How Much of China and World GDP Has The Coronavirus Reduced?*

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Abstract

Using a network approach, we estimate the output loss due to the lockdown of the Hubei province triggered by the coronavirus disease (COVID-19). Based on our most conservative estimate, China suffers about 4% loss of output from labor loss, and global output drops by 1% due to the economic contraction in China. About 40% of the impact is indirect, coming from spillovers through the supply chain inside and outside China.

1 Introduction

This paper provides an estimate on the economic impact of the coronavirus on China and the global economy. Closure of cities and restrictions on travel are thought to be detrimental to production, and our exercise starts with this supply shock. Using historical data on domestic travels during Chinese New Year in mainland China, we first calculate the impact of the loss of workers from Hubei to its own production and that of any other province in the country. Using the latest input-output tables and the industry compositions of each province, we back out the loss in aggregate output due to this loss in labor input. Clearly, a drop in output in China has repercussions for the rest of the world, and we further estimate the loss in global output based on the global trade linkages. Based on our benchmark estimates, the loss in Chinese output is about 4% and global output is about 1% in each period of Hubei lockdown compare with the case without the outbreak of the disease.

We keep the calculation simple and transparent, and the estimate is free from any endogeneity problem due to the unexpected nature of the lockdown. This exercise is also conservative

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that it only considers the loss of labor input from Hubei province. Drop in labor supply in other provinces, due to different kinds of government actions, is ignored. Effects from reduced international travels in and out of China are also not included. While it may be more realistic to incorporate all such disruptions, we would like to keep the exercise simple and focus on one supply shock constructed through a clean identification strategy. Also, the construction of other types of shocks may have endogeneity issues. On the other hand, this exercise may have overestimated the impact of the coronavirus as it does not allow for both fiscal and monetary policy responses. Again, to keep the exercise tractable and transparent, we leave such matters aside.

We borrow the modeling techniques from literature of the economics of networks, which is reviewed in Section 2. Some similar studies on other epidemics are also mentioned. Section 3 explains the model. Section 4 describes the different sources of data used in the exercise. The benchmark estimates are provided Section 5 and several sensitivity analyses are done in Section 6.

2 Literature

This paper fits into two strands of the literature, production networks and economic costs of epidemics.

Firms are interconnected through trade within and across sectors with specialized productions. The production linkages among firms serve to propagate shocks along the supply chain and ultimately affect the aggregate economy. Since Long and Plosser (1983), a large literature has focused on the aggregate volatility generated by idiosyncratic shocks. Two effects are at work, as presented by di Giovanni et al. (2014). First, owing to the direct effect, shocks can have sizable aggregate effect directly (Carvalho and Gabaix, 2013; Gabaix, 2011; Jovanovic, 1987). For example, the direct impact of the productivity growth of General Electric is a change in U.S. GDP by 0.24% in 2000, according to Gabaix (2011). Second, owing to the indirect network effect, shocks can contribute to aggregate fluctuations through contagion within the network (Acemoglu et al., 2012, 2015; Bak et al., 1993; Conley and Dupor, 2003; Dupor, 1999; Foerster et al., 2011; Horvath, 1998, 2000; Jones, 2011, 2013; Levine, 2012; Lu and Luo, 2019; Osotimehin and Popov, 2020; Shea, 2002, etc.). For example, a firm that encounters severe financial difficulties would be forced to defer payments or default on their accounts-payable to its suppliers, thus creating further illiquidity problems along the supply chain in a kind of chain reaction and affecting aggregate output negatively (Kiyotaki and Moore, 1997; Luo, 2019). Another application is Carvalho et al. (2016), who examine the propagation of shocks caused by the Great East Japan Earthquake of 2011 in the prodcution network. Clearly, the spillover of shocks also occurs in the global trade network and impacts the global economy. Lu and Luo (2019) estimate that the network effect is responsible for about 30 percent of the total global effect of the U.S. monetary policy shock. Borrowing ideas from the literature, this paper focuses on the domestic and global output impact of the supply shock triggered by the coronovirus outbreak in China. Given the increased inter-firm integration within China and across the globe, a network approach is essential to access the economic impact of the coronavirus.

