INTRODUCTION

In early 2020, a German parts and components supplier, Webasto SE, surfaced in the news. On January 19, an employee had travelled from China to Stockdorf, a Bavarian village, and during business meetings with her colleagues infected several of them with COVID-19 (see https://www.zdf.de/nachrichten/panorama/corona-bayern-china-webasto-100.html for some German media coverage). Just to be clear: where the virus originated and why is not of interest to us, what counts is the observation that business comes with co-work and travel—inside or outside the boundaries of firms, within...
and between countries. Human interaction is an important source of interdependencies, by creating information and knowledge spillovers, and by letting not only economic shocks but also germs and diseases spread.

On a worldwide basis, business trips account for a double-digit percentage of all travels; thus, in 2017, about 12% of flight tickets were issued to business travellers (see https://www.smallbizgenius.net/by-the-numbers/business-travel-statistics#gref). As much of the business trips tickets market involves business-class tickets, the share of turnover for business trips is significantly larger than that of the number of tickets sold. Due to the relatively deeper integration of markets within countries, the fraction of business trips and associated travel expenses is particularly large in China and the United States. The amount of business travel was not only large prior to the COVID-19 pandemic, but also positively trending.

One reason for the increasing intensity of business trips is the modern organisation of value chains (Baldwin, 2016). The importance of inputs for production and also exporting is well documented in the literature (Antrás et al., 2012; Fally, 2012; Hummels et al., 2001). Member countries of the OECD but also China are deeply integrated in the world’s production of output through global value chains (De Baker & Miroudot, 2014; see also the VoxEU article Baldwin & Weder di Mauro, 2020a, 2020b, entitled ‘Economics in the time of Covid-19: A new eBook’ as well as the e-Book).

As value chains create links, in network jargon *edges*, between firms or region-sector units which are called network *nodes*, they serve as a conduit for shocks to propagate. For this reason, economists for quite some time point to the role of value chains for the transmission of shocks on business cycles (Gangnes et al., 2012; Inoue and Todo, 2019a, 2019b), on exchange rates (see Camatte et al., 2021), or on firms’ stock-market valuations (see Egger & Zhu, 2021). The COVID-19 pandemic is a supply shock of unprecedented magnitude when considering the recent past, which makes it an interesting object of study from a value-chain point of view.

The latter came into the limelight of academic research only very recently. For instance, Hayakama and Mukonoki (2021) demonstrate that economic effects of the COVID-19 pandemic are particularly strong on value-chain links between Asian and other economies but less so within Asia. Gerschel et al. (2020) study the propagation of the economic shock induced by the pandemic through global value chains and the reliance on Chinese inputs with a particular focus on France and the travel restrictions associated with the pandemic. Inoue and Todo (2020) study the effect of lockdown measures in Tokyo on regions across Japan.

The present paper focuses on the early phase of the pandemic from January to March in 2020 and it zooms in on China. First, it decomposes the mobility of people between Chinese cities into a component that is systematically related to business through value chains within China and a non-value-chain remainder. The latter is done by employing input-output data and regional business statistics for China on the one hand and mobility data for people on the other. The paper utilises the latter as two network matrices between firms across Chinese cities and sectors: one value-chain mobility-related and the other one other mobility-related. Second, the paper conjectures that the propagation of the virus on a larger-scale map of China happened through trips for business in value chains and other, and it considers the effects of these interdependencies on stock-market valuations of Chinese firms.

We report a number of interesting findings. First, in the early phase of the pandemic, the propagation of infection was mostly local in a city and what mattered was the state of infections there for local future infections. For that reason, we also see that the effects on the stock market were mostly local initially. However, in the second month of the wider propagation, inter-city mobility started mattering and continued doing so primarily through value chains. This is why also shocks in the stock market started ‘travelling’ with a similar inter-firm and inter-city and inter-sector pattern after the first month of the crisis.
The remainder of the manuscript is organised as follows. The next section outlines our approach towards measurement of value-chain (and other)-related mobility effects on the spreading of infections in China as well as on associated business-cycle effects. That section also introduces the data used for measurement and analysis. Section 3 describes the outcomes in the various steps of empirical analysis. The last section concludes with a brief summary of the main insights.

