Global economic footprint of the COVID-19 pandemic

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Countries around the world have sought to stop the spread of the 2019 novel coronavirus (COVID-19) by severely restricting travel and in-person commercial activities. Here, we analyse the economic footprint of such "lockdowns" using detailed datasets of global supply chains and a set of pandemic scenarios. We find that COVID-related economic losses are largely dependent on the number of countries imposing lockdowns, and that losses are more sensitive to the duration of a lockdown that its strictness—suggesting that more severe restrictions can reduce economic damages if they successfully shorten the duration of a lockdown. Our results also highlight several key vulnerabilities in global supply chains: Even countries that are not directly affected by COVID-19 can experience large losses (e.g., >20% of their GDP)—with such cascading impacts often occurring in low- and middle-income countries. Open and highly-specialized economies suffer particularly large losses (e.g., energy-exporting Central Asian countries or tourism-focused Caribbean countries). Supply bottlenecks and declines in consumer demand lead to especially large losses in globalized sectors such as electronics (production decreases of 13-53% across our scenarios) and automobiles (2-49%). Although retrospective analyses will undoubtedly provide further policy-relevant insights, our findings already imply that earlier, stricter, and thus shorter lockdowns are likely to minimize overall economic damages, and that global supply chains will magnify economic losses in some countries and industry sectors regardless of direct effects of the coronavirus.

The disease caused by 2019 novel coronavirus (COVID-19) emerged in China in late December, but quickly spread to other major countries[1] in Asia, Europe and North America and was declared a pandemic by the World Health Organization (WHO) on March 11[2]. There are now confirmed COVID-19 cases in nearly every country in the world, and the WHO has urged affected countries to slow spread of the virus by imposing containment and suppression measures[3,4] ranging from strict controls on travel, social gatherings, and commercial activities aimed at "flattening the curve" (i.e. decreasing the rate of new infections to avoid overwhelming health care systems) to less strict measures designed to shield immunologically-compromised individuals, treating victims, and achieving "herd immunity" (i.e. a sufficiently large number of recovered and thus immune individuals to prevent effective spread of the virus)[5]. Differences in the rapidity with which countries imposed such policies and the strictness of the policies reflect divergent (and perhaps hasty) assessments of both the public health risk of COVID-19 and the social and economic impacts of the different policies[6,7]. Here, using a newly-developed disaster footprint model[8-10], we quantitatively assess the economic impacts of different containment strategies across countries and industry sectors in order to both inform ongoing efforts to contain COVID-19 and to reveal more generally how pandemic-related economic losses will be distributed along global supply chains.

Details of our analytic approach are provided in the *Methods* section. In summary, we model the short-term economic shocks of different COVID-19 response scenarios as sector-specific transportation and labour supply constraints. The model operates at weekly time-steps, using the latest available global input-output data[11] and taking into account interactions throughout complex global supply chains and the contexts of scarcity and imbalance that prevail in most markets[10, 12]. It should be noted that the goal of this study is not to predict the true cost of the COVID-19 pandemic, but to identify the most important factors (e.g., the strictness and duration of lockdowns) and test the sensitivity of economic impacts to those factors as those impacts ripple through global supply chains. Thus, in addition to showing how overall damages might change under different policy scenarios, the incidence of damages across sectors and countries may inform the allocation of international aid and economic stimulus.

Results

We designed three scenario sets (shown in Fig. 1 and Fig. S1) which describe different COVID-19 spreading trajectories and containment measures. Spatial spread refers to the global reach of the pandemic through the number of countries affected. Duration refers to the number of months the containment measures last. Strictness is measured by the percentage of loss in labour availability and transportation capacity[13] compared to pre-disaster levels. Given that the impacts of containment measures to labour availability depends on the characteristics of production, we develop a specific impact-to-labour 'multipliers' set for every sector based on three factors, i.e., the exposure level to the virus, lifeline sectors (e.g. electricity), and work at home (e.g. education). Therefore, the constraints to labour availability in each sector are determined by two parts, i.e., level of strictness of measures represented in the scenario (e.g. 80% -strictness to contain 80% population flows) and the multipliers for a sector (e.g. 0.5 for wheat production as the level of exposure is low and 0.1 for electricity and gas supply as lifelines). Detailed description is shown in *Methods*. All 36 scenarios are the combinations among three drivers, and results are represented in terms of economic footprint, measured in absolute terms of loss in value added (in billion US dollars) or relative terms (as percentage of pre-crisis Value Added).

In Fig 1. panel CN assumes that the virus is contained in China (this set is outdated, but still useful to explore propagation; panel NH assumes the virus and containment measures spread in major western developed countries in the Northern Hemisphere (e.g. the EU and the US); panel GB assumes that the virus becomes global (*see Supplementary Information – SI for more background information*). In the CN scenario, containment scenarios ranging from 2 to 6 months in duration and 20% to 80% in strictness are explored. In the NH scenario set, it is assumed that containment in China lasts 2 months at 80% strictness from January to March[14], and containment in other affected countries ranges between 20% and 80% in strictness and 2 and 6 months in duration (from March onwards). In the global scenario (GB), we assume that China maintains containment measures for 2 months at 80% from January to March, and western countries for 4 months at 60% from March to July. The containment in the rest of the world ranges between 2 to 6 months in duration (from April onwards) and 20% to 80% in strictness. (*see Methods* and *Fig. S1*).

