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Diversification, vertical integration and economic resilience: evidence from intercity truck flows during COVID-19 in China

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Abstract

This article examines economic resilience by combining high-frequency truck flows and the lockdown policy shock during COVID-19 in China. We discover that the truck flows in regions with higher levels of diversification and vertical integration see a smaller decrease in response to the COVID-19 shock. Dynamically, such moderating effects of diversification and vertical integration get smaller with the recovery of interregional economic linkages. Diversification and integration also mitigate the negative impact from nonlocal infection cases. The association between the industrial structure attributes and economic resilience is more prominent in regions with lower centrality in the nationwide intercity truck flow network.

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1. Introduction

A region's economic resilience—its resistance to a negative shock and recovery capability—is associated with regional industrial structures (Martin, 2012; Martin et al., 2016; Cainelli et al., 2018; Han and Goetz, 2019). Despite extant conceptual and descriptive studies on this association, causal evidence is still limited. This is potentially because (i) systemic unexpected negative shocks to the economy are rare and (ii) there is a lack of high-frequency data to capture economic dynamics with regional variations around a shock. As a result, evidence on mechanisms through which local industrial structure attributes shape economic resilience is limited due to the lack of empirical context and appropriate data to help identify potential mechanisms.

The COVID-19 pandemic induced an unexpectedly large shock to the economy, which allows us to examine economic resilience to a systemic negative shock. Furthermore, in this article, we exploit novel high-frequency truck flow data from China to estimate the effect of regional industrial diversification and vertical integration on economic resilience to the COVID-19 shock. Such context and data application help us partially overcome the aforementioned limitations. First, the unanticipated COVID-19 outbreak in China allows us to identify the role of pre-determined regional industrial structure attributes in moderating the negative impact of COVID-19. Second, the high-frequency truck flow information helps characterize rich economic dynamics across regions. Third, an important feature that distinguishes the COVID-19 shock from other adverse shocks is China's lockdown policy, which cuts off the linkages among regions. Moreover, the truck flow data provide direct measures of interregional commodity flows and trade networks. Therefore, the features of the COVID-19 shock and our data jointly help us identify the mechanism for diversification and vertical integration to shape economic resilience to a negative shock—higher levels of diversification and vertical integration strengthen a region's economic resistance in the absence of well-functioning interregional trade and personal linkages, through more complete supply chains within the region and lower dependence on external markets.

Our analysis is based on real-time global positioning system (GPS) information of over 1.8 million trucks on a logistic platform during 2018–2020. Truck flows (inflows and outflows) are strongly correlated with economic activities measured by the gross domestic product (GDP) over time and across regions in China, implying that it is appropriate to characterize the dynamics of economic activities during the pandemic. We take prefectures, the second-level sub-national units in China, as baseline geographical units for our analysis and aggregate the high-frequency truck flows at the prefecture level. We also construct pre-determined industrial diversification and vertical integration measures at the prefecture level based on China's population census data in 2010 and mini-census data in 2015. Diversification is measured by the log inverse of the Herfindahl–Hirschman index (HHI); it directly captures the opposite of industrial specialization. Vertical integration is constructed by combining industry shares across prefectures and inter-industry relationships captured by input–output tables; it measures the dependence of industries in a prefecture on *local* suppliers and customers.

We hypothesize that higher levels of industrial diversification and vertical integration within a prefecture would mitigate the negative impact of the COVID-19 shock on the prefectural economy because these regions can keep economic functioning self-contained. A more specialized prefecture relies more on suppliers and customers in other regions; when the interregional linkages are hindered due to the lockdown policy during the pandemic, they tend to have a lower capacity to maintain their economic operations. According to our hypothesis, the effect of diversification and vertical integration on regional resilience is significant only in the absence of well-functioning interregional economic linkages, and it would get smaller with the loosening of lockdown and the recovery of interregional trade and personal linkages.

We conducted two baseline analyses to examine our hypothesis. First, we correlate prefectural quarter-on-year growth in truck flows with diversification and vertical integration. We discover negative correlations between diversification, vertical integration and prefecture-level truck flow changes since the pandemic outbreak early in 2020. This correlation is consistent with the prediction of our hypothesis.

Second, we estimate a triple interaction regression following Dai et al. (2021) to treat the pandemic outbreak as an unexpected exogenous shock and identify the moderating effect of diversification and vertical integration on the negative impact of COVID-19. We find that one standard deviation higher diversification or vertical integration would cancel out the average negative impact of the COVID-19 shock on prefectural truck flows by over 40%. The estimates of a dynamic setting regression show that effects of diversification and vertical integration come into play only after the pandemic outbreak and become smaller over time as interregional linkages recover gradually. The dynamics in the estimated effects provide support to our hypothesized mechanism. The results keep largely unchanged with sample adjustments and alternative measures of industrial structure attributes. Our results remain robust if we include interaction terms between the COVID-19 shock variable and other prefecture-level characteristics. These characteristics include economic development levels, public healthcare conditions and composition of migrants. The robustness helps alleviate the concern that our results are driven by some prefecture-level factors that correlate with diversification and vertical integration.

We further conduct two analyses to extend our baseline results and explore potential mechanisms through the lens of heterogeneity across prefectures. First, we incorporate prefectural COVID-19 infection cases in our analysis. The number of infection cases captures local pandemic severity and determines the strictness of the local lockdown policy. We do not detect any significant correlations between the number of infection cases and the two variables of interest—diversification and vertical integration. We also construct nonlocal infections in other prefectures aggregated using pre-existing inter-prefectural truck flows as weights; we find significant and negative effects of nonlocal infections on local truck flows conditional on local infections. Furthermore, the negative effects of nonlocal infections are significantly mitigated by higher diversification and vertical integration levels. This result indicates the role of interregional linkages. For a given prefecture, a more restrictive lockdown policy in other prefectures due to more infections can hinder connections between firms in this prefecture with their nonlocal suppliers and customers. Such negative impact will be smaller if local firms rely less on nonlocal business relationships.

Second, we estimate our baseline regressions based on subsamples defined according to prefectures' centrality in the pre-existing countrywide truck flow network. We discover that the moderating effect of diversification and vertical integration tends to be larger in prefectures with lower network centrality; and the estimates are smaller and insignificant for prefectures with centrality higher than the 75th percentile. The result is consistent with our hypothesis since the central prefectures are more likely to recover their external linkages rapidly than others due to their critical positions in the countrywide commodity flow network. The result also implies that higher integration into the domestic market, proxied by higher network centrality, can mitigate the potential 'cost' of industrial specialization due to lower resilience to negative shocks.

Our article contributes to the literature in four respects. First, we contribute to studies on determinants of regional economic resilience, particularly the role of industrial structures. Many factors have been documented to associate with regional resilience to negative shocks, such as geographic location, availability of production factors, knowledge and social networks and industrial agglomeration (Martin, 2012; Martin and Sunley, 2015; Hu and Hassink, 2017; Di Caro and Fratesi, 2018; Faggian et al., 2018). In addition, a growing number of studies examine the effect of industrial structures on economic resilience (Bristow and Healy, 2018; Cainelli et al., 2018, 2019; Han and Goetz, 2019). Most of these studies focus on the negative shock of economic recessions and highlight the role of industrial diversity in mediating the negative impact. Unlike recessions, the exogenous COVID-19 shock hindered interregional trade and personal mobility. Recently, some papers have explored economic resilience to COVID-19 from macroeconomic perspectives, such as unemployment, international trade and economic growth (Gong et al.,2020; Jenny, 2020; Diop et al., 2021; Pei et al., 2022). However, only a few studies examine micro-level economic structures in shaping resilience to COVID-19. They demonstrate the effects of local financial structure, clusters and social networks, innovation, openness and local state agency on economic resilience to COVID-19 (Levine et al., 2020; Dai et al., 2021; Hu et al., 2022). We complement these studies by estimating the effects of diversification and vertical integration on resilience to COVID-19 based on high-frequency truck flows across all prefectures in China, exploring rich heterogeneities across space and time and identifying potential influencing mechanisms.