2 | MODEL, MEASUREMENT AND DATA

We consider the following set of regressions so as to gauge the direct effect of the local COVID-19 shock on local listed firms’ abnormal returns as well as the transmission effects on firms in other cities via people’s cross-city travels for leisure and business. We associate the latter with input–output value-chain-related spillover effects.

In a first step, the following models are estimated:

\[
\ln \text{Confirm}_{s,e} = \beta_0 + \beta_1 \ln \text{Confirm}_{s,e-6} + \beta_2 \text{WeightedLnConfirm}_{s,e-6} + \gamma_e + \xi_s + u_{s,e},
\]

(1)

where \( \ln \text{Confirm}_{s,e} \) is the (log of one plus the) number of confirmed COVID-19 cases in city \( s \) on event date \( e \) as the dependent variable and its lag-6(-days) value, \( \ln \text{Confirm}_{s,e-6} \), and the lag-6(-days) city-to-city mobility-weighted confirmed cases, \( \text{WeightedLnConfirm}_{s,e-6} \), are the independent variables. \( \gamma_e \) and \( \xi_s \) are event date and city-fixed effects. A variant of that model is

\[
\ln \text{Confirm}_{s,e} = \beta_0 + \beta_1 \ln \text{Confirm}_{s,e-6} + \beta_2 \text{IOWeightedLnConfirm}_{s,e-6} + \beta_3 \text{RestWeightedLnConfirm}_{s,e-6} + \gamma_e + \xi_s + u_{s,e},
\]

(2)

where the mobility-weighted spillover term of infections variable in Equation (1), \( \text{WeightedLnConfirm}_{s,e-6} \) is further decomposed into the business-related inter-city-movements-weighted cases, \( \text{IOWeightedLnConfirm}_{s,e-6} \) and leisure-related (or not input–output-travels-related) ones, \( \text{RestWeightedLnConfirm}_{s,e-6} \) as the independent variables.

In a second step, the following model is estimated:

\[
\text{AR}_{i,s,e} = \alpha_0 + \alpha_1 \ln \text{Confirm}_{s,e} + \alpha_2 \text{WeightedLnConfirm}_{i,s,e} + \gamma_e + \xi_s + u_{i,s,e},
\]

(3)

where the abnormal stock-market return of firm \( i \) in city \( s \) on event date \( e \), \( \text{AR}_{i,s,e} \), is the dependent variable, and the (log of one plus the) number of local confirmed cases and the firm-to-firm-input–output-weighted confirmed cases are the independent variables.

It will be useful to devote a separate subsection to the estimation of Chinese listed firms’ abnormal stock-market returns, and another to the design of the spillover terms (\( \text{WeightedLnConfirm}_{s,e} \), \( \text{IOWeightedLnConfirm}_{s,e} \), \( \text{RestWeightedLnConfirm}_{s,e} \) and \( \text{WeightedLnConfirm}_{i,s,e} \)).

2.1 | Measuring firms’ abnormal returns

Let us use \( i = 1, \ldots, F \) to denote firms, \( e = 1, \ldots, E \) to denote event dates, and \( t = 1, \ldots, T \) to denote time which is measured in days. Then, changes in firms’ stock-market returns are modelled as a function of time-invariant, firm-specific characteristics and time-specific common characteristics which also
matter in a firm-specific way. Using $r_{i,e+t}$ to denote the stock-market return of $i$ at day $e + t$, and $m_{e+t}$ for the (common) market return, a customary model of stock-market returns is

$$r_{i,e+t} = \alpha_{i,e} + \zeta_{i,e} m_{e+t} + u_{i,e+t}, \quad t \in [w_1, w_2],$$

(4)

where $\alpha_{i,e}$ is a stock- and event-specific constant and $\zeta_{i,e}$ is a stock- and event-specific slope parameter. Examples of estimates of this and similar equations can be found in O’Hara and Wayne (1990), Breinlich (2014), Moser and Rose (2014), Moenninghoff et al. (2015), Alfaro et al. (2017), Dewenter and Riddick (2018), or Egger and Zhu (2019).