Furthermore, there are numerous papers on the economic costs of epidemics. For example, Halasa et al. (2012) look at the medical costs of dengue in Puerto Rico in 2010, and Armien et al. (2008) do an earlier study for Panama. Yang et al. (1999) calculates the medical costs and market value losses for pigs due to the foot-and-mouth disease in Taiwan in 1997. Bloom and Mahal (1997) controls for potential simultaneity between the AIDS epidemic and economic growth and find that the epidemic has little impact on growth. This study differs from most previous studies in two aspects. First, the lockdown of Wuhan (and later most of the Hubei province) is an unprecedented move, and to highlight the drastic policy we only focus on the output loss, directly and indirectly, due to the stoppage of production. All other economic costs such as medical expenses and loss of quality of life are not considered in this study. Second, it is safe to assume that the policy came as a complete surprise, and as a result this study is free from endogeneity or simultaneity concerns.

3 A Simple Input-Output Model

We estimate the output loss based on a theoretical model. First, we look at how a drop in labor from the Hubei province affects production within mainland China through input-output network relationships across provinces. There are N sectors indexed by $i = 1, \cdots, N$, each of which produces one type of product. The firms within each sector are homogeneous and competitive. Those in sector i produce product m_i using a Cobb-Douglas production function with labor augmented productivity given by

$$m_i = (z_i l_i)^{\alpha_i} (\Pi_{j=1}^{N} m_{ij}^{\omega_{ij}})^{1-\alpha_i}, \tag{1}$$

where m_{ij} denotes the amount of product j used by firms in Sector i, l_i represents labor, and z_i denotes technology. The exponent ω_{ij} denotes the share of good j in the total intermediate input use of firms in Sector i and captures the production network structure. A discussion of the Cobb-Douglas specification is provided in Section 5.

All firms supply inputs that enter the production of the final good. The final output of the economy is

$$Y = \Pi_{i=1}^{N} \zeta_i^{-\zeta_i} y_i^{\zeta_i},$$

where y_i represents the intermediate output i used in the final production and ζ_i the share of product i in the final output. The market clearing condition of goods is $m_i = \sum_j m_{ji} + y_i$.

The model can be solved following the approach of Luo (2019). For any labor input l, the (equilibrium) aggregate output is given by

$$Y = \Pi_i \Xi_i^{\mathsf{v}_i} z_i^{\alpha_i \mathsf{v}_i} l,$$

where $\Xi_i \equiv \alpha_i^{\alpha_i}(1-\alpha_i)^{(1-\alpha_i)}\Pi(\omega_{ij})^{\omega_{ij}(1-\alpha_i)}$ is a constant. Let Ω denote the input matrix with entries $(1-\alpha_i)\omega_{ij}$, which capture the amount of j used as an input in producing \$1 worth of i output (i.e., $\frac{Sales_{j\to i}}{Sales_i}$). v is a vector of

$$\mathsf{v} = [I - \Omega']^{-1}\zeta,$$

where $(I-\Omega')^{-1}$ is the Leontief inverse matrix and ζ is a vector of the final share (ζ_i).

Notably, v captures the propagation of sectoral-level changes in labor productivity to other sectors and, ultimately, the aggregate impact of the changes. Each element v_i of the vector corresponds to the well-known notion of the *Bonacich centrality* (e.g., Acemoglu et al., 2015; Luo, 2019). It captures the systemic importance of each sector to the aggregate output. Mathematically, the geometric summation of the input matrix Ω, which equals $[I-\Omega]^{-1}$, captures both the direct use (represented by Ω) and the indirect use (represented by the higher-order terms, Ω^n, $n = 2, 3, \dots$) of inputs in the production network.