Second, we complement the literature on the impact of COVID-19 and lockdown policies, especially the disruption of supply chains. Social distancing and lockdown policies during the pandemic have been well-documented to have substantial negative effects on both supply and demand sides of an economy (Hsu et al., 2023; Chen et al., 2021). Some studies estimate the economic loss induced by lockdown policies (Allen 2022; Chen et al., 2022). The truck flow information in our study captures the changes in supply chains and production-related economic activities. Our study adds to the discussion on the impact of lockdown policies by exploring heterogeneity in industrial structures across regions and using the lockdown event to identify mechanisms for diversification and vertical integration to shape a region's resilience to the COVID-19 shock. In addition, Bonadio et al. (2021) estimate the economic loss in the pandemic due to the transmission through the global supply chain and further demonstrate that 'renationalization' does not raise an economy's resilience. We complement this discussion by characterizing the dynamics of supply chains across regions within China, a big country with strict nationwide lockdown during COVID-19, and shedding light on the implication of economic resilience from the perspective of regional industrial compositions and inter-industry linkages.

Third, our study enriches the literature on regional industrial structure characteristics, especially the tradeoff between specialization and diversification (Duranton and Puga, 2000). Regional industrial specialization makes the role of regional comparative advantages more significant (Svaleryd and Vlachos, 2005; Rodríguez-Clare, 2007; Pflüger and Tabuchi, 2019; Herzog, 2021); in a country with rich spatial heterogeneity such as China, specialization, industrial clustering and interregional trade is conducive to economic growth (Bai et al., 2004; Guo et al., 2020). At the same time, specialization could also weaken regional economic resilience under a systemic negative shock, which is supported in our article. Furthermore, our study highlights the role of higher network centrality, which makes the tradeoff between specialization and diversification less stringent. We also provide new insights into the benefits from inter-industry agglomeration and integration from the perspective of economic resilience (Jacobs, 1969; Ellison et al., 2010).

Fourth, our article adds to a small and emerging literature on applying high-frequency truck flow data in China. For example, Alder et al. (2021) use the real-time GPS information of trucks to evaluate the efficiency of road infrastructure in China; Chen et al. (2022) exploit truck flow changes during COVID-19 to structurally estimate the economic cost of lockdown in China; Fang and Guo (2022) estimate the effect of toll-free highway policy on economic recovery during COVID-19. Compared with existing studies, this article is the first to integrate truck flows, industrial structures and resilience to COVID-19 in one framework and test the theoretical predictions about industrial structures and economic resilience.

The rest of the article is organized as follows. Section 2 describes the background of COVID-19 and the lockdown policy in China. Section 3 introduces data sources and defines variables. Section 4 presents empirical analyses and results. Section 5 makes further discussions on the empirical results. Section 6 concludes.

2. Background

We now provide some background information on the outbreak of COVID-19 and the lockdown policy in China.

The first coronavirus-infected case was identified in Wuhan, China, in late 2019, and the virus was spread worldwide rapidly (Chen et al., 2020). Following the pandemic outbreak, the outbreak center, Wuhan, was locked down on January 23, 2 days before the Chinese New Year (CNY, also known as Spring Festival). The lockdown significantly reduced personal mobility and intense gathering during the holiday. The lockdown lasted for 76 days and was lifted on April 8. The lockdown in Wuhan confirmed the effectiveness of preventing virus transmission. Thus, many local governments in China imposed a stringent lockdown policy when new infection cases happened.

In the first 1 or 2 months after the pandemic outbreak, not only Wuhan, but also other cities across the country were strictly locked down, especially for cities with positive numbers of infection cases. Intercity personal mobility was highly restricted. Within cities, as long as there was one infection case in a community, the community would be strictly locked down. Residents were usually not allowed to go outside the communities or villages. In April 2020, the countrywide lockdown came to an end, but mobility in cities with infection cases was still restricted. According to the regulation policy issued by the central government, the strictness only depends on local pandemic severity levels (high, medium or low risk) defined by National Health Commission (NHC) based on local infection cases.[1]

The lockdown policy substantially cut off interregional trade linkages (Goolsbee and Syverson, 2021; Maria del Rio-Chanona et al., 2021; Douglas, 2022). According to Fang and Guo (2022), the nationwide lockdown policy from January 23 to April 8 caused a decline in road freight by about 40.42%. However, the decrease in truck flows was underestimated due to the 2-week overlap between the lockdown and CNY. Most business activities are reduced to a maintenance level during the CNY holiday for about 2 weeks until Lantern Festival. For example, the CNY in 2020 started on January 25, and economic activities would usually be restarted after the Lantern Festival on February 8 if there were no COVID-19 outbreak. During the lockdown, only local businesses can maintain a region's supply chain. Furthermore, the impact of lockdown on a regional economy does not disappear immediately with the lifting of lockdown, because restoring the supply chain disrupted by the policy takes some time.

In addition, there were heterogeneities in the degree of economic losses among regions when they suffered from the lockdown policy. For example, both Taiyuan and Xi'an adopted strict lockdown policies in response to the COVID-19 outbreak at the request of China's NHC, and they both experienced a decline in truck flows by about 13% in the first quarter (Q1) of 2020. The two cities have quite similar geography and socioeconomic conditions.[2] However, in the second quarter (Q2) of 2020, the two cities showed a significant gap in the speed of recovery in truck flows. The truck flows in Xi'an in Q2 of 2020 increased by over 25% compared with Q1 of 2020, while this quarterly growth rate was

1 The central government proposed the policy to recover production all over the country roughly 1 month after the pandemic outbreak. It is prohibited for any local government to set barriers to intercity freight and logistics, as claimed in the documents by the State Council (http://www.gov.cn/zhengce/content/2020-03/04/content_5486767.htm).

2 Both cities are provincial capital cities of inland provinces; their per capita GDP levels in 2020 are close (78,734 RMB in Taiyuan and 79,181 RMB in Xi'an).

only 5.1% in Taiyuan. Such variation across regions motivates us to explore potential determinants of resilience to COVID-19 at the regional level.

3. Data

This section describes data sources, defines variables and presents summary statistics.

3.1. Data sources

Our data are mainly from four sources: (i) a truck flow dataset from a logistic platform; (ii) Chinese population censuses; (iii) statistical yearbooks and (iv) NHC of China for the number of COVID-19 cases at the prefecture level.[3] We use the truck flow dataset to construct the measures of interregional commodity flows and examine the dynamics of regional economic activities and interregional trade. We then construct the regional (prefectural and provincial) measures of industrial structure attributes based on the employment across regions and industries recorded in the population censuses. We also use statistical yearbooks to generate variables of prefectural characteristics.

3.1.1. Truck flow dataset

We use truck flow data from one of China's leading logistic service companies. The company provides a platform to track real-time GPS information of over 1.8 million trucks, accounting for about 20% of the total long-haul trucks in China. The truck is the primary mode of domestic freight transportation in China (Alder et al., 2021).[4] We use the interprefectural truck flows to capture commodity flows between prefectures, following the practice of existing studies (Alder et al., 2021; Chen et al., 2022; Fang and Guo, 2022).[5]

3.1.2. Population censuses

We use 0.35% random sample of population census 2010 and 15% of mini-census 2015.[6] Collected and maintained by the National Bureau of Statistics in China, the data are nationally representative. For each individual employed at the survey time, the (mini-)censuses record his/her work industry (3-digit code by China Industrial Classification) and the current prefecture of residence. We use this information to construct measures of prefectural industrial structures. In addition, individuals' *hukou* and migration status are also recorded.[7]

3 The administrative divisions of China contain three levels: province, prefecture and county. The primary geographical unit in our analysis is prefectures, which we sometimes also refer to as 'cities'. Four municipalities—Beijing, Tianjin, Shanghai and Chongqing, are directly under the administration of the central government and have the same political and economic rights as a province. Each province includes a prefecture as its provincial capital city.

4 In 2019, road freight accounted for 73% of the total freight in China, according to official statistics.

5 The platform coverage experienced rapid growth before 2017 and has been stable since 2018; we mainly focus on the data from 2018 to 2020.

6 Since 1990, China has conducted a population census every 10 years, and an inter-census population survey in the middle year between two censuses, with a sampling fraction of 1% (also called 'mini-census').

7 Hukou is a system of household registration in China. Based on their registered place of residence, each Chinese citizen holds either a rural or urban *hukou*. A person's hukou is assigned according to his parents' registration status, and changes in *hukou* are rare.

3.1.3. Statistical yearbooks

We collect data on socioeconomic characteristics at the prefecture level from *China City Statistical Yearbook* (2018, 2019).

3.1.4. COVID-19 case data

We collect data from China NHC for daily new infection cases of COVID-19 at the prefecture level in 2020.

3.2. Variables

We now define major variables for our empirical analysis: intercity truck flows, industrial structure attributes (diversification and vertical integration), infection cases and network centrality. Other variables used in our empirical analysis are defined in Sections 4 and 5. Table 1 presents summary statistics for the variables.