The event-study literature is mainly interested in the residual, $u_{i,e+t}$, which is reflective of the abnormal returns of a stock or company. In what follows, we focus on estimates of $u_{i,e+t}$ (i.e. $t = 0$) using an estimation window of $[e-31, e-280]$ (i.e., $t \in [-31, -280]$). The number of days in the estimation window equals 250, which is the approximate number of trading days in one year.

2.2 Measuring firm (city)-to-firm (city) connectedness through value chains

We will make use of an $N \times N$ identity matrix, $I_N$, where $N \in \{C, F\}$ with $C$ and $F$ being the number of cities and firms, respectively, and $H \times 1$ vectors as well as $H \times H$ matrices of ones, $t_H$ and $J_H$, respectively. With regard to the latter, $H \in \{CS, FS\}$ indicates vectors and matrices of dimension $CS$ and $FS$, respectively, where $S$ indicates the number of sectors that the $F$ firms or $C$ cities together operate in, and $FS$ and $CS$ are just the number of firms times the number of sectors and the number of cities times the number of sectors, respectively. One useful matrix that will be used is

$$K_{NS} = (J_N - I_N) \otimes J_S,$$

(5)

where $\otimes$ is the Kronecker product.\(^1\) This matrix serves the purpose of summing all elements of post-multiplied vectors except for ones pertaining to the same firm or city in a given row.

Moreover, we will make use of an $NS \times 1$ vector of output shares, $h_{NS}$, where a typical element states how much firm $i$ or all the firms in city $i$ make operating income with sector-$s$-type output relative to the sector’s total operating income. Based on the latter, we define the matrix

$$H_{NS} = h_{NS} h'_{NS}. \quad (6)$$

After defining the Chinese sector-$S$-to-sector-$S$ input–output matrix, $O_S$, we can obtain the matrix $J_N \otimes O_S$ to arrive at the weighted input–output matrix

$$M_{NS} = H_{NS} \circ (J_N \otimes O_S), \quad (7)$$

where $\circ$ is the Hadamard (element-wise) product,\(^2\) and the firm(city)-sector-to-firm(city)-sector input–output matrix is

\(^1\)If $A$ is an $N \times N$ matrix with $ij$th element $a_{ij}$ for $i = 1, \ldots, N$ and $j = 1, \ldots, N$, and $B$ is any $S \times S$ matrix, then the Kronecker product of $A$ and $B$, denoted by $A \otimes B$, is an $NS \times NS$ matrix formed by multiplying each $a_{ij}$ element by the entire matrix $B$.

\(^2\)The Hadamard product is a binary operation that takes two matrices of the same dimensions and produces another matrix of the same dimension as the operands, where each element is the product of elements of the original two matrices.
After defining an $NS \times N$ matrix which computes sums of post-multiplied vectors across all firms (cities) for each firm (city) and sector and assigns that sum in all rows of a firm (city) and sector, we obtain the $N \times N$ firm(city)-to-firm(city) input–output matrix

The latter is an imputation of the sector-to-sector input–output matrix to serve greater spatial detail than just for the country as a whole. It relates to a fictitious global sector-to-sector input–output matrix in a similar way as the global country-sector-to-country-sector input–output matrix does.

### Measuring and decomposing city-to-city movements of people

We employ data on the city-to-city movement of people on a daily basis. The corresponding data are key to specify two sources of transmission, travel for leisure and travel for business. Note that the data do not explicitly distinguish between trips for business and non-business reasons. Therefore, we chose to decompose the corresponding data in the following way. Let us denote the percentage of people travelling from city $r$ to $s$ on day $e$ to the total population moving into the city $s$ on day $e$ by $m_{rse}$. Let us denote the input–output centrality coefficient between cities $r$ and $s$ (which due to the availability of country input–output and firm-level operating income data that do not vary from day to day) as $c_{rs}$. Then, we can decompose the mobility data by way of the following regression:

$$m_{rse} = \exp(\gamma_e c_{rs}) u_{rse},$$

where $\gamma_e$ is a day-specific parameter and $u_{rse}$ is a residual, where $E(u_{rse})=1$. An estimate of the business-related trips from $r$ to $s$ on day $e$ is $\hat{b}_{rse} = \exp(\hat{\gamma}_e c_{rs})$ and an estimate of other trips is $\hat{o}_{rse} = \frac{m_{rse}}{\hat{b}_{rse}}$. In the subsequent analysis, we will use travel-related network matrices containing the normalised trip-related typical elements:

$$B_{rse} = \left(\frac{\hat{b}_{rse}}{\sum_{r=1}^{R} \hat{b}_{rse}}\right),$$

$$O_{rse} = \left(\frac{\hat{o}_{rse}}{\sum_{r=1}^{R} \hat{o}_{rse}}\right),$$

respectively, with $B_{rse} = 0$ and $O_{rse} = 0$ whenever $r = s$.

