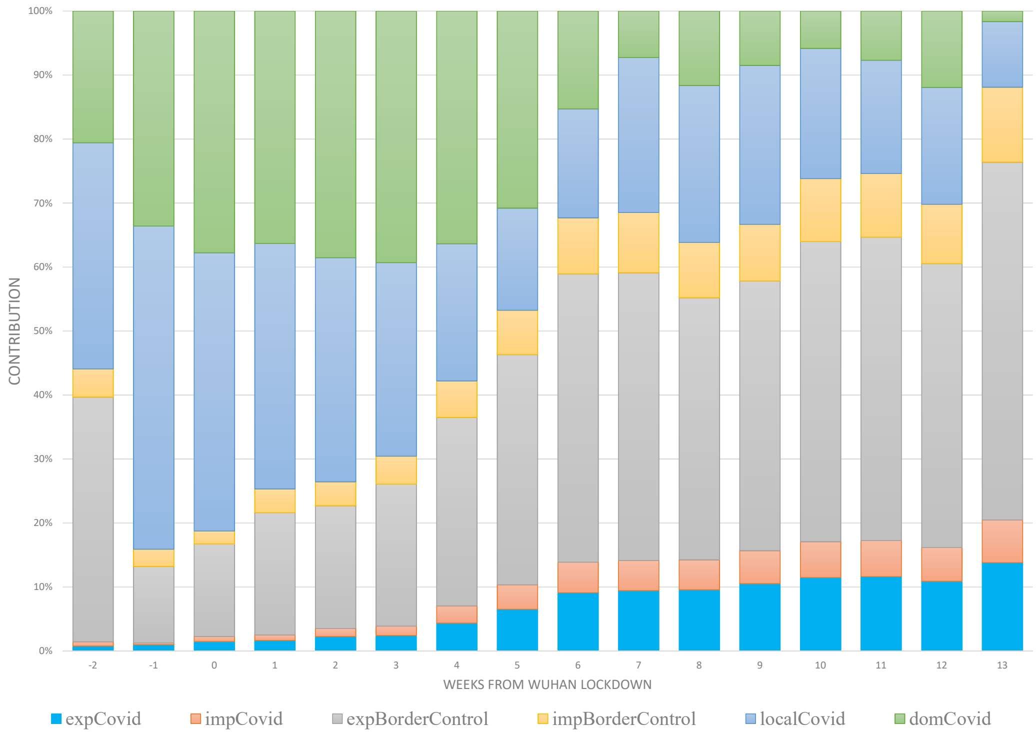


Figure 2: Contribution to reduction in job creation by component

Notes. In this figure, the bars plot the contribution of each shock to the reduction in job creation, according to the estimation result shown in Column (4) of Table 2.We compute the implied reduction in the number of jobs according to the estimated coefficients and the observed shocks. We then compute the share of each shock by dividing the implied reduction in job creation for a shock by the total implied reduction. The definition of each shock is provided in Table 1.