For the impact of shock analysis, we log-linearize the equilibrium system and define the following vector:

$$\mathbf{z} \equiv \begin{bmatrix} \alpha_1 \tilde{z}_1 \\ \alpha_2 \tilde{z}_2 \\ \vdots \\ \alpha_N \tilde{z}_N \end{bmatrix} \quad \mathbf{m} \equiv \begin{bmatrix} \tilde{m}_1 \\ \tilde{m}_2 \\ \vdots \\ \tilde{m}_N \end{bmatrix},$$

where terms with tilde denote the percentage deviation from their steady state values. $\mathbf{z}$ is the vector of sectoral labor productivity shock. $\mathbf{m}$ denotes the vector of sectoral output percentage deviation from the steady state case. The aggregate GDP deviation from its steady state, thus equals,

$$\tilde{Y} = \mathsf{v}'\mathbf{z}. \tag{2}$$

The above equation makes it clearer that the Bonacich centrality v_i captures the contribution of each sectoral shock to the aggregate output change. Further, we can decompose the aggregate effect to direct effect and indirect effect. The direct effect represents the direct impact of sectoral shocks to Y, represented as

$$\tilde{Y}^{direct} = \zeta'\mathbf{z}. \tag{3}$$

The indirect effect represents the spillover of shocks to other sectors through the production network and then affect the aggregate output,

$$\tilde{Y}^{indirect} = \tilde{Y} - \zeta'\mathbf{z}. \tag{4}$$

Furthermore, sectoral output change $\mathbf{m}$ can be written as a function of $\mathbf{z}$ after log-linear,

$$\mathbf{m} = [I - \Omega]^{-1}\mathbf{z}. \tag{5}$$

4 Combining Data with the Model

We consider two approaches to make use of the model, and other robustness checks are discussed in Section 6. The first approach makes use of a dataset from Baidu that contains inter-province traveling data.

4.1 Using inter-province labor movements

Sectoral Production Statistics: First, we construct the input-output matrix Ω using 2017 input-output table from National Bureau of Statistics of China, as is the final share ζ_i. The labor share α_i and the intermediate input share $1 - \alpha_i$ are calibrated using the 2017 GDP by Industry Value-Added Component Table. The input-output matrix is illustrated in Figure 2.

Labor Statistics: The construction of the labor loss in each sector is constrained by data availability. Here we approximate the sectoral labor shock using inter-province labor movement data and the province-sector production data.

The Lunar New Year is the most important holiday in China during which families get together for feasts. More than 80 percent migrant workers travel back home during the holiday.[1] The Chinese government especially implemented rules guarantee migrant workers New Year holiday travel.[2] However, on 24 January 2020, the central government unexpectedly imposed a lockdown in majority places inside Hubei province in an effort to quarantine the epicenter of the outbreak of coronavirus. Due to the lockdown, migrant workers back Hubei could not travel to their provinces for work. In addition, widespread of discrimination was present outside Hubei to Hubei people even if they had not returned home, not limited to travel and working restrictions.

Therefore, we measure labor loss of other provinces using the estimated number of Hubei migrant workers in each province. However, the actual number of Hubei working in each provinces is not available. Baidu Qianxi dataset reports the percentile of travelers from one province to others or to one province from others at daily frequency. We use Baidu Qianxi data

[1] Source: "Gei Duo Shao Qian Chun Jie Bu Hui Jia." by Aiyu Liu, March, 2011, *Chinese Workers*.
[2] Source: "Dai Zu Gong Qian Hui Jia Guo Nian." Jan 08, 2020, *People's Daily*.

to calculate the average percentile of travelers travel to Hubei from each other provinces during Jan 12 - Jan 24 of 2020, i.e. two weeks before the Lunar New Year. Denote this percentile as $\rho_i^{Hubei\rightarrow}$. Then, we assume $\rho_i^{Hubei\rightarrow}$ approximates the percentile of Hubei workers working in other provinces.[3]