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3Alternatively, one can normalize trip-related typical elements by the maximum row sum. We do this as a robustness check. Results are reported in Subsection 3.2. Note that row normalization (as any other row-vector normalization) destroys the notion of absolute distance in normalized network matrices, which is not the case for scalar-based normalizations of which maximum-row-sum-normalization is a prominent example (see Kelejian and Prucha, 2010).


**TABLE 1**  Summary statistics

| Variables | No. of observations | Mean | Std. Div. | Min   | P25    | P50    | P75    | Max    |
|-----------|---------------------|------|-----------|-------|--------|--------|--------|--------|
| $AR_{t,e}( \times 100)$ | 138,284 | 0.1458 | 3.0472 | -14.1326 | -1.4154 | -0.1811 | 1.3644 | 22.7586 |
| WeightedlnConfirm$_{t,e}$ | 138,284 | 4.2016 | 0.9695 | -2.6053 | 3.9110 | 4.4569 | 4.7825 | 6.2937 |
| lnConfirm$_{t,e}$ | 24,156 | 2.0699 | 1.9206 | 0.0000 | 0.0000 | 2.0794 | 3.3673 | 10.8199 |
| WeightedlnConfirm$_{t,e}$ | 24,156 | 2.4425 | 1.5488 | 0.0000 | 1.0856 | 2.5274 | 3.4896 | 8.8932 |
| IOWeightedlnConfirm$_{t,e}$ | 24,156 | 2.1238 | 0.6440 | 0.2728 | 1.5804 | 2.3548 | 2.7023 | 3.0676 |
| RestWeightedlnConfirm$_{t,e}$ | 24,156 | 2.4784 | 1.5873 | 0.0000 | 1.0745 | 2.5538 | 3.5590 | 8.8943 |

*Note:* P25, P50 and P75 refer to the 25th, the 50th and the 75th percentile of the distribution. Std. Dev., Min and Max refer to the standard deviation, the minimum and the maximum value in the data.
2.4 Data

We retrieve stock-return data on active companies listed on the Shanghai and Shenzhen Stock Exchanges and the market returns from China Stock Market and Accounting Research Database (CSMAR). We consider each day between 24 January 2020 and 29 March 2020 as a single event date \( e \) and retrieve the stock-market data on that day and the corresponding stock-market data in the estimation window \([e-31, e-280]\).\(^4\) The final sample includes 3462 stocks across all event days.

The China-China block in the World-Input-Output Database (WIOD) in 2011 as released in 2013 is used as \( O_S \) in the construction of the firm(city)-sector-to-firm(city)-sector input–output matrix \( O_{NS} \) above.\(^5\) We then retrieve firms’ sector-level operating income at the year end of 2017 from Datastream. Note that firms in Datastream have sector-level operating income recorded in one to ten sectors. The sector-level operating income of the firms is used to compute the sector-level total operating income and the firm(city)-specific share in it, when constructing the elements of \( h_{NS} \).

Data on the city-to-city movement of people on a daily basis between 24 January 2020 and 29 March 2020 are available from Baidu Migration, a travel map offered by the largest Chinese search engine, Baidu (Source: http://qianxi.baidu.com/). The Baidu Migration data set covers 133,956 pairs of cities per day for 366 Chinese cities between 24 January 2020 and 29 March 2020. The data are based on real-time location records for every smart phone using the company’s mapping app, and thus can reflect population movements between cities at a high time frequency. For the current study, we make use of the percentages of inflowing population that originates from each one of the top-100 cities of origin to the total population moving into the destination city.\(^6\)

Finally, we retrieve the COVID-19 recorded infections data time series from DingXiangYuan (Source: https://ncov.dxy.cn/ncovh5/view/pneumonia), an online community for healthcare professionals which provides real-time updates of pandemic-related data in China.