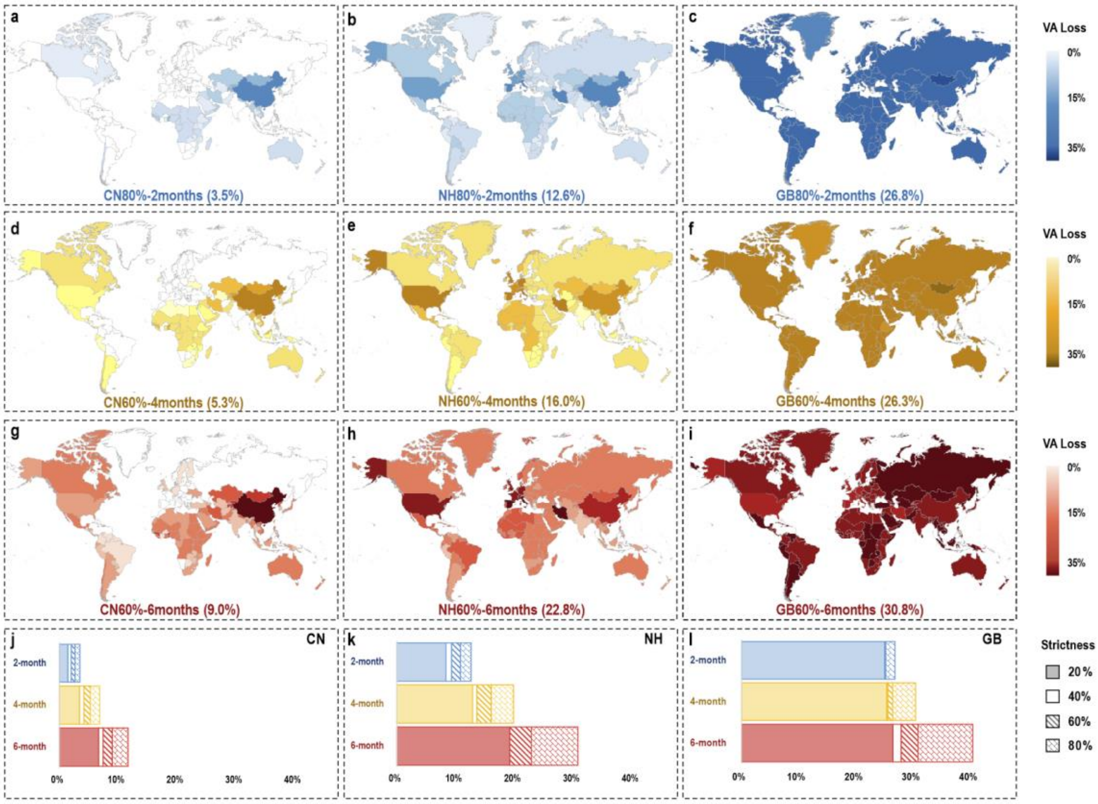

Fig.1 Economic footprint (measured by Value-Added loss) of COVID-19, from three scenario-sets of 36 scenarios in total, with different combinations among spatial spread, containment duration and strictness (see *Methods*, scenario set table). Each small map illustrates the corresponding scenario; where CN, NH and, GB represent the centre of the epidemic; 80%, 60%, 40% represents the strictness of the policies; and the following number represents the epidemic duration of 2, 4, 6 months. The brackets show the global footprint for each scenario. The colour changes in maps respond to the footprint for regions, from the smallest with lightest to the largest with darkest colour. **Fig.1 panel-CN** (vertical figure group) presents footprint distribution under different duration and strictness combinations when China is the only country affected. **Fig.1 panel-NH** builds upon the CN80%-2months scenario and presents footprint by adding scenarios for Iran, the EU (8 countries) and the US containment measures from 11th of March 2020. **Fig.1 panel-GB** further builds upon NH60%-4months scenario to assume further virus outbreak and containment measures placed by all countries including the least developed countries in the southern hemisphere. Same colour spectrum (horizontal group) gives footprint comparison along with the spatial spread of the virus under the same combination of duration and strictness. The bar charts (j-l) compare driving forces of global value-added losses between duration (2,4,6 months) and strictness (20%-80%) of implemented measures along with CN, NH and GB scenarios.

The first insight from the model is that the global cost of the pandemics depends foremost on the number of affected countries, and then on the required duration of containment policies; in contrast, the strictness of these policies is comparatively less important. The spatial extent of pandemics is the most important driver of the global cost. If only China was affected, the global economic footprints (measured by value-added) would reach 3.5% of global GDP (CN80%-2months, Fig.1a). With the spread in high-income western countries, the global economic footprints would increase almost four-fold to 12.6% (NH80%-2months scenario, Fig.1b). In the global pandemic scenario, the losses of global value-added would amount to 26.8% of global GDP (GB80%-2months, Fig.1c). Fig. 1d-i pairs up to illustrate the magnitude of duration in affecting global loss. By setting the same strictness, i.e. 60% in NH scenarios, the duration of containment extending from 4 to 6 months would add an additional 7% increase of global value-added (Fig 1e,h). Panel 1j-l show that global losses increase fast with the duration of the containment, especially in the CN and NH scenarios. In CN scenario set, if we set strictness at 80%, the global footprint would be \$2.6 trillion for a 2-month duration (Fig 1j-blue bar), and \$5.1 trillion for a 4-month duration (Fig 1j-yellow bar) and \$8.7 trillion (equivalent to 11.7% of global value-added) for a 6-month duration (Fig 1j-red bar).

Given the extent and duration of the pandemics, the strictness of containment measure would matter to a lesser extent. If we set the containment duration at 2 months, increasing the strictness from 20% to 80% would only increase the footprint by 2.0% (Fig 1j-blue bar, solid to bricks). We can see similar patterns in the NH and GB scenario sets. Although both duration and strictness determine domestic production (via labour supply) and transportation capacity linking to upstream suppliers and downstream consumers, the economic cost through international propagations are much more sensitive to the former.