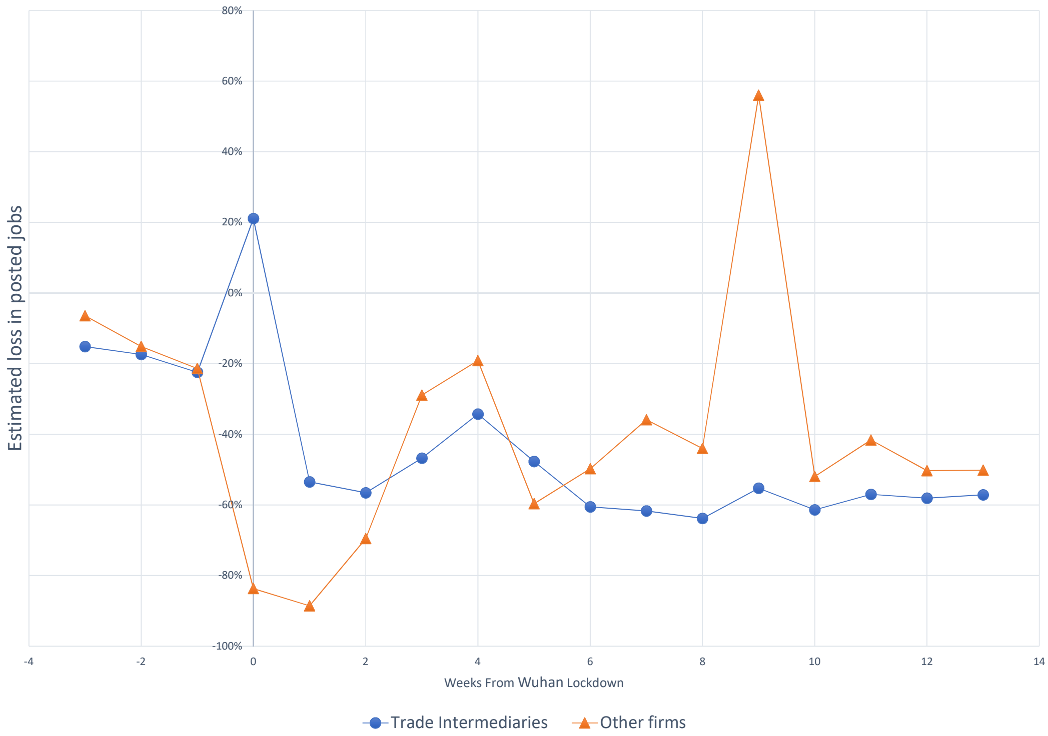


Figure 3: Estimated loss in posted jobs by firm type

Notes. In this figure, we plot the estimated loss in posted jobs for trade intermediaries and other firms using Eq. (S5).

Appendix

S1 Technical Details

S1.1 Measurements

To capture the foreign COVID-19 shocks, we construct the following variables,

$$expCovid_{it} = \sum_j exp_{ij} N_{jt}, \tag{S1}$$

which captures export demand shocks, and

$$impCovid_{it} = \sum_j imp_{ij} N_{jt}, \tag{S2}$$

which captures import supply shocks, where exp_{ij} is the share of city i's exports to foreign region j, imp_{ij} is the share of city i's imports from j, and N_{jt} is the number of newly confirmed cases in region j at period t. Similarly, we measure the exposure of each city to foreign COVID-19 policies using

$$\begin{aligned} expBorderControl_{it} &= \sum_j exp_{ij} BorderControl_{jt}, \\ impBorderControl_{it} &= \sum_j imp_{ij} BorderControl_{jt}. \end{aligned} \tag{S3}$$

where $BorderControl_{jt}$ is the border control policy imposed by region j at period t. To measure the exposure of local labors market to shocks from other domestic cities, we construct the following variable

$$domesticCovid_{it} = \sum_{k \neq i} \frac{1/dist_{ik}}{\sum_{j \neq i} 1/dist_{ij}} N_{kt}, \tag{S4}$$

which weights the exposure of city i to the pandemic in city k in terms of the number of cases N_{kt} by the inverse of the great-circle distance $1/dist_{ik}$. We normalize the weights such that they add up to one.

S1.2 Estimating equation for trading firms and other firms

To compare the impact of the COVID-19 shock on trade intermediaries versus other firms, we split firms in a given city into two groups: trade intermediaries and other firms, and then aggregate the job postings by group for each city and each week. Then we define dummies $Inter_{ikt}$ and $Others_{ikt} = 1 - Inter_{ikt}$ for trade intermediaries and other firms, respectively. We then run the following regression,

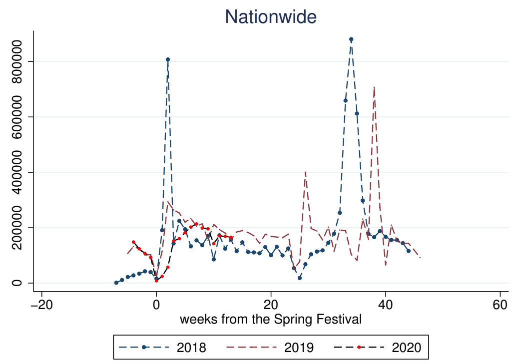
$$\ln(jobs_{ikt}) = \gamma Inter_{ikt} + \sum_{\tau=-m}^{M} \alpha_\tau \cdot Inter_{ikt} \cdot T_{\tau-t} + \sum_{\tau=-m}^{M} \beta_\tau \cdot Others_{ikt} \cdot T_{\tau-t} + \\ + M_t + Spring_t + Autumn_t + CityYear_{it} + \epsilon_{ikt}, \quad \text{(S5)}$$