We summarise some descriptive statistics on the variables of interest in Table 1. The table suggests we can estimate regression parameters for the infections–transmission models from some 24,000 city-day data points, and we can estimate the abnormal returns–response parameters to COVID-19 infections from some 130,000 firm-day data points. As we use normalised weighting matrices to obtain values of \( Weighted\ln\text{Confirms}_{s,e} \), \( IOWeighted\ln\text{Confirms}_{s,e} \), and \( RestWeighted\ln\text{Confirms}_{s,e} \), the respective measures have a similar average value as \( \ln\text{Confirms}_{s,e} \). Moreover, as \( Weighted\ln\text{Confirms}_{s,e} \), \( IOWeighted\ln\text{Confirms}_{s,e} \), and \( RestWeighted\ln\text{Confirms}_{s,e} \) represent some travel-weighted averages of \( \ln\text{Confirms}_{s,e} \), the variances of the former are smaller than that of the latter.

3 EMPIRICAL ANALYSIS

This section is composed of two subsections. In Sub section 3.1, we present the main results, and in Sub section 3.2, we present some robustness checks.

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\(^4\) As the Chinese stock market was closed during Jan 24, 2020 and Feb 3, 2020, the sample period starts on Feb 4, 2020 for the estimation of abnormal returns.

\(^5\) We also use the China-China block in the WIOD in 2014 as released in 2016 (which is the latest version that one currently can obtain) as a robustness check. Results are reported in Subsection 3.2.

\(^6\) Note that the cumulative percentage of the inflowing population from the top-100 cities reach 97% for the average city in the data.
| Variables                  | Jan 24–Feb 14 (1) | Feb 15–Mar 7 (2) | Mar 7–Mar 29 (3) | Jan 24–Feb 14 (4) | Feb 15–Mar 7 (5) | Mar 7–Mar 29 (6) |
|---------------------------|-------------------|------------------|------------------|-------------------|------------------|------------------|
| $\ln \text{Confirm}_{t-6}$ | 0.2755***         | 0.2601***        | 0.0713**         | 0.2631***         | 0.2578***        | 0.0908***        |
|                           | (0.023)           | (0.071)          | (0.031)          | (0.023)           | (0.071)          | (0.032)          |
| $\text{WeightedlnConfirm}_{t-6}$ | 0.2555***         | −0.0022          | −0.0263          | 0.2248            | −0.6215          | 4.4595**         |
|                           | (0.030)           | (0.042)          | (0.032)          | (0.256)           | (0.751)          | (2.177)          |
| $\text{IOWeightedlnConfirm}_{t-6}$ | 0.2681***         | −0.0013          | −0.0343          | 0.2681***         | −0.0013          | −0.0343          |
|                           | (0.030)           | (0.042)          | (0.033)          | (0.030)           | (0.042)          | (0.033)          |
| $\text{RestWeightedlnConfirm}_{t-6}$ | 2.0675***         | 2.2625***        | 3.7195*          | 2.0675***         | 2.2625***        | −9.8915*         |
|                           | (0.152)           | (0.077)          | (1.997)          | (0.152)           | (0.077)          | (5.947)          |
| Constant                  | 0.3602***         | 2.0675***        | 2.2625***        | 0.3602***         | 3.7195*          | −9.8915*         |
|                           | (0.040)           | (0.152)          | (0.077)          | (0.040)           | (1.997)          | (5.947)          |
| City-fixed effects        | Yes               | Yes              | Yes              | Yes               | Yes              | Yes              |
| Time-fixed effects        | Yes               | Yes              | Yes              | Yes               | Yes              | Yes              |
| No. of observations       | 8052              | 8052             | 8052             | 8052              | 8052             | 8052             |
| $R^2$                     | .759              | .091             | .082             | .760              | .091             | .084             |
| No. of cities             | 366               | 366              | 366              | 366               | 366              | 366              |

Note: Columns (1)–(3) and (4)–(6) of this table report results on the baseline model of Equations (1) and (2), respectively, in three different time windows of the early phase of the COVID-19 pandemic: January 24 to February 14; February 15 to March 7; and March 8 to March 29. Robust standard errors adjusted for heteroskedasticity and city-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5% and 1% levels are marked *, ** and *** respectively.
Main results

In Table 2, we present results. As the coefficients should not be expected to stay constant for various reasons—behavioural patterns, events which led to abnormal propagations, etc.—we estimate the coefficients of the equations in three alternative time windows of the early phase of the COVID-19 pandemic: January 24 to February 14; February 15 to March 7; and March 8 to March 29. The table indicates that for each window, the coefficients are identified from a data set of 366 major cities and 22 days, so that the number of observations in each column of the table is 8052.