There are two types of labor forces in China, formal and informal. Most informal workers are rural workers (or workers from rural areas, "Nong Min Gong"), who are restricted by the Hukou system, and more than half of the labor force are rural informal workers. There is no available dataset on the number of total informal workers in each province. Instead, we have the number of formal workers in each province from National Bureau of Statistics of China, and we assume that the provincial share of informal workers relative to the national aggregate is approximately equal to the share of formal workers. Denoted this share as γ_i. Thus, the provincial share of total workers and the provincial share of informal workers are the same and equals γ_i. According to Bureau of Statistics of Hubei, the total number of rural migrant Hubei workers working in other provinces is $L_{rural}^{Hubei\rightarrow} = 6.1922$ million, while the total number of rural workers in China is $L_{rural} = 281.71$ million in 2016.[4] Thus, we estimate the share of Hubei rural workers working in each province using, $\rho_i^{Hubei\rightarrow} L_{rural}^{Hubei\rightarrow} / (\gamma_i L_{rural})$, and assume it equals the share of Hubei formal workers as well as the share of Hubei workers in total. Thus, the percentile of labor loss in each province (excluding Hubei) is assumed equal to $\tilde{L}_{i\neq Hubei}^{province} = -\rho_i^{Hubei\rightarrow} L_{rural}^{Hubei\rightarrow} / (\gamma_i L_{rural})$. The vector of $\tilde{L}_{i\neq Hubei}^{province}$ is denoted as $\tilde{L}_{\neq Hubei}^{province}$.

We infer sectoral labor loss using the provincial labor loss estimates. More specifically, we construct the provincial share of production in each sector using the 2017 Industrial Production Yearbook and Statistics Yearbook of China. Denote $\Xi^{sector,province}$ as the matrix with entry ij representing province j's share of production in sector i, which is presented in Figure 1. Thus, $\Xi^{sector,province}$ is row normalized. The sectoral labor loss is constructed using a vector of $\tilde{L}_{\neq Hubei}^{sector} = \Xi^{sector,province} * \tilde{L}_{\neq Hubei}^{province}$.

Finally, sectoral shock is considered as a labor augmented productivity shock of

$$\mathbf{z}^{labor} = -\alpha \circ \tilde{L}_{\neq Hubei}^{sector} - \alpha \circ \Xi^{sector,province} \mathbf{1}^{Hubei}, \tag{6}$$

where $\mathbf{1}^{Hubei}$ denotes a vector of zeros with the element representing $Hubei$ being 1. To distinguish this measure of the shock from the second approach, we further denote it as $\mathbf{z}_1^{labor}$.

In addition, we construct a second shock,

$$\mathbf{z}^{labor+Hubei} = -\alpha \circ \tilde{L}_{\neq Hubei}^{sector} - \Xi^{sector,province} \mathbf{1}^{Hubei}, \tag{7}$$

[3]The data do not distinguish between different types of travelers. Besides migrant workers, there are also tourists and students traveling across the country too. But during the Chinese New Year holiday, which for many it is the only time to go back to their hometown, it is reasonable to assume that most travelers are migrant workers. We have some sensitivity analyses to address this potential upward bias in labor loss.

[4]Source: "Hubei Sheng Nong Min Gong Jiu Ye Te Zheng Ji Zhuan Yi Qu Shi Fen Xi" http://tjj.hubei.gov.cn/tjsj/tjfx/qstjfx/201910/t20191026_24731.shtml

where the second term represents the complete stoppage of Hubei production. To distinguish this measure of the shock from the second approach, we further denote it as $\mathbf{z}_1^{labor+Hubei}$. Both $\mathbf{z}_1^{labor}$ and $\mathbf{z}_1^{labor+Hubei}$ are illustrated in Figure 3.

4.2 Without using inter-province labor movements

With the second approach, we directly estimate sectoral labor loss using sector size relative to total production. Denote the sectoral size vector as s . In particular, we obtain rural worker share in each industry η_i from National Bureau of Statistics of China.[5] Denote the vector of η_i as η. We then approximate the rural worker in each sector using $s_i L_{rural}$. Finally, we assume that the share of Hubei migrant rural workers in each industry relative to the total Hubei migrant rural workers equals that of the national level η. Thus, we construct sectoral labor loss outside Hubei as $\tilde{L}^{sector}_{\neq Hubei} = (\eta \circ L^{Hubei\rightarrow}_{rural})/(s \circ L_{rural})$. Finally, sectoral shock follows Equations 6 and 7. We denote them as $\mathbf{z}_2^{labor+Hubei}$ and $\mathbf{z}_2^{labor+Hubei}$. $\mathbf{z}$ in this approach is illustrated in Figure 3.

4.3 From national to global impact

Once the shock is calculated, we can infer the change in GDP using 2, and sectoral output change can be calculated using 5. Furthermore, we can decompose the GDP change into direct and indirect impacts following 3 and 4.