where $T_{\tau-t}$ is a time dummy which equals one if time t is τ periods away from the Wuhan Lockdown. α_τ and β_τ are the coefficients of interest which capture how job postings by trade intermediaries and other firms evolved before and after the lockdown. To obtain the difference between α_τ and β_τ, we can substitute $Others_{ikt} = 1 - Inter_{ikt}$ into Eq. (S5) and get the following equation

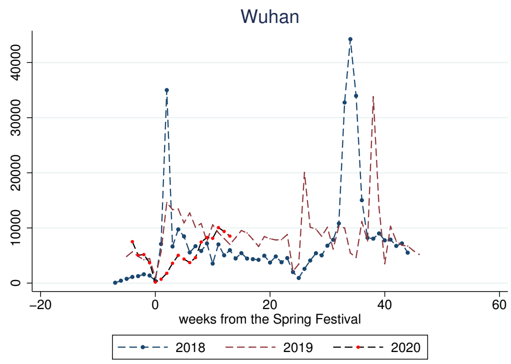
$$\ln(jobs_{ikt}) = \gamma Inter_{ikt} + \sum_{\tau=-m}^{M} \delta_\tau \cdot Inter_{ikt} \cdot T_{\tau-t} + \sum_{\tau=-m}^{M} d_\tau T_{\tau-t} \\ + M_t + Spring_t + Autumn_t + CityYear_{it} + \epsilon_{ikt}, \quad \text{(S6)}$$

where $\delta_\tau = \alpha_\tau - \beta_\tau$. We plot the estimated δ_τ and associated ninety-five percent confidence intervals in Figure S2.

S2 Additional Figures



(a)



(b)

Figure S1: Weekly number of job ads: Nationwide and Wuhan

Notes. The figures plot the number of posted ads. Figure (a) is for the whole nation and figure (b) is for the Wuhan city.

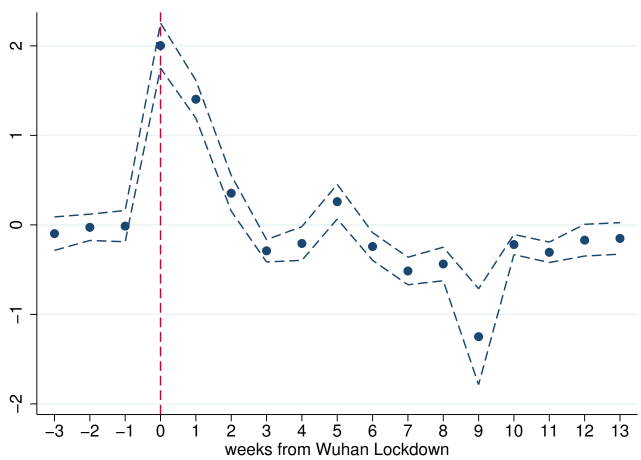


Figure S2: COVID-19 and job creation: trade intermediaries versus other firms

Notes. This figure plots the coefficients of interaction terms between time dummies and a dummy for trade intermediaries from a difference-in-difference estimation using data that aggregate job postings by trade intermediaries and other firms for each city and period. The dash lines represent 95% confidence intervals, which are constructed by clustering standard errors at the provincial level.