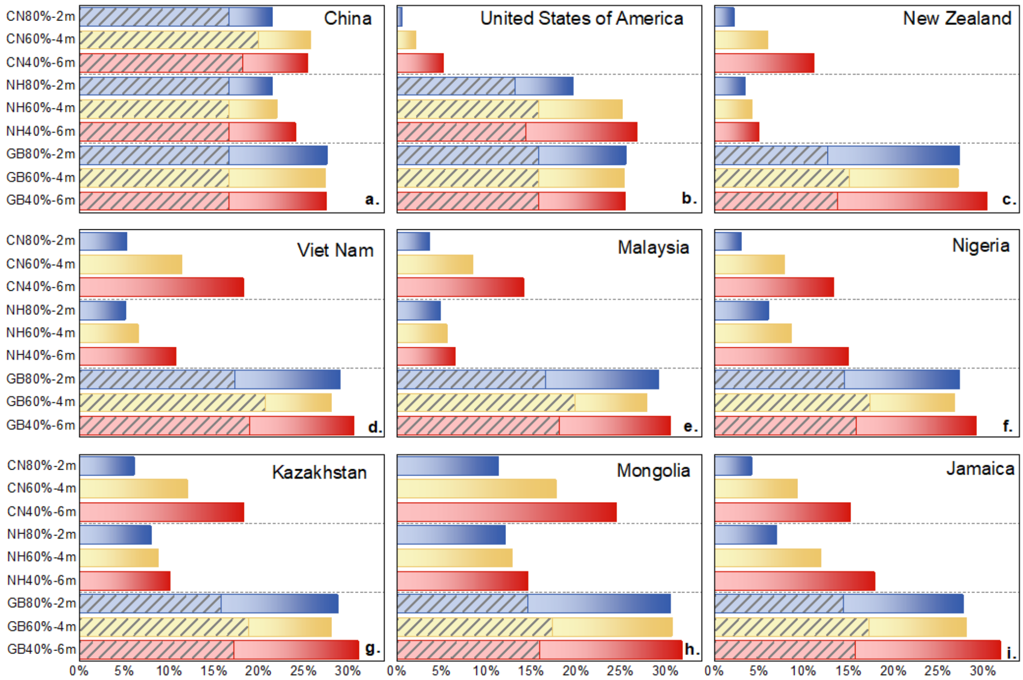

Fig. 2 Direct and indirect value-added losses of COVID-19 in selected countries under 9 scenarios. The bar charts a-i present economic footprint (measured by the percentage of value-added losses) in selected nine countries. The top row country includes China (affected in CN scenario), and developed countries such as the US (affected in NH scenario) and New Zealand (only affected in GB scenario). The middle row is countries (affected in GB scenario) which have close supply chain relationships with China to assess propagation effect. The bottom row is countries with a dominant economic sector. Each sub-figure contains three selected scenarios from the three scenario sets (12 per figure). Three colour bars respond to 2 (blue), 4 (yellow), 6 (red) months in duration. The gridded area in bars represent direct losses due to containments and the solid area represents the propagation.

The second insight is the importance of propagation through global supply chains: even countries that are not directly affected by the virus experience large losses, and low- and middle-income countries are more vulnerable to indirect effects. Fig. 2 presents direct (due to domestic containment measures such as lockdown or suppression) and propagation effects via international supply chains across the three scenarios sets. In the CN80%-2months scenario, in which only China is directly affected by the virus, there are major economic losses in China (16.7% of annual GDP, Fig 2a), but also forward and backward propagation effects both within China and with other countries. The propagations through the economic system add 4.8% to China's direct loss to make an overall footprint of 21.5% of annual value-added. Further, although the United States (US) and New Zealand are not directly affected by the epidemic, they still suffer from 0.6% and 2.2% value-added losses under scenario CN80%-2 months due to declines in China's output (**negative forward effect**) as well as shrink of China's final demand for their products (**negative backward effect**). Under the same scenario, countries such as Vietnam, Malaysia and Nigeria, which are closely linked to China's supply chains, experience losses of 5.2%, 3.6% and 3.1% of their GDP. Specialized economies like Kazakhstan (energy), Mongolia (livestock), and Jamaica (tourism) experience even larger losses, with 6.1%, 4.2% and 11.4% drops in their annual GDP, respectively (Fig.2d-i). Countries where the virus has been controlled can be continuously affected by imported losses. Assuming the virus is controlled in China over two months but spread globally, China suffers secondary economic downturn due to propagations: $1.73 trillion (scenario NH60%-4months, Fig. S1, NH-China) and $5.77 trillion (scenario GB40%-6months, Fig. S1, GB-China).

In spite of the propagation of containment costs through supply chains[15], pandemics control remains a public goods. In particular, non-affected countries benefit massively from effective containment implemented in affected countries but bear only a fraction of the cost. If only China is affected, most of the impact in the rest of the world is delayed by weeks or months depending on countries (see Fig. S1), as firms use their inventories to smooth the shock. Non-affected countries may place travel bans and reduce transportation capacities to affected countries. In the scenario with the 2 months of the strictest containment measures in China (CN80%-2months), assuming that the virus had contained in the country, economic costs for the rest of the world would still be visible, but, unsurprisingly, much smaller than if they are directly affected (see Fig 2, the gridded versus solid area in different scenario bars). Whilst China is borne with most of the cost of containment (e.g. 21.6% of its value-added), other countries experience indirect impacts (for instance Italy and the UK are losing less than half percent of their value-added and 1.2% to Ethiopia, see Fig. S1 panel CN). This compares with double-digits direct costs if they are hit by the virus (NH scenarios). Similarly, if the virus could have been ended in the western countries with a strict 2-months containment (scenario NH80%-2months), the EU and the US would have suffered from direct losses around 15%-20% of their GDP, compared with only 2.5% for Ethiopia. A 6-month containment would have bigger impacts on other countries, with Ethiopia losses increasing four-fold to 9.8% of its value-added (Fig. S2). But this is still much less than the 27.9% losses under the GB40%-6months scenario, in which the country is directly hit. A successful containment strategy is to prevent propagation costs to global supply chains as it has a high benefit-cost ratio at global level, but the much less for the country alone.