The coefficients indicate local conditions in terms of infections 6 days earlier were particularly decisive in the first time window, but its importance declined monotonically as time progressed. Moreover, value-chain links established gained in importance in terms of a (business-mobility-related) channel through which COVID-19 propagated in China. Conversely, other (migration-related) mobility forces declined in importance between the first and the last window. Not disentangling the two sources of mobility, the one through value-chain links and the rest conceals the latter pattern, as can be seen when comparing Column (1) with Column (4) and then Column (3) with Column (6). Table 2 suggests the propagation parameters are not constant in time as hypothesised above.

Note that the number of degrees of freedom is large, and the size of the cross section of 336 cities is big enough to allow for further flexibility than in Table 2 in terms of the regression parameters. In fact, it even permits estimating coefficients on a daily basis. Of course, it is then not possible to report results as in Table 2. However, we can summarise daily coefficients by way of plots, and do so in Figures 1 and 2.

Figures 1 and 2 suggest the following conclusions. First, the dynamic patterns of daily coefficients explaining the number of confirmed COVID-19 cases from both figures are consistent with the patterns we observed on the basis of Table 2. As the results in Column (3) are inferior to their
counterparts in Column (6) in Table 2 and Figure 1 corresponds to the former while Figure 2 corresponds to the latter, let us focus on a discussion of Figure 2.

In general, the pattern of daily confirmed new cases is spiky, as was the case also in other countries. This is most likely the result of a combination of special infection events as well as the recording thereof. This pattern also results in somewhat spiky response–parameter patterns as can be seen from the figures. Figure 2 suggests two insights. First, there was a convergence of value-chain-weighted indirect impacts and local ones over time. Second, the importance of non-value-chain-related mobility effects diverged from those of local conditions as well as value-chain-related transmissions. In fact, non-value-chain mobility links vanished as a driver of local infections in the course of time, whereas value-chain transmissions became the most important factor towards the end of the observation window.

Table 3 focuses on abnormal stock returns. Consistent with our expectations, both the local conditions in terms of infections and firm-to-firm-input–output–(business)-related infections have an adverse impact on firm values. Interestingly, the coefficient on the input–output-weighted COVID-19-reported case numbers is bigger in absolute value than the one of local infections, there.

Figure 3 plots the sector-level density estimates of each regressor based on estimates of Equation (3) underlying Table 3. We see that the distributions of the predictions with regard to each regressor exhibit distinct features. In terms of magnitude, the effect of local conditions is smaller in absolute value than that of business-related contagions, consistent with the earlier table. And the indirect input–output-weighted impact varies much more strongly across sectors, cities and time than the effect of local numbers of confirmed cases. Hence, value chains exacerbate the variation in shocks due to the heterogeneity of exposure, apart from adding indirect effects to the direct ones of local shock impulses.
Figure 4 plots the daily (cross-sector average) predictions based on Equation (3) estimates. Apart from being smaller in absolute value, the effect of local conditions in terms of infections on abnormal returns is absolutely less volatile over time. Hence, value-chain interdependencies are capable of adding to volatility of abnormal returns, because they permanently ‘import’ shocks from strongly connected places. At times where shocks are relatively spatially (or sectorally) concentrated, value-chain-type network effects distribute shocks to a wider range of regions and sectors and may, hence,

**TABLE 3** The determinants of abnormal returns (the dependent variable is $AR_{i,s,e} \times 100$)

| Variables          | (1)            | (2)            |
|--------------------|----------------|----------------|
| $\ln\text{Confirm}_{i,s,e}$ | $-0.0147^*$    | $-0.0140^*$    |
|                    | (0.008)        | (0.008)        |
| $\text{Weighted}\ln\text{Confirm}_{i,s,e}$ |                | $-0.0969^{**}$ |
|                    |                | (0.046)        |
| Constant           | 0.5450***      | 0.9261***      |
|                    | (0.077)        | (0.203)        |
| Firm-fixed effects | Yes            | Yes            |
| Time-fixed effects | Yes            | Yes            |
| No. of observations | 138,284        | 138,284        |
| $R^2$              | .0512          | .0512          |
| Number of Firms    | 3462           | 3462           |