3.2.1. Intercity truck flows

We aggregate the truck flows from origin to destination prefectures by month based on the real-time GPS information of 1.8 million trucks on the platform, then get the monthly number of truck flows from one prefecture to another. Based on the bilateral truck flows, we calculate prefecture-level total inflows and outflows by month as the main dependent variable for our analysis. The thematic map in Figure 1 displays that the number of truck flows (inflows plus outflows) during 2018–2019 varied substantially across prefectures. The truck flows were concentrated in coastal prefectures with higher population density and larger economic sizes than other regions. The truck flows were also high in some inland provincial capital prefectures that serve as regional logistic hubs of domestic road freight.

Figure 2 shows high correlations between truck flows and GDP across time and space. During 2018–2020, the quarterly growth rates of the countrywide GDP and aggregate truck flows were quite similar and shared a primarily parallel trend over time in Figure 2(a).[8] Cross-sectionally, the number of prefecture-level truck flows strongly correlated with prefectural GDP in 2018 (Figure 2(b), correlation = 0.86).

We provide further evidence in our Supplementary Appendix to support the ability of the truck flow data to track economic fluctuations. First, in Supplementary Appendix Table A1, we find that the quarter-on-year growth rate of truck flows strongly correlated with GDP growth at the province level during 2018–2020. Second, we correlate the month-on-year growth of truck flows with that of electricity consumption and industrial value added at the province level for the same period, and also find strong positive correlations, as shown in Supplementary Appendix Table A2.[9]

3.2.2. Industrial structure attributes

We construct measures of prefecture-level industrial structure attributes based on the population census 2010. We use two measures for our baseline analysis. We also construct some other

8 During the first two quarters of 2020 (just after the outbreak of COVID-19 in China), truck flows saw larger volatility than GDP. This is possibly because the truck flows mainly capture economic activities in tradable sectors, which tend to be more vulnerable to the lockdown during COVID-19.

9 The correlational results are very similar if we use quarter-on-quarter or month-on-month growth rates.

Table 1. Summary statistics for main variables

Variable	Observations	Mean	Std. dev.	Min	Max
A. Prefecture-month-level variables					
Truck flows	7370	5387.77	10,515.98	0	83,840
Truck inflows	7370	2693.64	5251.57	0	41,777
Truck outflows	7370	2694.13	5264.78	0	42,063
Local infections	2010	41.90	1056.59	0	47,016
Nonlocal infections	2010	187.95	820.86	0	25,166
B. Prefecture-level variables					
Diversification	335	0.00	1.00	−5.16	2.33
Vertical integration	335	0.00	1.00	−3.97	1.97
Network centrality	335	3.31	2.11	1.04	11.42

Notes: The variables are defined in Section 3.2. Truck flows are the sum of inflows and outflows. Diversification and vertical integration are standardized across prefectures with a mean of 0 and a standard deviation of 1. The variables of local and nonlocal infections are summarized for the time period since January 2020.

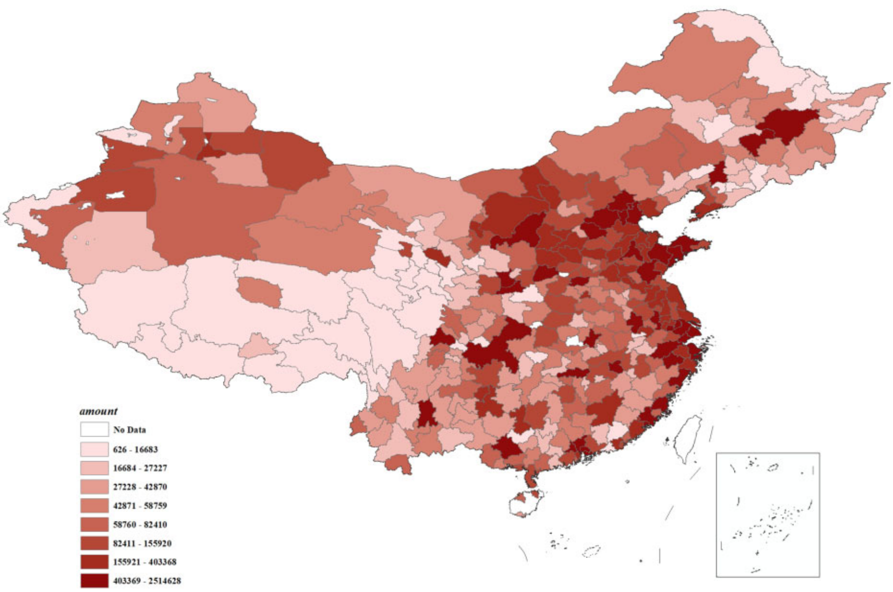

Figure 1. Prefecture-level total truck flows during 2018-2019.

measures for robustness checks (Supplementary Appendix B). We focus on manufacturing sectors and use three-digit Chinese Industry Classification codes to classify industries.[10] There are 169 manufacturing industries in the sample. The two measures are defined as follows:

10 As a robustness check, we measure industrial structure attributes based on all sectors rather than only manufacturing sectors. We discuss the results in Section 4.

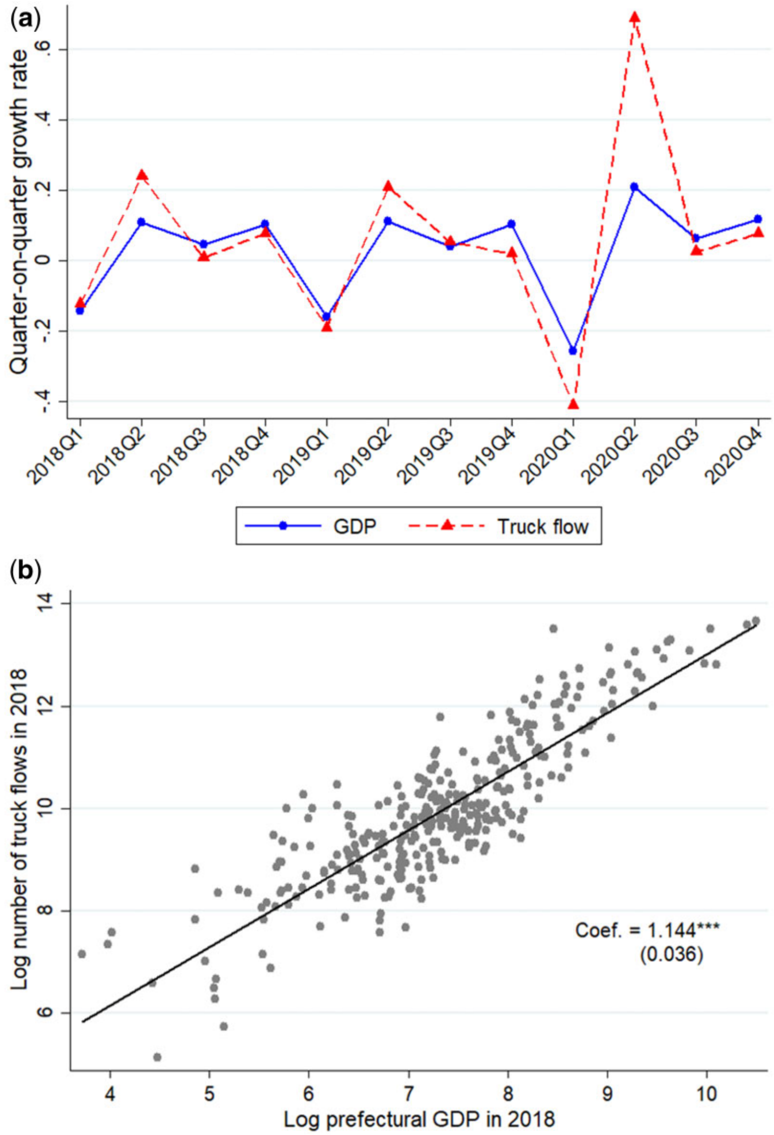

Figure 2. Comparisons between truck flows and GDP. (a) Quarterly growth rates (b) Prefecture-level Correlation in 2018.

1. *Diversification*. We measure the diversification of the industrial structure in a prefecture using the log inverse of the HHI. HHI is a widely recognized measure of the industrial structure in a region (Duranton and Puga, 2000; Palan, 2010; Fu and Hong, 2011; Tanaka and Hashiguchi, 2020), which is defined as the sum of squared shares of each industry, that is, $\sum_i \text{share}_{ic}^2$, where share_{ic} is the employment share of industry i in manufacturing sectors in city c, subject to $\sum_i \text{share}_{ic} \equiv 1$ for any c. We define diversification as $\log\left(\frac{1}{\sum_i \text{share}_{ic}^2}\right)$, that is, the reverse of specialization.