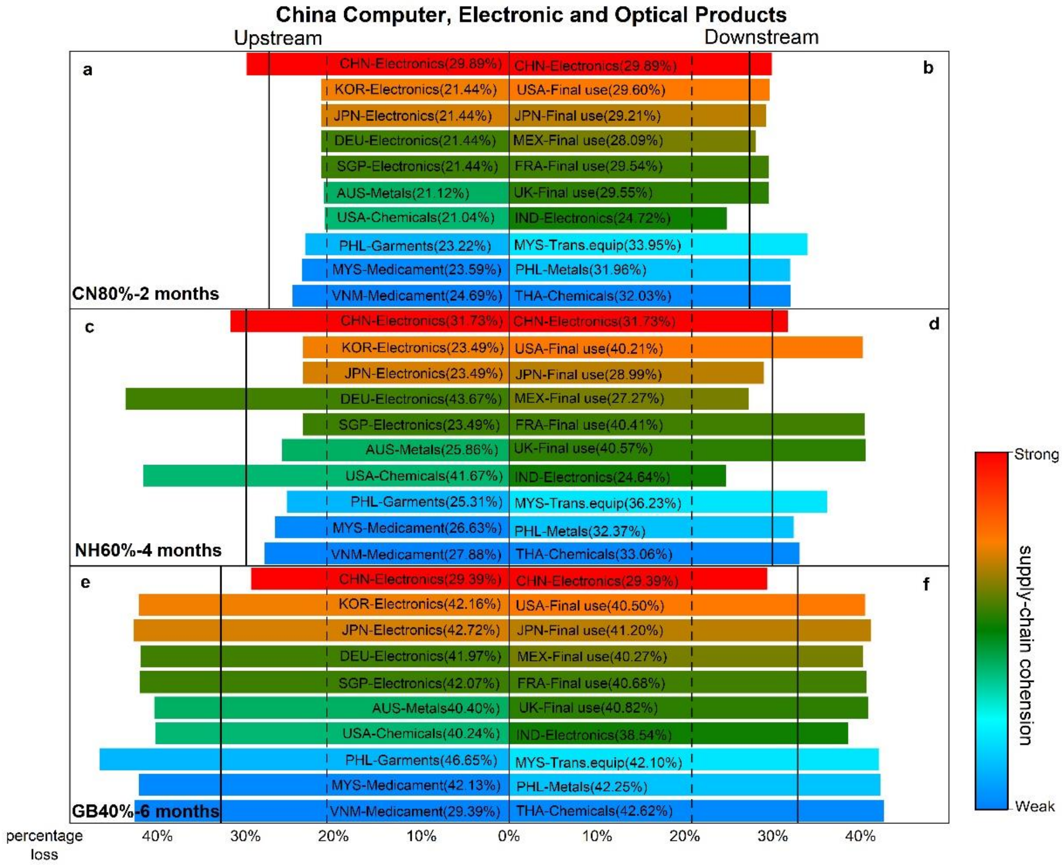

Fig. 3 Supply chain footprint to China's electronic-manufacturing industries under three scenario-sets (CN80%-2 months (a, b), NH60%-4 months (c, d) and GB40%-6 months (e, f)). **a, c** and **e** show the economic footprints to supply chain upstream of China's electronics industry and **b, d, f** represent the economic footprints from the perspective of downstream supply chain. Different colours of each bar represent the strength of linkage between industries and China's electronics industry (change from blue to red). In the upstream supply chains, the redder the bar is, the more important suppliers of China's electronics industry would be; in the downstream, the redder bar means that sector of this country is the main clients of China's electronics industry. The length of bars in a-f depict the industries' relative production losses compared with the original capacity under different scenario-sets. The black vertical dashed lines and grey vertical dashed lines in a-f represent the total losses and the direct losses of original production capacity of China's electronics industries, respectively, under different scenario-sets.

The third insight is that global value chains are very vulnerable, even if containment remains localized. We investigate in more details China's electronic industry and Germany's car-making industry, because of their positions in global supply chains and importance for their national economies. **China's electronics supply-chain is labour intensive and has 'scale-free' property[7], i.e. there is a clustered hub in China with connections to a large number of firms in electricals, chemical and metal production in Asian countries[16]. This supply chain is highly to the spatial spreading and duration of containment measures.** If the COVID-19 has remained only in China (in CN80%-2 months scenario), the value created by this supply chain would have been reduced by 27.3% (including 20.8% in direct loss) (Fig. S14). China's electronics sector is closely linked with both international electronics and metals production and would trigger production declines by around 21% for Korean electronics, Japan electronics and Australian metals (Fig. 3a). **Although electronic products are largely substitutable, major production lines are centralised in China[16]. Downstream impact is due to shortage of supply, therefore forcing a decline of consumption by final users**. Final consumption in the US, Japan, Mexico and France would be most affected, with reductions by more than 28% (Fig. 3b). In the global pandemic scenario (GB40%-6months), China's labour supply and transportation availability is back at its pre-disaster level. However, due to propagations through global supply chains (largely forward effect from China's upstream Asian countries), sectoral output further reduced from 29.9% to 32.8% (Fig. 3e, Fig. S14). The production of upstream sectors would rebound from mid-May (week 15, shown in SI Fig. S14). Downstream consumption in the US, Japan, Mexico and France would be reduced by a total of 40% (Fig. 3f).