*Note:* This table reports results on the baseline model of Equation (3). The dependent variable is scaled by 100. Robust standard errors adjusted for heteroskedasticity and firm-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5% and 1% levels are marked *, ** and ***, respectively.

**FIGURE 3** Estimated effects of confirmed COVID-19 cases on firms’ abnormal returns (in per cent).

Notes: This figure plots the sector-level density estimates of the effects (scaled by 100) of each regressor in Equation (3) based on the estimation results in Table 3. The sector-level effect of $\ln\text{Confirm}_{i,s,e}$ is calculated as $(\exp(\hat{\beta}_1 \ln\text{Confirm}_{i,s,e}) - 1) \times 100$, and the sector-level effect of $\text{Weighted}\ln\text{Confirm}_{i,s,e}$ is calculated as $(\exp(\hat{\beta}_2 \text{Weighted}\ln\text{Confirm}_{i,s,e}) - 1) \times 100$ [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 4 plots the daily (cross-sector average) predictions based on Equation (3) estimates. Apart from being smaller in absolute value, the effect of local conditions in terms of infections on abnormal returns is absolutely less volatile over time. Hence, value-chain interdependencies are capable of adding to volatility of abnormal returns, because they permanently ‘import’ shocks from strongly connected places. At times where shocks are relatively spatially (or sectorally) concentrated, value-chain-type network effects distribute shocks to a wider range of regions and sectors and may, hence,
serve as a conduit of volatility spikes. Of course, at ‘normal’ times where smaller shocks are widely distributed, value chains are powerful in mitigating them locally and in smoothing individual effects. Finally, similar to the results of Equation (2), firm-to-firm value-chain links gained in importance with respect to firm value as the COVID-19 pandemic propagated in China.

3.2 | Robustness checks

In this subsection, we conduct two types of robustness checks. First, we use maximum-row-normalised travel-based network weights matrices instead of row-normalised ones. As said above, row-normalising a network matrix ensures that the entries in each row of the matrix sum up to unity. In general, this destroys the concept of absolute centrality and peripherality for the nodes in the network. In our context, it means that the notion is lost that some firms (and city-sector tuples) are absolutely more central than others. Maximum-row normalisation as a form of scalar normalisation of network matrices does not involve this problem, because every element in the network matrix is normalised by the same (rather than a row-specific) scalar (see Kelejian & Prucha, 2010).

We report the results corresponding to Columns (4)–(6) of the row normalisation-based Table 2 in Table 4, where we use maximum-row normalisation instead. It turns out that the parameter estimates in Table 4 are qualitatively and quantitatively similar to their counterparts in Table 2.

Moreover, we reproduce the results in Columns (4)–(6) of Table 2 and of Column (2) in Table 3 using the latest version of the WIOD as released in 2016, pertaining to data from 2014. We report the corresponding parameters in Tables 5 and 6. To keep the results as closely comparable as possible, we use row-normalised network matrices in Tables 5 and 6 as we did in Tables 2 and 3.
A comparison of the results in Tables 5 and 6 with their counterparts in Tables 2 and 3 suggests that the (normalised) network matrices are not very different, and, accordingly, the results are qualitatively and quantitatively close to the original ones.

### 4 | CONCLUSIONS

This paper looks for a twofold role of value chains at times of crises as the one induced by the COVID-19 pandemic. What is specific to diseases that spread with human interaction is that value chains play two types of role: first, they are a reason for the mobility of humans and, hence, they participate in disease propagation; second, they are a conduit of the propagation of economic shocks and, with lockdown measures being taken for disease control, lead to a spreading of economic shocks and volatility at times, where those shocks were originally locally bound.