Given the output loss in mainland China, what is the impact for global economy? We make use of the IMF Direction of Trade Statistics data to construct a trade network and World bank data for country GDP. Availability of bilateral trade data and country-level GDP data restricts our sample size to 116 countries. Denote $\zeta_i^G =$ (Country-i GDP)/(Global GDP), $1 - \alpha_i^G =$ (aggregate Country-i import)/(Country-i GDP), $\omega_{ij}^G =$ (the share of Country-i imports from Country-j). Ω^G ij-th entry is $(1-\alpha_i^G)\omega_{ij}^G$. Construct global shock z^G as a zero vector with China's entry being the drop in output calculated using one of the above methods, and global GDP impact can be calculated as $\zeta^{G'}(I - \Omega^{G'})^{-1} z^G$.

5 Benchmark Results and Sensitivity Analysis

Direct and indirect impact decomposition results along with the total impact are presented in Figure 5 and Table 1. If there is only a labor drop in the Hubei province, China will suffer an output loss from 3.9% to 4.6%, and the global impact is around 1%. Translating into US dollar amount (in 2017 value), the per month loss is approximately 40 billion dollars in China and 65 billion dollars globally (including China). Obviously, the impact is larger if we assume a

[5] Source: "2017 Nian Nong Min Gong Jian Ce Diao Cha Bao Gao," http://www.stats.gov.cn/tjsj/zxfb/201804/t20180427_1596389.html

complete production stoppage of the Hubei province: the loss in China and globally roughly doubles. It is also worth noting that about 40% of the impact comes indirectly, either from the network production structure inside China and the trade network globally.

Furthermore, we conduct a sensitivity analysis of adding or cutting 50% from the 6.19 million Hubei rural worker estimate. As shown by the error bars in Figure 5, the magnitude is not affected noticeably.

Sectoral output drops are presented in Figure 4. They partly reflect the size of the sectoral shocks, and they also reflect the input-output relationship across sectors. Agriculture, finance and real estate, manufacturing, retail and transport, service and food are the most affected.

Figure 6 illustrates country level output drop geographically through the first approach with z^{Labor} shock, which is our most conservative measure. Table 2 presents the estimated output drop by continents. Not surprisingly, due to the tighter trade linkage, Asia suffers more from the coronavirus than all other continents. The least affected is Europe, which has weaker trade relationship with China.

Our estimates are conservative in the following two aspects. First, we only consider the loss of labor inputs from Hubei province, while other types of shocks are not considered here, such as demand shocks and liquidity shocks. Second, the Cobb-Douglas specification in the model may underestimate the aggregate impact of the Hubei lockdown. The Cobb-Douglas specification is a very popular set-up in the macroeconomics modeling with good empirical fit, which brings us clean closed-form equilibrium results in this analysis. However, it may bias the prediction by specifying unit elasticity of substitution between all inputs. The aggregate output responses after shocks depend on the level of this elasticity. A lower elasticity of substitution tends to amplify the impact of shocks. For instance, consider an economy with perfectly complementary inputs, the input allocation is unaffected by the ex-post price changes after shocks. Thus, the restricted commodity reallocation would reinforce the aggregate impact of shocks. However, a measure of the elasticity of substitution of sectoral inputs in China is not available in the literature and an estimation of that would significantly complicates the study in this paper. Based on an estimate of the U.S. economy by Atalay (2017), the elasticity of substitution between domestic intermediate inputs is 0.1. Through a study about the 2011 Tōhoku earthquake impact on the U.S. economy, Boehm et al. (2019) find that the elasticity of substitution across imported material inputs in the U.S. is about 0.2, while the elasticity between material inputs and capital/labor is around 0.03. Thus, in a low elasticity of substitution environment, we underestimate the output impact.

6 Conclusion

This paper provides a timely estimation of the economic impact of the coronavirus, both at the local and global levels. To keep the exercise simple and transparent, we have to abstract from several aspects of the epidemic, and hence we do not claim that this is the most comprehensive calculation. We mostly want to highlight the network nature of the economic impact. With more closely connected production network within mainland China and trade network across countries, we show that the coronavirus has a non-negligible effect on output.