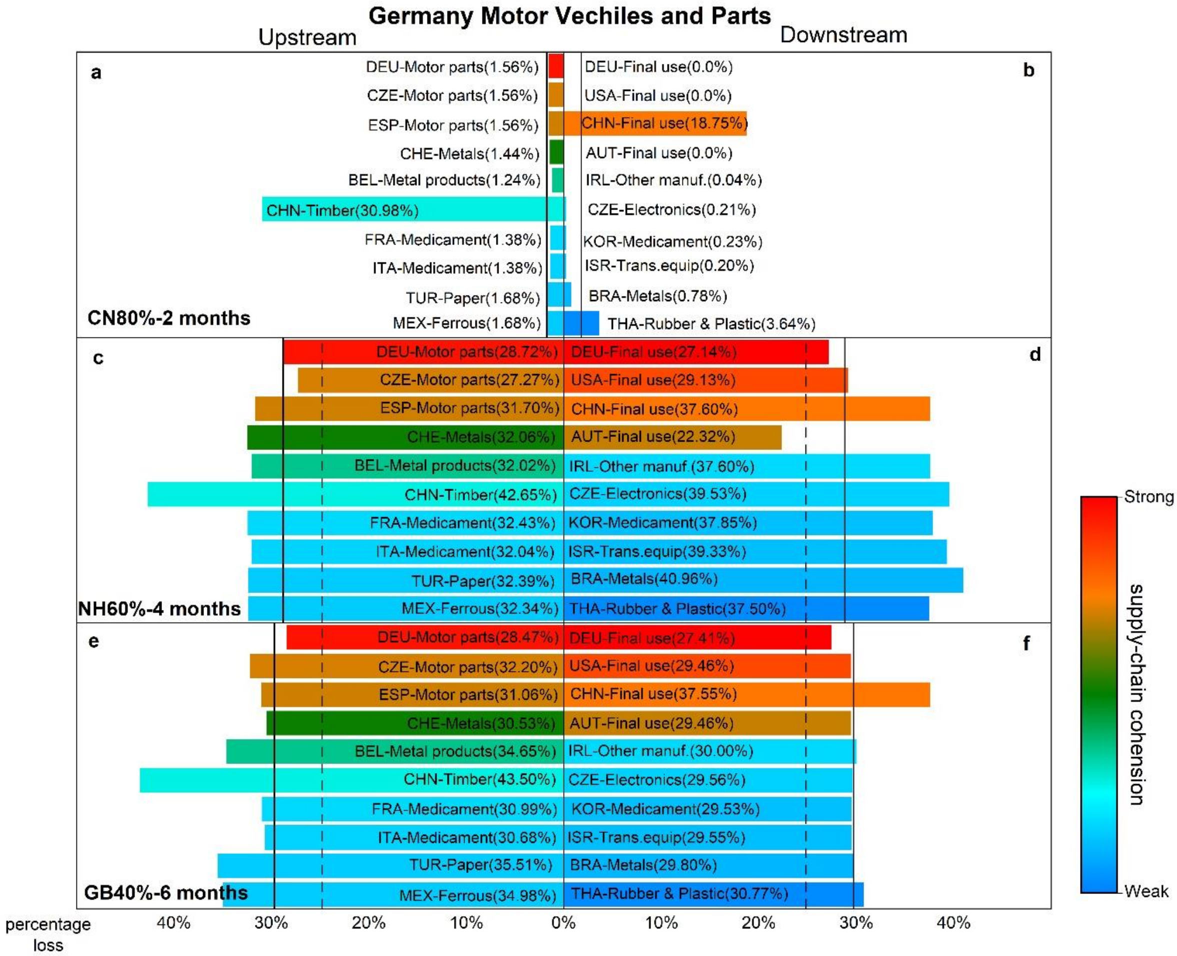

Fig. 4 Supply chain footprint to German automobile industries under three main scenario-sets. **a, c** and **e** show the economic footprints to supply chain upstream of German automobile industries and **b, d, f** represent the economic footprints from the perspective of downstream supply chain. The setting of scenario-sets, circle colour and area are similar with that of Fig 3. The length of bars in a-f depict the industries' relative production losses compared with the original capacity under different scenario-sets. The black vertical dashed lines and grey vertical dashed lines in a-f represent the total losses and the direct losses of original production capacity of German automobile industries, respectively, under different scenario-sets.

The suppliers of the automobile sector are scattered globally, with highly specialized suppliers,

making short-term substitution very difficult[17]. Shocks to any node of the supply chain create cascading effects[18]. The footprint of German automobile industry would have only declined by 1.8% if the virus had been contained in China (in CN80%-2 months scenario), as China's demand to German motor parts and final car consumption would have been reduced by 25% (see in Fig. S15). Motor parts production in the US and the UK as well as electronics in Germany, which supply essentials to Germany's automobile sector, would also be affected due to reduced capacities in various upstream sectors in China (e.g. electronics, metals and rubber and plastics). Closure of car dealers in China would trigger negative backward effect, leading to a 19.2% decline in final consumption of German cars (Fig 4b). In the NH60%-4months scenario, due to the restrictions on the labour force and transportation in Germany and the supply capacity of auto parts and raw materials in Germany, China, Italy and France decline largely (Fig. S15), Germany automobile production would experience a reduction in production by 28.8% (24.8% directly due to local containment, and 4.0% due to constraint capacity in propagated upstream supply chain effects, Fig. 4c). Upstream suppliers not only within Germany but in Hungary, Spain, Italy and the US would also be affected, with effects on German car production. Due to lower downstream consumer demand, losses of final consumption in the US, China and Austria would reach 29.1%, 37.6%, 29.2% and 22.3%, respectively (Fig. 4d). In the global pandemic scenario, the output of German automobile industries would drop by an additional 0.9% (GB40%-6months, Fig. 4e). In this case, the unavailable supplies from low- and middle-income countries to Germany (Fig. S15) would lead German producers to look for new suppliers ("substitution effect"). For instance, the production of motor parts in the US would rebound slightly. However, the overall impacts remain strongly negative everywhere, with final consumption in the US and Austria decreased by 29.5%. After China's epidemic situation is controlled, the model assumes that China's demand for German cars back at its pre-disaster level, but due to supply and international transportation constrains, China consumption of German cars would still have to decline by 37.5%.

High-exposure final-consumption sector like catering and tourism are the most vulnerable to containment[19], as they are exposed to a drop in demand and to propagation from upstream suppliers such as food and business sectors[20]. In the NH60%-4months scenario, the value added by the Jamaican tourism industry would decrease by 13.8%, mainly because of a drop in the number of tourists from western countries (Fig. S16). The substantial decline in Jamaican tourism would trigger a 32% reduction in its imports of US beverage and tobacco production. Final demand from China, Korea, US and UK would decrease by 37.8%, 9.6%, 48.5% and 48.5% (Fig. S12d). In the model, a global pandemic scenario (GB40%-6months scenario) leads to a massive decline in both domestic and international travel and tourism (Fig. S16). Therefore, the Jamaican tourism industry would decline by 56.3%. The effect on the import of beverages and tobacco products from the US would rebound to 46.7% of pre-disaster level.