2. *Vertical Integration*. We measure industries' vertical integration in a prefecture by combining prefectural industry shares and inter-industry input–output linkages. A prefecture's industrial structure exhibits a higher level of vertical integration if industries in the prefecture have a higher level of dependence on *local* suppliers and customers. We define prefectural vertical integration as follows: First, for industry i in prefecture c, its integration with vertically related industries is defined as $Upstream_{ic} = \sum_j w_{i\leftarrow j} \times \frac{E_{jc}}{E_j}$ and $Downstream_{ic} = \sum_j w_{i\rightarrow j} \times \frac{E_{jc}}{E_j}$, where E_{jc} denotes the employment in industry j in prefecture c, and E_j is the total employment in industry j in China, thus $\frac{E_{jc}}{E_j}$ measures the employment share of prefecture c in industry j; $w_{i\leftarrow j}$ and $w_{i\rightarrow j}$ are weights constructed based on the input–output table published by National Bureau of Statistics in China in 2012.[11] Then, we calculate two measures of upstream integration ($Upstream_c$) and downstream integration ($Downstream_c$) for prefecture c. We aggregate the prefecture-by-industry level measures at the prefecture level using industrial employment shares as weights, that is, $Upstream_c = \log(\sum_c share_{ic} \times Upstream_{ic})$ and $Downstream_c = \log(\sum_c share_{ic} \times Downstream_{ic})$.[12] Finally, we use the maximum between the $Upstream_c$ and $Downstream_c$ to reflect the level of industrial integration at the prefecture level, that is, $Integration_c = \max\{Upstream_c, Downstream_c\}$. Taking the maximum induces negligible loss of information because the two variables $Upstream_c$ and $Downstream_c$ are strongly correlated (correlation = 0.99).[13]

Our vertical integration measure is similar to the industrial cluster index constructed by Ruan and Zhang (2015) and used in Dai et al. (2021). Similar to their index, our measure is also based on shares of regions (prefectures) in an industry in the country. The key difference is that they use the inter-industry proximity based on revealed comparative advantages (RCAs) to capture inter-industry integration, and we use the weights from input–output tables to capture inter-industry vertical linkages. The aggregation method using input–output weights is commonly used in the literature to capture vertical agglomeration and spillover effects (Javorcik, 2004; Greenstone et al., 2010).

Supplementary Appendix Figure A2 in Supplementary Appendix presents the spatial pattern of the two measures at the prefecture level using thematic maps. There are significant variations across prefectures. The levels of diversification and vertical integration tend to be higher in coastal regions and in provincial capital cities. Supplementary Appendix Table A3 presents the highest and the lowest five prefectures and the prefecture with the median value of the index for each of the two measures.

The spatial patterns of the industrial structure attribute measures keep stable over time. To show this, we construct the measures using the same methods based on the mini-census 2015. For each of the two measures, we find strong correlations between the variable measured in 2010 and that in 2015 (Supplementary Appendix Figure A3), which is

11 The weight $w_{i\leftarrow j}$ is the share of industry j in the intermediate inputs for production in industry i, where $\sum_j w_{i\leftarrow j} \equiv 1$ for any i; the weight $w_{i\rightarrow j}$ is the share of industry j among all industries using industry i's output as intermediate inputs, where $\sum_j w_{j\leftarrow i} \equiv 1$ for any i.

12 We take logarithms for the two variables to make their distributions more similar to normal distributions.

13 We also use the two variables, $Upstream_c$ and $Downstream_c$, separately in our analysis and the results remain robust, as discussed in Section 4.2.

consistent with the existing literature (Duranton and Puga, 2000). We use the measures in 2015 as a robustness check in our analysis in Section 4.2.

3.2.3. Infection cases

We construct two variables on the number of COVID-19 infection cases at the prefecture-level by month. The data are from prefecture-level numbers of daily newly reported infection cases publicly disclosed by China NHC.

1. *Local infections*. We aggregate the number of new infection cases to prefecture-by-month level since January 2020.
2. *Nonlocal infections*. Given the network structure of intercity truck flows, more strict regulations in one prefecture induced by more local infections can affect other prefectures linked with it by the truck flow network (Chen et al., 2022). To incorporate this spatial spillover effect, we construct the variable of nonlocal infections as the weighted average of infections in other cities using shares of intercity truck flows before COVID-19 as weights. Formally, we define nonlocal infections as

$$\text{Infections}_{ctm}^{\text{nonlocal}} = \sum_{c' \neq c} w_{cc'} \times \text{Infections}_{c'tm}^{\text{local}}$$

where $\text{Infections}_{c'tm}^{\text{local}}$ denote monthly local infections in prefecture c'; the weight $w_{cc'}$ is defined as $w_{cc'} \equiv \frac{X_{c'c}+X_{cc'}}{\sum_{d \neq c}(X_{dc}+X_{cd})}$; $X_{c'c}$ is the total number of truck flows from prefecture c' to prefecture c during 2018–2019, that is, the two years before the pandemic outbreak.

3.2.4. Network centrality

To explore the heterogeneous effects of diversification and vertical integration, we define a prefecture's trade network centrality—a measure of its position in the inter-prefectural truck flow network. We base our calculation on the truck flows during 2018–2019, that is, before the pandemic outbreak. Following the literature (Katz, 1953; Bonacich and Lloyd, 2001; Richmond, 2019), we define the network centrality in prefecture i as the ith component of the vector derived from a matrix on the basis of bilateral truck flows between prefectures:

$$v_i = \left[(\boldsymbol{I} - W')^{-1} \mathbf{1} \right]_i,$$

where $\boldsymbol{I}$ is an identity matrix and $\mathbf{1}$ is a vector of ones; $W = [w_{ij}]$ is an $n \times n$ matrix (n is the number of prefectures in our sample, that is, $n = 335$) calculated based on numbers of truck flows between prefectures, where i and j denote prefectures and $w_{ij} = w_{ji} = \frac{X_{ij}+X_{ji}}{Y_i+Y_j}$; X_{ij} denotes truck flows from prefecture i to prefecture j during 2018–2019; $Y_i \equiv \sum_j X_{ij}$ represents total truck outflows for prefecture i. A higher value of v_i represents a more central position for prefecture i in the inter-prefectural truck flow network. Supplementary Appendix Figure A4 presents the spatial pattern of the network centrality variable by prefecture using a thematic map. The variable has substantial variations across space and tends to be higher for coastal prefectures, which echoes the spatial pattern of truck flows shown in Figure 1.

4. Effects of industrial structure attributes on economic resilience to COVID-19

We now examine how diversification and vertical integration shape prefectural economic resilience to the COVID-19 shock through the lens of truck flows. We first describe truck flow dynamics around the pandemic outbreak and correlate them with prefectural industrial structure attributes. We then use a triple-interaction regression to estimate the moderating effects of diversification and vertical integration on the impact of COVID-19 based on prefecture-by-month-level truck flows. Finally, we study the dynamics of the moderating effects.

4.1. Descriptive and correlational analysis

In this section, we describe the dynamics of truck flows around the outbreak of COVID-19 and correlate changes in truck flows with measures of diversification and specialization at the prefecture level.

As discussed in Section 3.2, the truck flow data can primarily capture variations in economic activities across space and time. We show that it also captured the economic dynamics during COVID-19. Figure 3 plots the monthly truck flows before and after the Chinese New Year (Spring Festival) in 2019 and 2020. We have three observations from Figure 3. First, the trends in truck flows were roughly parallel before the CNY, that is, before the lockdown in Wuhan (as discussed in Section 2), for 2019 and 2020. Second, for both 2 years, truck flows became lower during the CNY month. This reflects that CNY plays a significant role in economic cycles within a year; production and investments during the CNY month tend to be lower than in other months.[14] Third, truck flows exhibited different dynamic patterns after the CNY month for the 2 years. In 2019, truck flows went back to the normal level right after the CNY month; in 2020, however, there was a further drop in truck flows in the month after CNY, that reflected the impact of the lockdown policy which was implemented in the CNY month and kept strict in the month after CNY. The lockdown regulation was loosened in the second month, March 2020, after the pandemic outbreak and entirely lifted in April 2020, when the truck flows went back to the level before the COVID-19 outbreak, reflecting the rapid recovery of production and interregional economic linkages.