Data Availability:

The authors confirm that all the unrestricted data underlying the findings are fully available without restriction.

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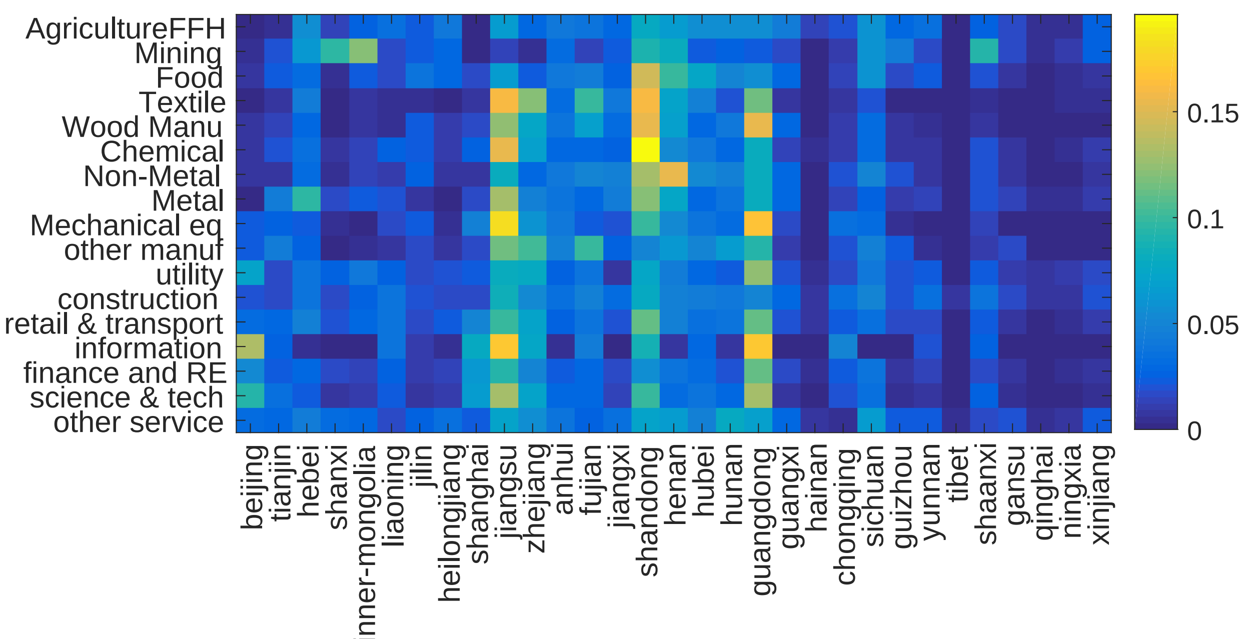
Table 1: Aggregate Impact

approach		z_1^{Labor}	z_2^{Labor}	$z_1^{Labor+Hubei}$	$z_2^{Labor+Hubei}$
China	in %	-3.86%	-4.62%	-9.36%	-8.12%
	in billion $	$ -39.03	$-42.80	$-94.77	$-82.20
Global	in %	-0.96%	-1.16%	-2.34%	-2.03%
	in billion $	$-63.53	$-76.18	$-154.27	$-133.81