Discussion

Because the global economic cost of the pandemics depends on the number of affected countries, required duration of containment policies and the strictness of these policies, the economic footprint depends on the policy choices made across the globe[21, 22]. Our findings suggest that it is much better to implement stricter measures earlier, provided that it allows to have them in place for a shorter duration.

Costs are distributed every heterogeneously, however. Countries implementing the strictest containment are experiencing larger losses, while most of the benefits are outside their borders[23, 24]. If they could contain the virus, the strictest restriction we consider in China would reduce the global GDP by 3.5 percent, but cost China's GDP by 21 percent.

The heterogeneity in the cost of early action – with the emergent countries experiencing most of the losses – makes pandemics containment a classical public goods problem, leading to under-investment and delayed action. Thinking about the next emerging disease, a cost sharing instrument at the global level, ensuring a fair distribution of the cost of disease surveillance and early containment and suppression, would remove some of the disincentive for early action and could generate massive global benefits over the long term.

Data availability

All data and R codes are deposited at our data publishing website – China Emission Accounts and Datasets (http://www.ceads.net/?ddownload=3188). Those data can be also obtained from the corresponding author on reasonable request.

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Methods

Disaster footprint model. Our disaster footprint model is an extension of the adaptive regional input-output (ARIO) model[23, 24], which was widely used in the literature to simulate the propagation of negative shocks throughout the economy[11, 12, 25-27]. Our model improves the ARIO model in two ways. The first improvement is related to the substitutability of products from the same sector sourced from different regions. Second, in our model, clients will choose their suppliers across regions based on their capacity. These two improvements contribute to a more realistic representation of bottlenecks along global supply chains.
Our disaster footprint model mainly includes 4 modules, i.e., production module, allocation module, demand module and simulation module. The production module is mainly designed for characterizing the firm's production activities. The allocation module is mainly used to describe how firms allocate output to their clients, including downstream firms (intermediate demand) and households (final demand). The demand module is mainly used to describe how clients place orders to their suppliers. And the simulation module is mainly designed for executing the whole simulation procedure.

Production module. The production module is used to characterize production processes. Firms rent capital and employ labour to process natural resources and intermediate inputs produced by other firms into a specific product (see figure S1). The production process for firm i can expressed as follows,

$$x_i = f\left(\text{for all } p, z_i^p; va_i\right)$$

where x_i denotes the output of the firm, in monetary value; p denotes type of intermediate products; z_i^p denotes intermediate products used in production processes; va_i denotes the primary inputs to production, such as labour (L), capital (K) and natural resources (NR). $f(\cdot)$ is the production function for firms. There are a wide range of functional forms, such as Leontief [28], Cobb-Douglas (C-D) and Constant Elasticity of Substitution (CES) production function[29]. Different functional forms reflect the possibility for firms to substitute an input for another. Considering that epidemics often cause large-scale economic fluctuations in the short term, during which economic agents do not have enough time to adjust other inputs to substitute temporary shortages, we use Leontief production function which does not allow substitution between inputs.

$$x_i = min\left(\text{for all } p, \frac{z_i^p}{a_i^p}; \frac{va_i}{b_i}\right)$$

where a_i^p and b_i are the input coefficients calculated as

$$a_i^p = \frac{\bar{x}_i}{\bar{z}_i^p}$$

and

$$b_i = \frac{\bar{x}_i}{\overline{va}_i}$$

where the horizontal bar indicates the value of that variable in the equilibrium state. In an equilibrium state, producers use intermediate products and primary inputs to produce goods and services to satisfy demand from their clients. After a disaster, output will decline. From a production perspective, there are mainly the following constraints:

Labour supply constraints. Labour constraints after a disaster may impose severe knock-on effects on the rest of the economy[30-32]. This makes labour constraints a key factor to consider in disaster impact analysis. For example, in the case of a pandemic, these constraints can arise from employees' inability to work as a result of illness or death, or from the inability to go to work and the requirement to work at home (if possible). In this model, the proportion of surviving productive capacity from the constrained labour productive capacity (x_i^L) after a shock is defined as:

$$x_i^L(t) = \left(1 - \gamma_i^L(t)\right) * \bar{x}_i$$

Where $\gamma_i^L(t)$ is the proportion of labour that is unavailable at each time step t during containment. $(1 - \gamma_i^L(t))$ contains the available proportion of employment at time t.

$$\gamma_i^L(t) = (\bar{L}_i - L_i(t))/\bar{L}_i$$

The proportion of the available productive capacity of labour is thus a function of the losses from the sectoral labour forces and its pre-disaster employment level. Following the assumption of the fixed proportion of production functions, the productive capacity of labour in each region after a disaster (x_i^L) will represent a linear proportion of the available labour capacity at each time step. Take COVID-19 as an example, during an outbreak of an infectious disease, authorities often adopt social distancing and other measures to reduce the risk of infection. This imposes an exogenous negative shock on the economic network.

Constraints on productive capital. Similar to labour constraints, the productive capacity of industrial capital in each region during the aftermath of a disaster (x_i^K) will be constrained by the surviving capacity of the industrial capital[25, 33-36]. The share of damage to each sector is directly considered as the proportion of the monetized damage to capital assets in relation to the total value of industrial capital for each sector, which is disclosed in the event account vector (EAV) for each region (γ_i^K), following[37]. This assumption is embodied in the essence of the IO model, which is hard-coded through the Leontief-type production function and its restricted substitution. That is, as capital and labour are considered perfectly complementary as well as the main production factors, and the full employment of those factors in the economy is also assumed, we assume that damage in capital assets is directly related with production level and therefore, value added level. Then, the remaining productive capacity of the industrial capital at each time step is defined as:

$$x_i^K(t) = \left(1 - \gamma_i^K(t)\right) * \bar{x}_i$$

Where, $\bar{K}_i$ is the capital stock of firm i in the pre-disaster situation, and $K_i(t)$ is the surviving capital stock of firm i at time t during the recovery process.

$$\gamma_i^K(t) = (\bar{K}_i - K_i(t))/\bar{K}_i$$

Supply constraints. Firms will purchase intermediate products from their supplier in each period. Insufficient inventory of a firm's intermediate products will create a bottleneck for production activities. The potential production level that the inventory of the p^{th} intermediate product can support is

$$x_i^p(t) = \frac{S_i^p(t-1)}{a_i^p}$$

where $S_i^p(t-1)$ refers to the amount of p^{th} intermediate products held by firm i at the end of time step $t-1$.