S3 Additional Tables

Table S1: COVID-19 and the number of job ads

Dependant variable	ln(number of job ads)			
	(1)	(2)	(3)	(4)
ln(localCovid)	-0.306***	-0.180***	-0.195***	-0.186***
	(0.0351)	(0.0334)	(0.0368)	(0.0340)
ln(domCovid)		-0.127***	-0.191***	-0.162***
		(0.0135)	(0.0153)	(0.0141)
ln(expCovid)			-0.0458***	-0.00120
			(0.00937)	(0.00992)
ln(impCovid)			-0.0407***	-0.0148*
			(0.00858)	(0.00819)
expBorderControl				-0.174***
				(0.0376)
impBorderControl				-0.0440*
				(0.0242)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.882	0.883	0.885	0.885
No. of observations	40641	40641	40641	40641

Notes. The dependant variable is the number of job ads in each city. The control variables are time dummies that capture major hiring seasons in the spring and autumn. To address the issue of zeros in the data, we do an $ln(1 + x)$ transformation for variables with zeros. The models are estimated using the Stata *reghdfe* package developed by (24), which drops singletons during estimation. The numbers in the parentheses are robust standard errors, clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05, and 0.01, respectively.

Table S2: COVID-19 and job creation: robustness check on variables

Dependant variable	ln(number of jobs)			
	(1)	(2)	(3)	(4)
localCovid/population	-1596.9***	825.2	854.8	866.9
	(343.3)	(627.7)	(649.1)	(656.3)
domCovid/population		-42797.6***	-43615.5***	-43894.8***
		(14261.6)	(14767.6)	(14891.6)
ScaledExpCovid/population			-2164.6***	1555.2
			(782.9)	(1299.9)
ScaledImpCovid/population			-2594.8**	926.5
			(1089.9)	(2034.2)
ScaledExpPolicy				-0.0124**
				(0.00542)
ScaledImpPolicy				-0.0106*
				(0.00529)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.827	0.828	0.828	0.828
No. of observations	39567	39567	39567	39567

Notes. In this table, the numbers of newly confirmed COVID-19 cases in domestic cities and foreign regions/countries are normalized by the local population. When considering foreign COVID-19 shocks faced by a Chinese city, we scale the shocks by the city export to GDP ratio and import to GDP ratio (variables with prefix "ScaledExp" and "ScaledImp," respectively). For the policy variables ("ScaledExpPolicy" and "ScaledImpPolicy"), we consider a wider spectrum of policies used by governments to contain the epidemic than border controls. The control variables are time dummies that capture major hiring seasons in spring and autumn. The models are estimated using the Stata *reghdfe* package developed by Correia (24), which drops singletons during the estimation. The numbers in the parentheses are robust standard errors clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05, and 0.01, respectively.

Table S3: COVID-19 and job creation: robustness check on the transformation

Dependant variable	ln(number of jobs)			
	(1)	(2)	(3)	(4)
ln(1-min(localCovid)+ localCovid)	-0.714**	-0.326**	-0.311**	-0.323**
	(0.264)	(0.150)	(0.149)	(0.149)
ln(1-min(domCovid)+domCovid)		-0.194***	-0.285***	-0.218***
		(0.0154)	(0.0207)	(0.0180)
ln(1-min(expCovid)+expCovid)			-0.0908***	-0.00370
			(0.0228)	(0.0225)
ln(1-min(impCovid)+impCovid)			-0.0569**	0.0188
			(0.0221)	(0.0259)
expBorderControl				-0.206***
				(0.0528)
impBorderControl				-0.0646**
				(0.0262)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.821	0.823	0.824	0.824
No. of observations	40710	40710	40710	40710

Notes: Our baseline uses the $\ln(1 + x)$ transformation which drops observations that are negative. In this table, we use a $\ln(1 - (min(x)) + x)$ transformation and include those negative observations. The control variables are time dummies which capture major hiring seasons in spring and autumn. The models are estimated using the Stata *reghdfe* package developed by Correia (24) which drops singletons during estimation. The numbers in the parentheses are robust standard errors clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05 and 0.01, respectively.