Table 2: Impact by Continent

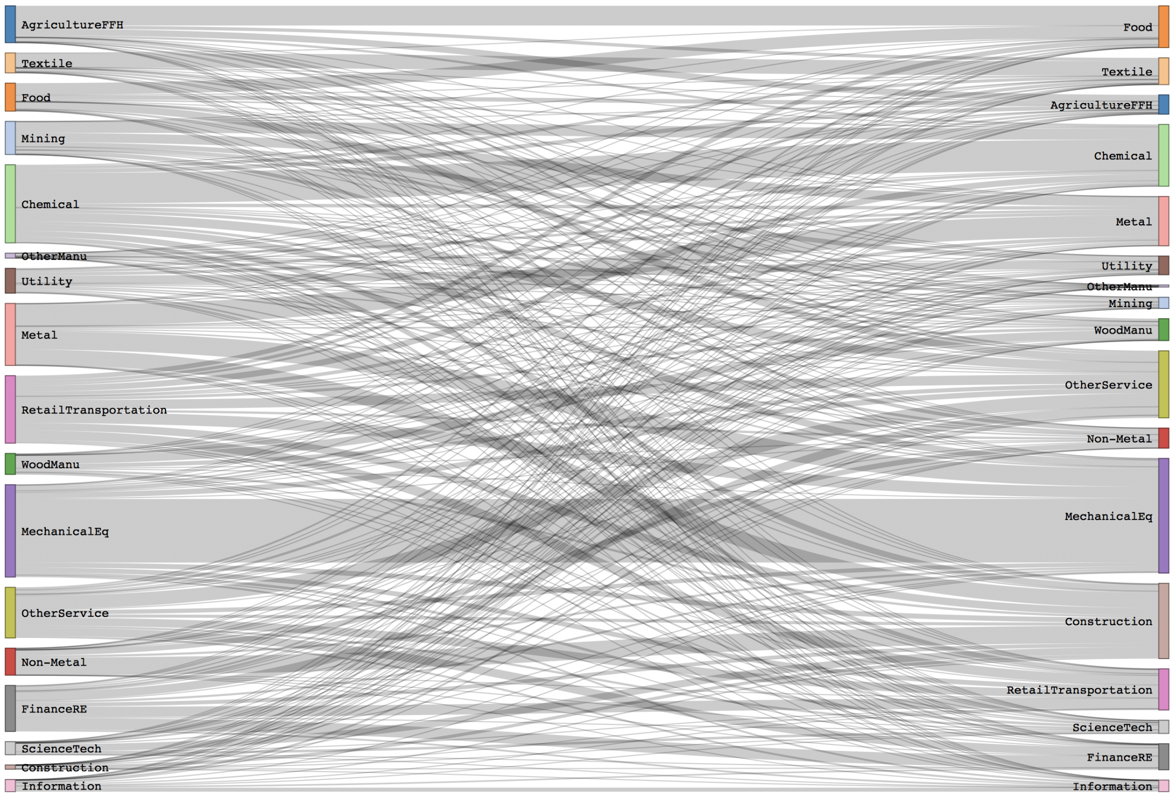
Continent	z_1^{Labor}	z_2^{Labor}	$z_1^{Labor+Hubei}$	$z_2^{Labor+Hubei}$
Asia	-2.07%	-2.48%	-5.02%	-4.36%
Oceania	-0.49%	-0.58%	-1.18%	-1.02%
Africa	-0.48%	-0.57%	-1.16%	-1.01%
North America	-0.44%	-0.53%	-1.08%	-0.93%
South America	-0.44%	-0.53%	-1.07%	-0.92%
Europe	-0.24%	-0.28%	-0.58%	-0.50%

Figure 1: Province Share in Each Sector



Province's share of production in each sector. Row sum =1. Hubei's top sector: FoodTeaCigra, AgricultureFFH, Non-metal, Manufacturing,Service, textile