Considering all the limitation mentioned above, the maximum supply capacity of firm i can be expressed as

$$x_i^{max}(t) = min\left(x_i^L(t); x_i^K(t); \text{for all } p, x_i^p(t)\right)$$

The actual production of firm i, $x_i^a(t)$, depends on both its maximum supply capacity and the total orders the firm received from its clients (see the Demand Module),

$$x_i^a(t) = min(x_i^{max}(t), TD_i(t-1))$$

The inventory held by firm i will be consumed during the production process,

$$S_i^{p,used}(t) = a_i^p * x_i^a(t)$$

Allocation module. The allocation module mainly describes how suppliers allocate products to their clients. When some firms in the economic system suffer a negative shock, their production will be constrained by a shortage to primary inputs such as a shortage of labour supply in the outbreak of COVID-19. In this case, a firm's output will not be able to fill all orders of its clients. A *rationing scheme* that reflects a mechanism based on which a firm allocates an insufficient amount of products to its clients is needed[23, 38]. For this case study, we applied a *proportional* rationing scheme according to which a firm allocates its output in proportion to its orders. Under the proportional rationing scheme, the amounts of products of firm i allocated to firm j and household h is as follows,

$$FRC_j^i(t) = \frac{FOD_i^j(t-1)}{\left(\sum_j FOD_i^j(t-1) + \sum_h HOD_i^h(t-1)\right)} * x_i^a(t)$$

$$HRC_h^i(t) = \frac{HOD_i^h(t-1)}{\left(\sum_j FOD_i^j(t-1) + \sum_h HOD_i^h(t-1)\right)} * x_i^a(t)$$

Firm j received intermediates to restore its inventories,

$$S_j^{p,restored}(t) = \sum\nolimits_{i \to p} FRC_j^i(t)$$

Therefore, the amount of intermediate p held by firm i at the end of period t is

$$S_j^p(t) = S_j^p(t-1) - S_j^{p,used}(t) + S_j^{p,restored}$$

Demand module. The demand module represents a characterization of how firms and household issues orders to their suppliers at the end of each period. Firm orders its supplier because of the need to restore its intermediate product inventory. We assume that each firm has a specific target inventory level based on its maximum supply capacity in each time step,

$$S_i^{p,*}(t) = n_i^p * a_i^p * x_i^{max}(t)$$

Then the order issued by firm i to its supplier j is

$$FOD_j^i(t) = \begin{cases} \left(S_i^{p,*}(t) - S_i^p(t)\right) * \dfrac{\overline{FOD_j^i} * x_j^a(t)}{\sum_{j\to p}\left(\overline{FOD_j^i} * x_j^a(t)\right)}, & \text{if } S_i^{p,*}(t) > S_i^p(t); \\ 0 & \text{if } S_i^{p,*}(t) \le S_i^p(t). \end{cases}$$

Households issue orders to their suppliers based on their demand and the supply capacity of their suppliers. In this study, the demand of household h to final products q, $HD_h^q(t)$, is given exogenously at each time step. Then, the order issued by household h to its supplier j is

$$HOD_j^h(t) = HD_h^q(t) * \frac{\overline{HOD_j^h} * x_j^a(t)}{\sum_{j\to q}\left(\overline{HOD_j^h} * x_j^a(t)\right)}$$

The total order received by firm j is

$$TOD_j(t) = \sum_i FOD_j^i(t) + \sum_h HOD_j^h(t)$$

Simulation module. At each time step, the actions of firms and households are as follows:

1. Firms plan and execute their production based on three factors: a) inventories of intermediate products they have, b) supply of primary inputs, and c) orders from their clients. Firms will maximize their output under these constraints.
2. Product allocation. Firms allocate outputs to clients based on their orders. In equilibrium, the output of firms just meets all orders. When production is constrained by exogenous negative shocks, outputs may not cover all orders. In this case, we use a proportional rationing scheme proposed in the literature[23, 38](see Allocation Module) to allocate products of firms.
3. Firms and household issue orders to their suppliers for the next time step. Firms place orders with their suppliers based on the gaps in their inventories (target inventory level minus existing inventory level). Households place orders with their suppliers based on their demand. When a product comes from multiple suppliers, the allocation of orders is adjusted according to the production capacity of each supplier.

This discrete-time dynamic procedure can reproduce the equilibrium of the economic system, and can simulate the propagation of exogenous shocks, both from firm and household side, or transportation disruptions, in the economic network. From the firm side, if the supply of a firm's primary inputs is constrained, it will have two effects. On the one hand, the decline in output in this firm means that its clients' orders cannot be fulfilled. This will result in a decrease in inventory of these clients, which will constrain their production. This is the so-called forward or downstream effect. On the other hand, less output in this firm also means less use of intermediate products from its suppliers. This will reduce the number of orders it places on its suppliers, which will further reduce the production level of its suppliers. This is the so-called backward or upstream effect. Similarly, these two effects can also occur if the transport of a firm to its clients or suppliers is restricted. For instance, during the outbreak of COVID-19 in China, the authorities adopted strict isolation measures. These measures have placed constraints on the supply of labour and the transportation of products. This led to a decline in China's output and also triggered the forward and backward effect, which make the shock to propagate to the global economic network. From the household side, the fluctuation of household demand caused by exogenous shocks will also trigger the aforementioned backward effect. Take tourism as an example, during the outbreak of COVID-19 in China, the demand for Chinese tourism from households all over the world will decline significantly. This influence will further propagate to the accommodation and catering industry through supplier-client links.