We document the two channels through which value chains are relevant in infectious-disease-related supply shocks by focussing on the early phases of the COVID-19 pandemic in China. We see that local infections are an important initial condition for subsequent local infections, but also value-chain-transmitted infections are important. In fact, the latter gained in importance with time during the pandemic, whereas other mobility-related transmissions declined in importance with time, at least between January and March 2020.

Moreover, we see that value-chain-related transmissions are quantitatively important in explaining stock-market reactions in the early phases of the pandemic. In fact, they were quantitatively more important than even local infection conditions, on average. Consistent with expectations, we document

### Table 4
Determinants of the number of confirmed cases when the travel-related dependent variables are constructed using maximum-row-sum-normalised travel-related network matrices

| Variables                  | Jan 24–Feb 14 (4) | Feb 15–Mar 7 (5) | Mar 7–Mar 29 (6) |
|----------------------------|-------------------|------------------|------------------|
| lnConfirms$_{e-6}$        | 0.2778***         | 0.2534***        | 0.0885***        |
|                           | (0.023)           | (0.070)          | (0.031)          |
| IOWeightedlnConfirms$_{e-6}$ | 0.3362            | −0.2511          | 5.3834**         |
|                           | (0.237)           | (0.439)          | (2.381)          |
| RestWeightedlnConfirms$_{e-6}$ | 0.2568***       | 0.0087           | −0.0358          |
|                           | (0.031)           | (0.042)          | (0.033)          |
| Constant                  | 0.3602***         | 2.6678**         | −11.6536*        |
|                           | (0.040)           | (1.079)          | (6.162)          |
| City-fixed effects        | Yes               | Yes              | Yes              |
| Time-fixed effects        | Yes               | Yes              | Yes              |
| No. of observations       | 8052              | 8052             | 8052             |
| $R^2$                     | .759              | .091             | .083             |
| No. of cities             | 366               | 366              | 366              |

**Note:** The results in this table should be compared to the ones in Columns (4)–(6) of Table 2. Columns (4)–(6) of this table report results on the baseline model of Equations (2) in three different time windows of the early phase of the COVID-19 pandemic: January 24 to February 14; February 15 to March 7; and March 8 to March 29, when the dependent variables IOWeightedlnConfirms$_{e-6}$ and RestWeightedlnConfirms$_{e-6}$ are constructed using travel-related network matrices with their typical elements normalised by the maximum-row sum. Robust standard errors adjusted for heteroskedasticity and city-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5% and 1% levels are marked *, ** and ***, respectively.
that in an environment with locally bound shocks, value chains tend to increase the volatility for the average node in a network, which in our case is a stock-market-listed firm in China. The reason is that value chains carry shocks to nodes (here, firms) that had not been directly exposed to the shock. This documents adverse effects in terms of shock transmissions of value-added chains in cases where shocks are negative and locally bound. The latter is in contrast to the smoothing effects of value chains regarding homogeneously distributed shocks across a large number of nodes.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Peter H. Egger  https://orcid.org/0000-0002-0546-1207
Jiaqing Zhu  https://orcid.org/0000-0002-4300-9959
TABLE 6  The determinants of abnormal returns when $\text{WeightedInConfirm}_{i,e}$ is constructed using the WIOD of 2014 as released in 2016

| Variables                        | (2)                      |
|----------------------------------|--------------------------|
| $\text{lnConfirm}_{i,e}$         | $-0.0138^*$              |
|                                  | (0.008)                  |
| $\text{WeightedInConfirm}_{i,e}$ | $-0.1175^{**}$           |
|                                  | (0.049)                  |
| Constant                         | 1.0097^{***}             |
|                                  | (0.211)                  |
| Firm-fixed effects               | Yes                      |
| Time-fixed effects               | Yes                      |
| No. of observations              | 138,284                  |
| $R^2$                            | .0512                    |
| Number of Firms                  | 3462                     |

Note: The results in this table should be compared to the ones in Column (2) of Table 3. This table reports results on the baseline model of Equation (3) when the independent variable $\text{WeightedInConfirm}_{i,e}$ is constructed using the China-China block in the WIOD in 2014 as released in 2016. The dependent variable is scaled by 100. Robust standard errors adjusted for heteroskedasticity and firm-level clustering are in parentheses. Coefficient estimates significantly different from zero at the 10%, 5% and 1% levels are marked *, ** and *** respectively.

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