S4 Additional results for trading firms

Instead of estimating a dynamic difference-in-difference specification given by Eq. (S6), we estimate the following specification

$$\begin{aligned}\ln(jobs_{ikt}) = \gamma Inter_{ikt} + \alpha_1 T_{1t} + \alpha_2 T_{2t} + \beta_1 Inter_{ikt} \cdot T_{1t} + \beta_2 Inter_{ikt} \cdot T_{2t} \\ + M_t + Spring_t + Autumn_t + CityYear_{it} + \epsilon_{ikt}\end{aligned} \quad \text{(S7)}$$

T_{1t} is a time dummy for periods in which the epicenter was China (from the week of Wuhan lockdown to Week 6), and T_{2t} is a dummy for periods in which the epicenter was outside China (Weeks 7 - 13). The result of the estimation is shown in Table S4. According to Column (1), the number of jobs posted by trade intermediaries is much lower than that of other firms in general. As expected, when the coronavirus hit China, firms reduced their job postings, and as the epicenter moved outside China, there was a slight recovery of job creation. In Column (2), when we introduce the interaction term, we find that trade intermediaries' job postings fell by less than other firms. However, as the epicenter moved outside China, their job postings fell much deeper than other firms. A similar pattern holds for the number of job ads when we look at Columns (3) and (4).

So far, we have defined firms to be trade intermediaries by their names, which might miss other firms which also participate in international trade directly. To deal with such concern, we exploit another a variable in our job posting data which describes the main business of the firm. We look for Chinese characters meaning "import", "export", or "trade". Together with information from the firm name, we enlarge the sample of trade firms to about 10 percent of the population of firms in our data. Using the broader definition of trading firms, we again estimate Eq. (S7). Table S5 presents the estimation results. Overall, we find a pattern similar to the results in Table S4.

Table S4: Job creation by trade intermediaries versus other firms: robustness checks

Dependent Variable:	ln(total number of jobs)		ln(total job ads)	
	(1)	(2)	(3)	(4)
Epicenter in China × intermediary		0.471***		0.494***
		(0.0494)		(0.0380)
Epicenter outside China × intermediary		-0.432***		-0.246***
		(0.0423)		(0.0238)
Intermediary	-3.626***	-3.628***	-2.897***	-2.911***
	(0.171)	(0.171)	(0.148)	(0.147)
Epicenter in China	-0.664***	-0.905***	-0.588***	-0.839***
	(0.0636)	(0.0635)	(0.0458)	(0.0421)
Epicenter outside China	-0.539***	-0.330***	-0.541***	-0.424***
	(0.0729)	(0.0798)	(0.0410)	(0.0355)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.838	0.839	0.868	0.869
No. of observations	80765	80765	80765	80765

Notes. This table uses data that aggregate job postings by trade intermediaries and other firms for each city and period. The control variables are time dummies that capture major hiring seasons in spring and autumn. The models are estimated using the Stata *reghdfe* package developed by Correia (24) which drops singletons during estimation. The numbers in the parentheses are robust standard errors clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05 and 0.01, respectively.

Table S5: Job creation by trade intermediaries versus other firms: robustness checks

Dependent Variable:	ln(total number of jobs)		ln(total job ads)	
	(1)	(2)	(3)	(4)
Epicenter in China × intermediary		0.283***		0.278***
		(0.0437)		(0.0314)
Epicenter outside China × intermediary		-0.268***		-0.178***
		(0.0565)		(0.0210)
Intermediary	-2.958***	-2.964***	-2.373***	-2.383***
	(0.124)	(0.124)	(0.108)	(0.107)
Epicenter in China	-0.620***	-0.762***	-0.551***	-0.690***
	(0.0688)	(0.0591)	(0.0452)	(0.0386)
Epicenter outside China	-0.583***	-0.450***	-0.599***	-0.511***
	(0.0848)	(0.0973)	(0.0498)	(0.0468)
Control Variables	Y	Y	Y	Y
Month Fixed Effect	Y	Y	Y	Y
City × Year Fixed Effect	Y	Y	Y	Y
adjusted R squared	0.831	0.832	0.873	0.873
No. of observations	81272	81272	81272	81272

Notes. This table uses data that aggregate job postings by trade intermediaries and other firms for each city and period. Trade intermediaries are identified using information from the firm name and a variable describing the firm's main business. The control variables are time dummies that capture major hiring seasons in spring and autumn. The models are estimated using the Stata *reghdfe* package developed by Correia (24) which drops singletons during estimation. The numbers in the parentheses are robust standard errors clustered at the provincial level. Significance levels are indicated by *, **, *** at 0.1, 0.05 and 0.01, respectively.