We then examine associations of truck flow changes with industrial structure attributes, diversification and vertical integration, at the prefecture level. Figure 4 plots the coefficients (with 95% confidence intervals) from univariate regressions of the differences in log number of truck flows over time on prefectural diversification and vertical integration, respectively. The dependent variable is the difference in truck flows between 2019 and 2018 in Panel A, between the first quarter in 2020 and the first quarter in 2019 in Panel B, and between the second quarter in 2020 and the second quarter in 2019 in Panel C.

14 The celebration of CNY persists for over half a month. During the CNY, migrant workers, who account for a large share of manufacturing workers in China, would return to their hometowns to celebrate the CNY with their families.

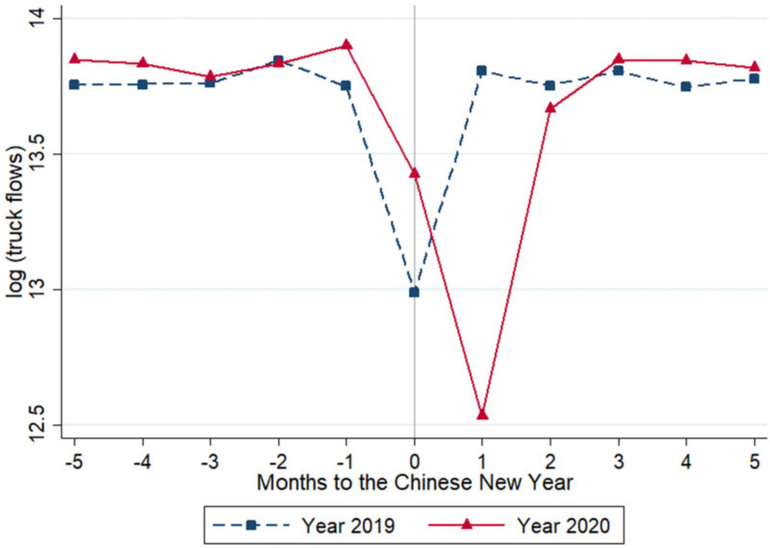

Figure 3. Truck flows before and after Chinese New Year, 2019 and 2020.

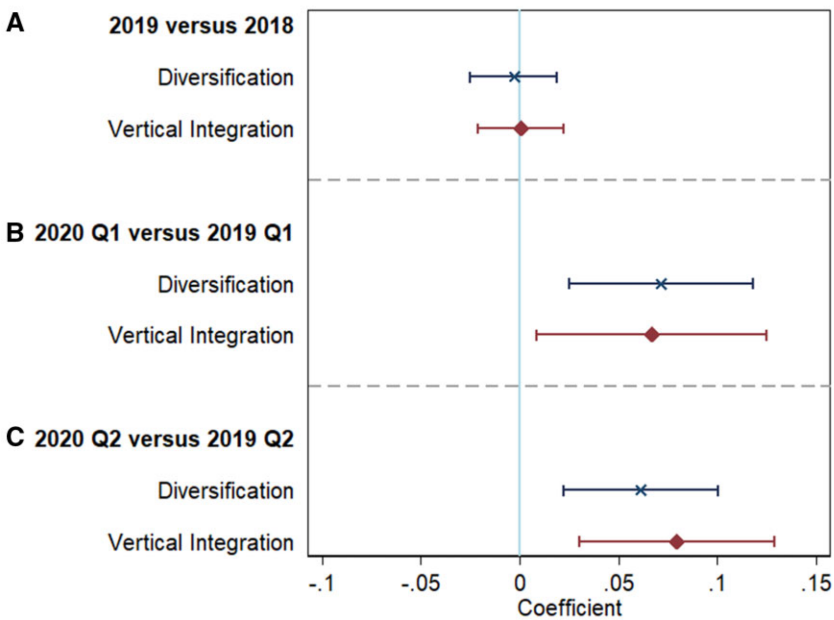

Figure 4. Correlations between industrial structure attributes and growth in truck flows at the prefecture level.

The explanatory variables, prefectural diversification and vertical integration, are standardized across prefectures with a mean of 0 and a standard deviation of 1.

We have three findings from Figure 4. First, before the pandemic outbreak, the correlation between industrial structure attributes and prefecture-level truck flow growth during 2018–2019 is small and insignificant (Panel A). Second, after the outbreak of COVID-19 and the implementation of the lockdown policy, we find positive correlations between quarter-on-year truck flow growth and diversification, as well as vertical integration (Panels B and C). This indicates that prefectures with higher levels of diversification and vertical integration tend to have smaller decreases in truck flows during COVID-19. Third, the magnitudes of the regression coefficients in panel C are similar to those in panel B. The results indicate that diversification and vertical integration play a significant role in the resistance to the lockdown shock and the economic recovery after the lockdown, given that the lockdown policy was lifted on 8 April 2020.

4.2. Triple interaction regression

We now examine the role of diversification and vertical integration in shaping economic resilience to COVID-19 using a more rigorous specification (Dai et al., 2021). We estimate the following triple interaction regression:

$$\log(\text{Truckflow}_{ctm}+1) = \alpha \times D_{2020,t} \times \text{After}_m \times \text{Structure}_c + \beta \times D_{2020,t} \times \text{After}_m + \eta_{ct} + \delta_{cm} + \epsilon_{ctm}, \tag{1}$$

where c, t and m denote prefectures, years and months in a year, respectively. The variable Truckflow_{ctm} is the number of truck flows (inflows plus outflows) in prefecture c in month m of year t. $D_{2020,t}$ is a dummy indicating the year 2020. After_m is a dummy variable that takes 1 for the CNY month and months after CNY each year, and takes 0 for months before CNY. Structure_c is the standardized measures of industrial structure attributes, diversification and vertical integration, in prefecture c. η_{ct} denotes prefecture-by-year dummies; δ_{cm} denotes prefecture-by-month dummies. ϵ_{ctm} is the error term. Standard errors are clustered at the prefecture level. The time window of the analysis is 5 months before and after the CNY month each year, that is, the range of m is $[-5, 5]$ and the variable After_m takes 1 for $m \in [0, 5]$. In our analysis, we use a panel of 335 prefectures and 22 months, that is, 11 months around the 2019 CNY and 2020 CNY, respectively.[15] For the dependent variable, as there are some zero values (about 7% prefecture-month observations) in Truckflow_{ctm}, we use the transformation of $\log(1+Y)$ for the dependent variable (Y is Truckflow_{ctm}).

According to Bellégo et al. (2022), this transformation of $\log(1+Y)$ would, in general, lead to biased estimates under reasonable assumptions. Therefore, we conduct two sensitivity analyses. First, we try different transformations of the truck flow variable (Y), including $\log(0.25+Y)$, $\log(0.5+Y)$, $\log(2+Y)$ and $\log(Y+\sqrt{1+Y^2})$, and estimate our baseline regression with these dependent variables (Bellégo and Drouard, 2019). Second, we follow Bellégo et al. (2022) and use the iterated OLS method to deal with zero values in log-linear regressions. We report the results of the two analyses in Supplementary

15 The CNY month is February in 2019 and January in 2020. Thus, the 22 months used in our sample are September 2018 to July 2019 (around the 2019 CNY), and August 2019 to June 2020 (around the 2020 CNY).

Table 2. Estimates of moderating effects of diversification and vertical integration on the impact of COVID-19

	Dependent variable: $\log(\text{Truckflow}_{ctm}+1)$				
	(1)	(2)	(3)	(4)	(5)
$D_{2020,t} \times \text{After}_m$	-0.195^{***}	-0.195^{***}	-0.195^{***}		
	(0.015)	(0.014)	(0.014)		
$D_{2020,t} \times \text{After}_m \times \text{Diversification}_c$		0.084^{***}		0.084^{***}	
		(0.021)		(0.021)	
$D_{2020,t} \times \text{After}_m \times \text{Vertical Integration}_c$			0.083^{***}		0.083^{***}
			(0.023)		(0.023)
Prefecture-by-year fixed effects	Yes	Yes	Yes	Yes	Yes
Prefecture-by-month fixed effects	Yes	Yes	Yes	Yes	Yes
Year-by-month fixed effects	No	No	No	Yes	Yes
Observations	7370	7370	7370	7370	7370
R-squared	0.974	0.975	0.975	0.993	0.993

Notes: The table presents estimates of Equation (1). Diversification and vertical integration are standardized across prefectures with a mean of 0 and a standard deviation of 1. Standard errors are clustered at the prefecture level. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Appendix Tables A4 and A5, respectively. Although there are slight changes in coefficient sizes across different dependent variable definitions or regression methods, the estimates are primarily similar to our baseline estimates (Table 2) in terms of coefficient signs and levels of significance. This lends support to the robustness of our baseline results.