Economic footprint. We define the value-added decrease of all firms in a network caused by an exogenous negative shock as the disaster footprint of the shock. For the firm directly affected by exogenous negative shocks, its loss includes two parts: a) the value-added decrease caused by exogenous constraints, and b) the value-added decrease caused by propagation. The former is the direct loss, while the latter is the indirect loss. A negative shock's total economic footprint ($TEF_{i,r}$), direct economic footprint ($DEF_{i,r}$), and propagated economic footprint ($PEF_{i,r}$) for firm i in region r are,

$$TEF_{i,r} = \overline{va}_{i,r} * T - \sum_{t=1}^{T} va_{i,r}^{a}(t)$$

and,

$$DEF_{i,r} = \overline{va}_{i,r} * T - \sum_{t=1}^{T} va_{i,r}^{max}(t)$$

and,

$$PEF_{i,r} = TEF_{i,r} - DEF_{i,r}$$

Global supply-chain network. We build a global supply chain network based on version 10 of the Global Trade Analysis Project (GTAP) database[39]. GTAP 10 provides a multiregional input-output (MRIO) table for the year of 2014. This MRIO table divides the world into 141 economies, each of which contains 65 production sectors. If we treat each sector as a firm (producer), and assume that each region has a representative household, we can obtain the following information in the MRIO table: a) suppliers and clients of each firm; b) suppliers for each household, and c) the flow of each supplier-client connection under the equilibrium state. This provides a benchmark for our model.
When applying such a realistic and aggregated network in the disaster footprint model, we need to consider the substitutability of intermediate products supplied by suppliers from the same sector in different regions. The substitution between some intermediate products is fairly straightforward. For example, for a firm that extracts spices from bananas it does not make much of a difference if the bananas are sourced from the Philippines or Thailand. However, for a car manufacturing firm in Japan, which use screw from Chinese auto parts suppliers and engines from German auto parts suppliers to assemble cars, the products of the suppliers in these two regions are non-substitutable. If we assume that all goods are non-substitutable as in the traditional IO model, then we will overestimate the loss of producers such as fragrance extraction firm. If we assume that products from suppliers in the same sector can be completely substitutable, then we will significantly underestimate the losses of producers such as Japanese car manufacturing firm. In order to alleviate the shortcomings of the evaluation deviation under the two assumptions, we set the possibility of substitution for each firm based on the region and sector of supplier supply (see Allocation Module of the model).

Spread and containment scenarios. The number of affected countries, the duration of the containment and the strictness of the containment are the three important factors influencing the loss caused by the epidemic. Using these three indicators as dimensions, and then referring to the actual epidemic situation, we designed three sets of scenarios, i.e., CN, NH and GB. Different sets of scenarios represent different areas of influence of COVID-19, while scenarios in the same scenario set have different assumptions about duration of the containment and the strictness of the containment.

Our first scenario set, CN, assumes that the outbreak of COVID-2019 is only in mainland China. In this scenario set, labour supply and transportation in mainland China will be restricted due to the need for epidemic control from the fourth week of 2020 (i.e., 2020.01.22). To examine the impact of policy strictness and duration of the outbreak on the world economic system, we set four strictness (i.e., 20%, 40%, 60%, 80%) and three durations (i.e., 2, 4, 6 months), see the yellow block in the table below. For instance, the scenario "CN20-2" means that the epidemic lasts for two months with labour supply and transportation restrictions of 20%.

Isolation measures have different effects on labour supply in different sectors. We set a specific multiplier for each sector based on three factors, i.e., the exposure level of the sector's work, whether it is the lifeline, and whether it is possible to work at home. If a sector's work exposure level is low, or it is the lifeline sector, or it is easy to work at home, its' multiplier will be small, vice versa.

Then, the constraints on labour supply in each sector are determined by two parts, i.e., benchmark constraint in the scenario and multipliers for the sector. For instance, we assume that the multiplier for the wheat production sector is 0.5 because the level of exposure to its production activities is relatively low. Then, in the scenario "CN20-2", the labour supply in the wheat production sector will fall by 10%, i.e., 20% multiplied by 0.5.

At the same time, in the scenario set CN, transportation between mainland China and other regions will also fall by 50% during the duration of the epidemic.

The epidemic not only affects the global economic system from the supply side, but also affects economic output through its impact on consumer demand. Most obviously, tourism demand for the region with COVID-2019 outbreaks will drop significantly. Due to lack of data, we simply assume that the final demand for the two sectors, "Recreation and other services" and "Accommodation, Food and service activities", in the outbreaking area fell by 99% during the duration of the outbreak.

Scenario-sets table

		Duration (month)				**Duration (month)**				**Duration (month)**		
		2	**4**	**6**		**2**	**4**	**6**		**2**	**4**	**6**
Strictness	**20%**	CN20-2	CN20-4	CN20-6		NH20-2	NH20-4	NH20-6		GB20-2	GB20-4	GB20-6
	40%	CN40-2	CN40-4	**CN40-6**		NH40-2	NH40-4	**NH40-6**		GB40-2	GB40-4	**GB40-6**
	60%	CN60-2	**CN60-4**	CN60-6		NH60-2	**NH60-4**	NH60-6		GB60-2	**GB60-4**	GB60-6
	80%	**CN80-2**	CN80-4	CN80-6		**NH80-2**	NH80-4	NH80-6		**GB80-2**	GB80-4	GB80-6

In the second set of scenarios (NH), we assume that regions with the current severe epidemic situation have taken measures from the eleventh week (2020.03.11) to control their epidemic. These countries include the United States, France, Germany, Italy, the Netherlands, the United Kingdom, Switzerland, Spain, and Iran. The labour and transportation restrictions are consistent with the settings of the scenario set CN, and take "CN80-2" as default in mainland China, which basically matches the reality we observe from big data.

In the last set of scenarios (GB), we assume that in addition to the mainland China and the economies in the scenario set NH, other economies in the world also began to take measures to control the epidemic in the 15th week (2020.04.08). The labour and transportation restrictions are consistent with the settings of the scenario set CN, and take "CN80-2" as default in mainland China, "NH60-4" as default in economies in the scenario set NH.

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