Because the pandemic occurred in the month of CNY in 2020, and within-year economic cycles without the pandemic saw a lower intensity of economic activities in the CNY month (usually January or February), we choose the month of CNY as the cutoff. In Equation (1), β captures the effect of the COVID-19 shock on truck flows, where the months around 2019 CNY are the 'control' group and those around 2020 CNY are the 'treated' for the prefecture with a level of diversification or vertical integration equal to countrywide mean ($\text{Structure}_c = 0$). We aim to estimate α, which captures the moderating effect of Structure_c on the impact of COVID-19 and thus indicates the association of industrial structure attributes with economic resilience.

To interpret the estimated α as the causal effect of diversification and vertical integration on the impact of the COVID-19 shock, we assume that without the pandemic outbreak, the trends of month-on-year growth rates of truck flows should be parallel across prefectures with different levels of diversification and vertical integration. We validate the assumption by showing no pre-trends in the dynamic specification in Section 4.3. Another risk of identification is that the variables being considered—diversification and vertical integration—might correlate with other factors which themselves could affect the impact of the COVID-19 shock. To deal with this, we estimate an expanded specification with additional prefecture-level controls interacted with the time variables of interest ($D_{2020,t} \times After_m$).

Table 2 presents the estimates of Equation (1). Column (1) does not include the triple interaction term; Columns (2) and (3) contain triple interactions with diversification and vertical integration, respectively. On average, the COVID-19 shock decreased truck flows by 0.195 log points (about 17.7%). One standard deviation higher diversification and vertical integration would cancel out this negative effect by 0.084 log points and 0.083 log points (43.1% and 42.6%), respectively. The results remain unchanged in a more restrictive specification where we further control for year-by-month fixed effects which absorb the variable $D_{2020,t} \times \text{After}_m$ (Columns (4) and (5)).

Moreover, when we simultaneously include the interaction terms with the two variables, diversification and vertical integration, in one regression, the estimated coefficients for the two interaction terms both keep positive and statistically significant, and the coefficients become smaller, as shown in Supplementary Appendix Table A6. This indicates that neither of the two can dominate the other variable in terms of the moderating effect on the impact of the COVID-19 shock.

The result remains robust across five sensitivity analyses. First, we use measures of diversification and vertical integration constructed based on mini-census 2015 instead of those based on census 2010. The result remains consistent (Supplementary Appendix Table A7).

Second, we use alternative measures of diversification and vertical integration, which capture similar information as the two measures used for our baseline analysis. For diversification, we use three alternative measures: (i) one minus the largest industry share (Duranton and Puga, 2000); (ii) two minus Krugman-type specialization index (Krugman, 1991; Crescenzi et al., 2007; Rupasingha and Marré, 2020) and (iii) the Shannon Entropy Index (SEI) (Aiginger and Pfaffermayr, 2004; Basile et al., 2017). Measures (i) and (ii) capture the opposite of diversification—specialization. We present details for construction of the measures in Supplementary Appendix B. We choose three alternative measures for vertical integration: Upstream_c, Downstream_c and a vertical integration index constructed using the same method but taking provinces instead of prefectures as the geographical units. Equation (1) estimates with the alternative measures are consistent with our hypothesis (Supplementary Appendix Table A8).

Third, we estimate Equation (1) based on different subsamples to show that the baseline estimates in Table 2 are not driven by some special subsamples (Supplementary Appendix Table A9). We define subsamples in multiple ways: (i) We exclude the five prefectures with the highest and the lowest values for each industrial structure measure; (ii) we exclude prefectures in Hubei province, which is the center of the pandemic outbreak; (iii) we exclude Xinjiang and Tibet, where economic activities are much more scarcely distributed than other provinces and (iv) we restrict the time window to 3 months instead of 5 months before and after the CNY, that is, the range of m becomes $[-3,3]$ in Equation (1).

Fourth, we add controls of interactions of $D_{2020,t} \times \text{After}_m$ and other prefecture-level covariates to address the potential concern that other prefectural characteristics instead of diversification and vertical integration drive our estimates. Prefecture-level covariates to be interacted with $D_{2020,t} \times \text{After}_m$ include (i) log GDP, (ii) log GDP per capita, (iii) health system capacity measured by log number of hospital beds per capita,[16] (iv) public finance capacity proxied by log government expenditure per capita, (v) transportation infrastructure proxied by log area of paved roads per capita, (vi) the share of migrants in local residents, (vii) the share of Wuhan-origin residents,[17] (viii) economic structure measured by

16 The health system capacity is associated with a prefecture's capability to deal with the pandemic shock (Li et al., 2021). The result remains robust if we use prefecture-level number of hospital employees over population.

17 The variables (vi) and (vii) are calculated based on the mini-census 2015, which records people's migrant status and the origin prefectures of migrants (Li et al., 2021).

shares of primary and secondary industries and (ix) prefectural administrative level measured by indicators for provincial capitals and municipalities. We find the estimates of α in Equation (1) keep primarily unchanged in terms of signs and significance levels (Supplementary Appendix Table A10), indicating that the estimated moderating effects of diversification and vertical integration are less likely to be confounded by other prefecture-level characteristics.

Fifth, related to our article, Dai et al. (2021) find that the counties with a higher level of industrial clustering tend to have higher resilience to COVID-19, reflected by the number of new firms, using an index for industrial clusters constructed based on RCA. As a comparison, we follow their method to construct the RCA-based industrial cluster index at the prefecture level, with details for construction reported in Supplementary Appendix B. The RCA-based industrial cluster index positively correlates with our measures of diversification and vertical integration (with correlation coefficients of 0.42 and 0.86, respectively). We estimate Equation (1) with the RCA-based cluster index and report the results in Supplementary Appendix Table A11. Using prefectural truck flows as the dependent variable, we find significantly positive moderating effects of the cluster index, indicating higher cluster index is associated with higher resilience. In addition, the magnitude of the estimated coefficient α (0.038) is less than half of those for diversification and vertical integration (0.084 and 0.083).[18]

4.3. Dynamic effects

We now estimate the dynamic effects of diversification and vertical integration on the impact of the COVID-19 shock. We estimate the following equation:

$$\log(\text{Truckflow}_{ctm} + 1) = \sum\nolimits_{m \neq -1} \alpha_m \times D_{2020,t} \times D_m \times \text{Structure}_c + \eta_{ct} + \delta_{cm} + \psi_{tm} + \epsilon_{ctm}, \tag{2}$$

where D_m denotes the dummy of month m (relative to the CNY month, $m \in [-5, 5]$), ψ_{tm} denotes year-by-month fixed effects. All other notations have the same meanings as in Equation (1). We aim to estimate coefficients α_m, which capture the moderating effect of diversification and vertical integration (Structure_c) on the magnitude of the Covid-19 shock in month m. The month before the CNY month is taken as the omitted group ($m = -1$). Standard errors are clustered at the prefecture level.[19]

Figure 5 reports the estimates for Equation (2), with results for diversification in panel (a) and those for vertical integration in panel (b). We have two main findings in Figure 5. First, before the pandemic outbreak, that is, for months of $m < 0$, estimated effects of diversification and vertical integration were small and insignificant. The result indicates that the prefecture-level month-on-year truck flow growth rates without the pandemic are not associated with diversification or vertical integration, consistent with the correlational

18 The smaller magnitude is possible because the RCA cluster index in Dai et al. (2021) captures the level of industrial clustering better at the county level than the prefecture level. Our estimate with this index constructed at the prefecture level is thus subject to potential downward bias due to measurement error.

19 In Equation (5), we adopt a more rigorous specification with the year-by-month fixed effects (ψ_{tm}), which practice is consistent with that in Dai et al. (2021). The year-by-month fixed effects absorb the interactive effects between the indicator for 2020 and month dummies, that is, the dynamic version of β in Equation (1). The estimates for α_m keep largely unchanged if we do not include ψ_{tm}, and instead control for interactions between $D_{2020,t}$ and month dummies.

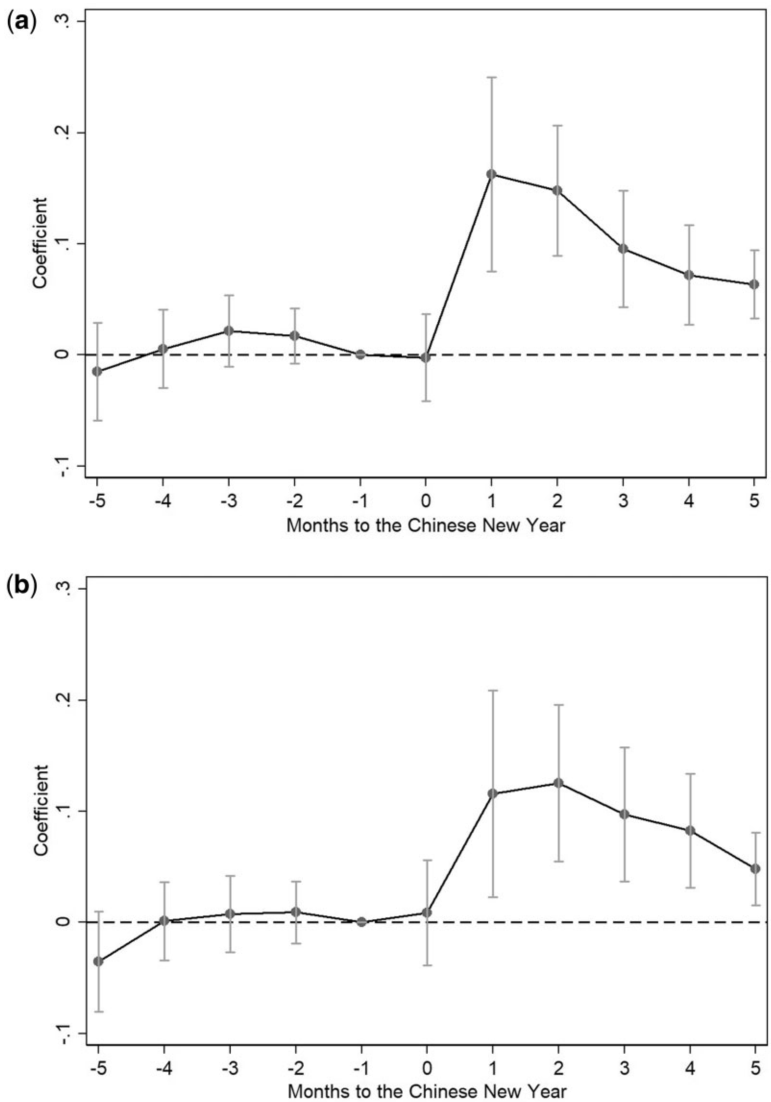

Figure 5. Estimates of the dynamic effects of industrial structure attributes. (a) Diversification (b) Vertical integration.

evidence in Section 4.1 (Figure 4, Panel A). This result supports the parallel trend assumption for estimating Equation (1).

Second, the moderating effect estimates became significant right after the outbreak of COVID-19 ($m = 1$); the effects of diversification and vertical integration kept significant for 5 months after the outbreak and the magnitudes began to decline roughly in the third month after the outbreak when the lockdown was lifted. The result indicates that the effects of diversification and vertical integration get smaller with the recovery of interregional economic linkages. This is consistent with our hypothesized mechanism that regions with higher levels of diversification and vertical integration would be more resilient to shocks that cut off interregional linkages, such as the lockdowns, due to higher reliance on the local market. The roles of diversification and vertical integration are prominent in the absence of well-functioning interregional linkages. Several months after the pandemic outbreak, there were sporadic outbreaks of local infections and the restrictions on personal mobility were still strict in areas with infection cases. Therefore, the country-wide interregional integration did not recover to the level before COVID-19, and this helps explain the significant estimates of α_m 5 months after the pandemic outbreak in Figure 5.

The estimated dynamic patterns presented in Figure 5 remain consistent in two sensitivity analyses. First, we simultaneously include the interaction terms of the month dummies with both diversification and vertical integration and re-estimate Equation (2). Supplementary Appendix Figure A5 shows that the estimated dynamic moderating effects of the two variables keep largely consistent with those in Figure 5. Second, we control for interaction terms of the month dummies and other prefecture-level characteristics, as in a robustness check for the baseline results.[20] The estimates of α_m in Equation (2) remain consistent with those in Figure 5 in terms of coefficient signs and magnitudes, as shown in Supplementary Appendix Tables A12 and A13. This result alleviates the concern that the dynamic pattern is driven by some prefecture-level factors that correlate with our variables of interest—diversification and vertical integration.

5. Further discussion

We now extend the discussion of our estimation results in the last section. We first incorporate infection cases to estimate the moderating effects of diversification and vertical integration by exploiting the prefecture-level variation in pandemic severity. We then examine the heterogeneity in the estimates of moderating effects from the perspective of prefectures' centrality in the interregional network of truck flows.

5.1. Estimates using infection cases

We use prefecture-level infection cases to explore the variation in the strictness of restrictions on inter-prefectural mobility across regions to complement our estimates in the last section, that mainly uses the time variation of COVID-19. During the pandemic, prefecture-level truck flows are not only an outcome of local economic activities but also local strictness of restrictions on inter-prefectural transportation. As discussed in Section 2, the strictness solely depends on local pandemic severity levels (high, medium or low risk) determined by local infection cases. Incorporating the potential impact of infection cases enriches our analysis of the role of diversification and vertical integration in shaping prefectural resilience to COVID-19.

Using the two variables constructed in Section 3.2, local and nonlocal infection cases, we conduct three analyses. First, we examine correlations of infections with diversification and vertical integration. The correlation estimates are small and mostly statistically insignificant (Supplementary Appendix Table A14). The result minimizes the potential concern that our estimates above on the effect of diversification and vertical integration might be

20 The nine prefecture-level controls are the same as those used in the robustness checks for the baseline results (Table A10).

confounded with infections if prefectural industrial structure attributes were associated with the number of infection cases, which determined the strictness of restrictions on personal mobility.

Second, we add the two variables into Equation (1) as control variables, where we use the functional form of the logarithms of one plus the variables, which take the value of 0 for months before January 2020. We report the results in Supplementary Appendix Table A15. The estimate of α remains robust in terms of signs and significance levels, further indicating that infection cases are less likely to confound our baseline estimates of Equation (1). In addition, we find significant negative effects of network-aggregated nonlocal infections and insignificant effects of local infections when the two infection variables are added into the regression simultaneously.[21] This result indicates the higher importance of inter-prefectural network and nonlocal infections in determining prefecture-level truck flows relative to local pandemic severity, highlighting the role of interregional linkages which we emphasize in our story. Given that Hubei province was the epidemic center and implemented the strictest lockdown policy, we exclude Hubei province from our regression. The results (Supplementary Appendix Table A15, Panel B) remain unchanged.

Third, we restrict the time horizon to the COVID-19 period in our study (January 2020 to June 2020) and use prefecture-month-level local and nonlocal infections as key treatment variables for COVID-19. We estimate the following equation:

$$\begin{aligned}\log(\text{Truckflow}_{cm}+1) = {} & \beta_1 \times \log\left(1+\text{Infections}_{cm}^{\text{local}}\right) \times \text{Structure}_c \\ & + \beta_2 \times \log\left(1+\text{Infections}_{cm}^{\text{local}}\right) + \gamma_1 \times \log\left(1+\text{Infections}_{cm}^{\text{nonlocal}}\right) \\ & \times \text{Structure}_c + \gamma_2 \times \log\left(1+\text{Infections}_{cm}^{\text{nonlocal}}\right) + \lambda_c + \theta_m + \epsilon_{cm},\end{aligned} \tag{3}$$

where $\text{Infections}_{cm}^{\text{local}}$ and $\text{Infections}_{cm}^{\text{nonlocal}}$ denote local and nonlocal infections as defined in Section 3.2, respectively; λ_c and θ_m are prefecture and month fixed effects, respectively. Standard errors are clustered at the prefecture level. We aim to estimate β_1 and γ_1, which capture moderating effects of diversification and vertical integration on the impact of local pandemic severity and the severity in other prefectures through the existing inter-prefectural truck flow network, respectively.

To address the potential concern arising from the endogeneity of prefecture-level infection cases, for example, truck drivers might spread the virus, we conduct two sensitivity checks. First, we examine correlations of local and nonlocal infection cases with the number of truck inflows and outflows in the previous one or 2 months, conditional on the lagged infections to control for cumulative effects, and find the correlations statistically insignificant (Supplementary Appendix Table A16). Second, we use the lagged terms of the infection variables, that is., the local and nonlocal infections in the previous month, instead of those in the current month as explanatory variables in estimating Equation (3).

Table 3 reports the estimates of Equation (3), where Panel A presents the moderating effect estimates for local infections and Panel B presents those for nonlocal infections. We find that estimates of β_1 in Panel A are small and statistically insignificant except for one regression (Column 3); by contrast, estimates of γ_1 in Panel B are all significantly

21 When the two infection variables are added into the regressions separately, both have significantly negative coefficients.

Table 3. Estimates of regressions with interactions of diversification and vertical integration with local and non-local infections

	Dependent variable: $\log(\text{Truckflow}_{cm} + 1)$			
	(1)	(2)	(3)	(4)
A. Moderating effects for local infections				
Local infections × diversification	0.008			
	(0.005)			
Local infections × vertical integration		0.002		
		(0.006)		
Lagged local infections × diversification			0.020***	
			(0.007)	
Lagged local infections × vertical integration				0.004
				(0.009)
Observations	2010	2010	1675	1675
R-squared	0.978	0.978	0.979	0.979
B. Moderating effects for nonlocal infections				
Nonlocal infections × diversification	0.019***			
	(0.006)			
Nonlocal infections × vertical integration		0.020***		
		(0.007)		
Lagged nonlocal infections × diversification			0.024***	
			(0.006)	
Lagged nonlocal infections × vertical integration				0.032***
				(0.008)
Observations	2010	2010	1675	1675
R-squared	0.978	0.978	0.979	0.979
Local infections	Yes	Yes	No	No
Nonlocal infections	Yes	Yes	No	No
Lagged local infections	No	No	Yes	Yes
Lagged nonlocal infections	No	No	Yes	Yes
Prefecture fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes

Notes: The table presents estimates of Equation (3). Diversification and vertical integration are standardized across prefectures with a mean of 0 and a standard deviation of 1. Panel A (Panel B) contains results for regressions with interactions between local (nonlocal) infections and the two industrial structure variables—diversification and vertical integration. We control for (1-month lagged) local and nonlocal infections in Columns (1) and (2) (Columns (3) and (4)). We also control for prefecture fixed effects and month fixed effects in all regressions. Standard errors are clustered at the prefecture level. ***, ** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

positive. The result suggests that diversification and vertical integration shape prefectural resilience to the COVID-19 shock mainly by mitigating the negative impact of nonlocal pandemic severity transmitted through the inter-prefectural network, conditional on local pandemic severity. The reason is that for a given prefecture, infections in trade-related prefectures and subsequent mobility restrictions weaken its outside links, which makes the role of local diversification and vertical integration prominent. The result remains robust if we exclude prefectures in Hubei province, the central province of the pandemic outbreak, as shown in Supplementary Appendix Table A17.

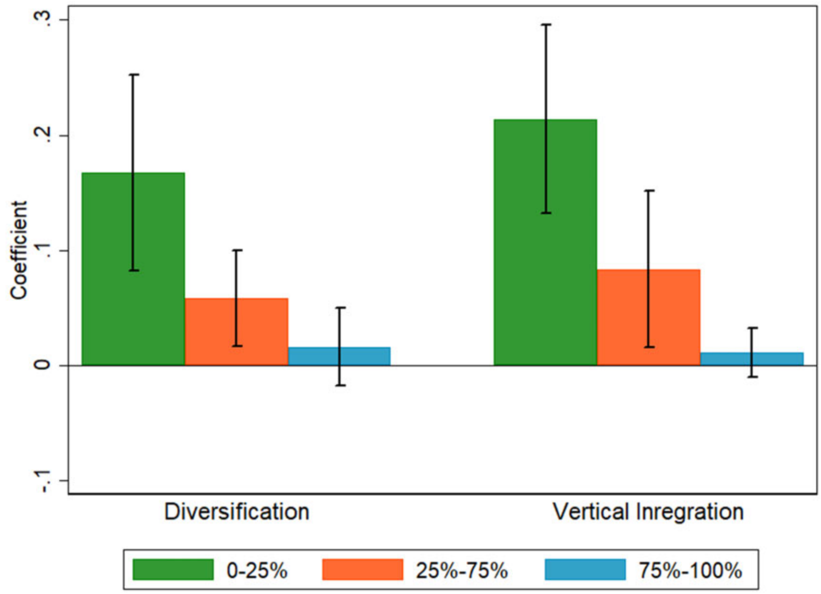

Figure 6. Subsample estimates based on network centrality.

5.2. Heterogeneity in terms of network centrality

We now examine the heterogeneity in the moderating effects of diversification and vertical integration from the perspective of prefectural centrality in the truck flow network. First, we divide prefectures into three groups according to three percentiles of the network centrality variable defined in Section 3.2, lower than 25%, 25–75% and higher than 75%. We then separately estimate Equation (1) based on the subsamples and plot the estimated coefficients with 95% confidence intervals in Figure 6.

Figure 6 shows that the estimated moderating effects of diversification and vertical integration tend to be smaller and less significant for prefectures with higher centrality. Moreover, the moderating effects are close to zero and insignificant for the subsample with the highest centrality (the 75–100% group). It is reassuring to find that this pattern of heterogeneity remains robust for alternative measures of diversification and vertical integration, as discussed in Section 4.2 (Supplementary Appendix Figure A5).

The result is consistent with our hypothesized mechanism. We argue that the role of diversification and vertical integration in shaping resilience to COVID-19 works mainly through higher resistance to hindered inter-prefectural linkages due to the lockdown policy. As a result, prefectures with lower centrality are less integrated into the countrywide market; their external economic linkages, for example, supplier–customer relationships, are more fragile under adverse shocks to interregional supply chains. On the contrary, prefectures with higher centrality in the network play more important roles in countrywide supply chains. Even if they specialize in particular industries, they tend to have larger market shares and lower substitutability; nonlocal trade partners thus have stronger incentives to recover business connections with these prefectures. Therefore, prefectures with higher centrality depend less on local diversification and vertical integration for economic recovery from the pandemic shock.

Our findings have further implications for the pros and cons of industrial specialization and agglomeration in a region, highlighting the complementarity between specialization and spatial integration with other regions. Compared with local diversification, specialization benefits the regional economy by exerting local comparative advantages; the potential cost from specialization, that is, lower resilience under negative shocks to interregional supply chains, can be mitigated by higher levels of integration into the domestic market revealed by higher centrality in the interregional trade network.

6. Conclusion

In this article, we combine high-frequency truck flow data and the unexpected lockdown policy shock during COVID-19 in China to examine the role of regional industrial structures in shaping economic resilience. We find that prefectures with higher diversification and vertical integration tend to have stronger resilience to the COVID-19 shock. Because these prefectures tend to have lower dependence on other regions for supplier–customer relationships, they are more capable of maintaining economic operations without well-functioning interregional trade and personal linkages. We support this mechanism through the examination on dynamic effects as well as estimations that incorporate local and trade-network-aggregated nonlocal COVID-19 infections. Furthermore, exploring the heterogeneous effects from the perspective of an interregional truck flow network, we discover that the estimated associations between diversification, vertical integration and regional resilience are stronger in prefectures with lower centrality in the network.

Our findings shed light on the pros and cons of agglomeration forces that shape cities' industrial compositions under the circumstance of a negative shock to the intercity linkages (Duranton and Puga, 2000, 2001; Ellison et al., 2010). Localization benefits industrial growth due to larger intra-industry externalities, but might lower regional economic resilience. On the other hand, a complete industrial chain integrated at the local level can benefit local economic stability when facing negative shocks. Also, we provide new insights into the crucial role of the interregional trade network in supporting industrial specialization. The costs of specialization vary across regions with different levels of network centrality when a sudden negative shock hits the interregional linkages. Higher centrality in the trade network can mitigate the potential costs of specialization under an adverse shock. As for the policy implications, our findings help deepen the understanding of heterogeneous economic costs of lockdown during the pandemic.

For future studies, it is worth quantifying the welfare implications of the association among industrial structure, interregional supply chains and economic resilience, which we demonstrate at the regional level using a reduced-form approach in the current article. Although a more diversified and locally integrated industrial structure can mitigate the loss of a region's economy from lockdown during the pandemic, the region's higher centrality in the trade network may help the local economy overcome some potential costs under an adverse shock. If the lockdown policy induces regions to localize more diversified industries and rely less on external suppliers and customers, there would be a loss of efficiency at the country level due to decreased gains from trade based on regional comparative advantages and specialization. Such ambiguous welfare consequences warrant further quantitative examination.

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Supplementary material

Supplementary data for this paper are available at *Journal of Economic Geography* online.

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