Figure 2: China Input-Output Relationship



Left: production sector. Right: consumption sector

Figure 3: Estimated Sectoral Shock

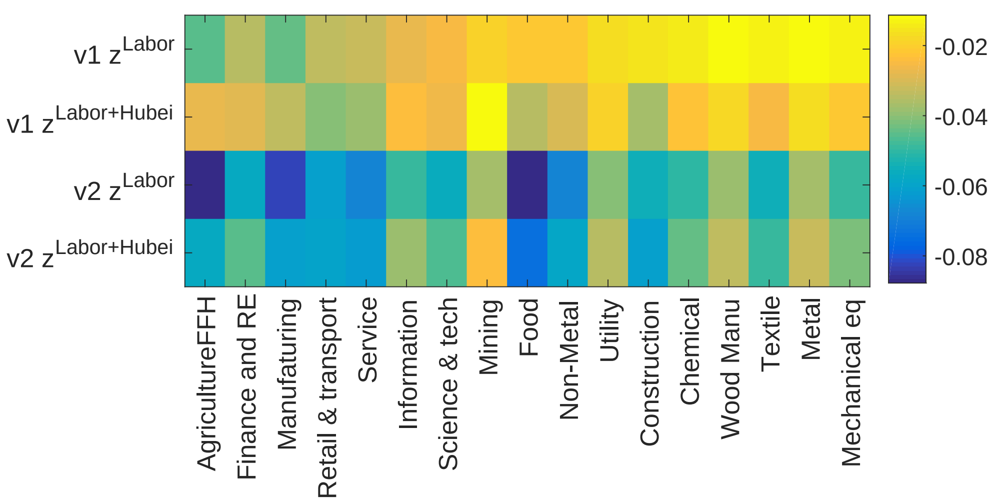


Figure 4: Sectoral Output Loss

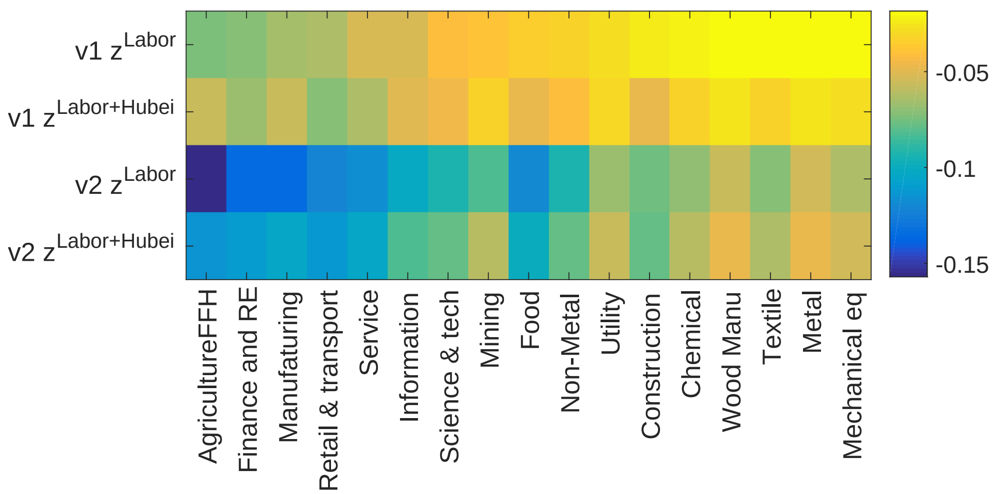
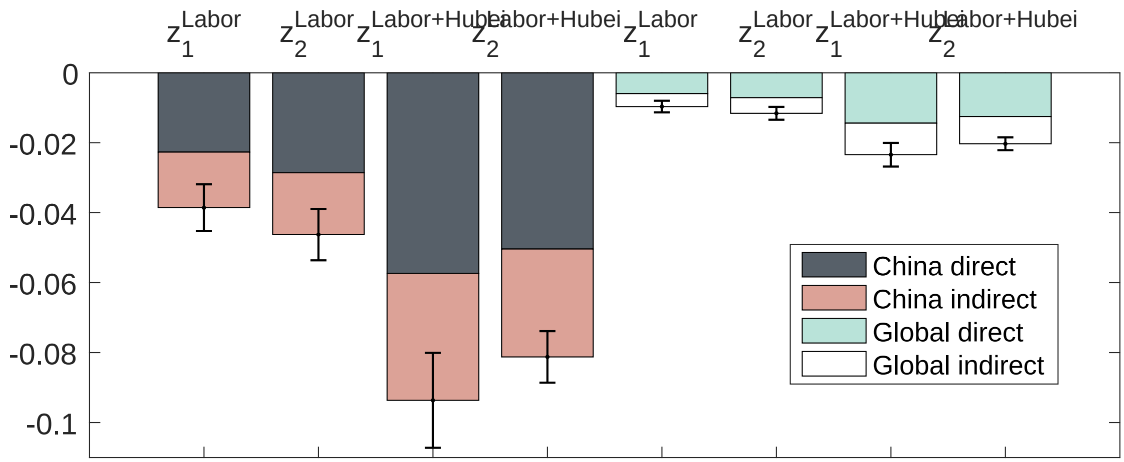
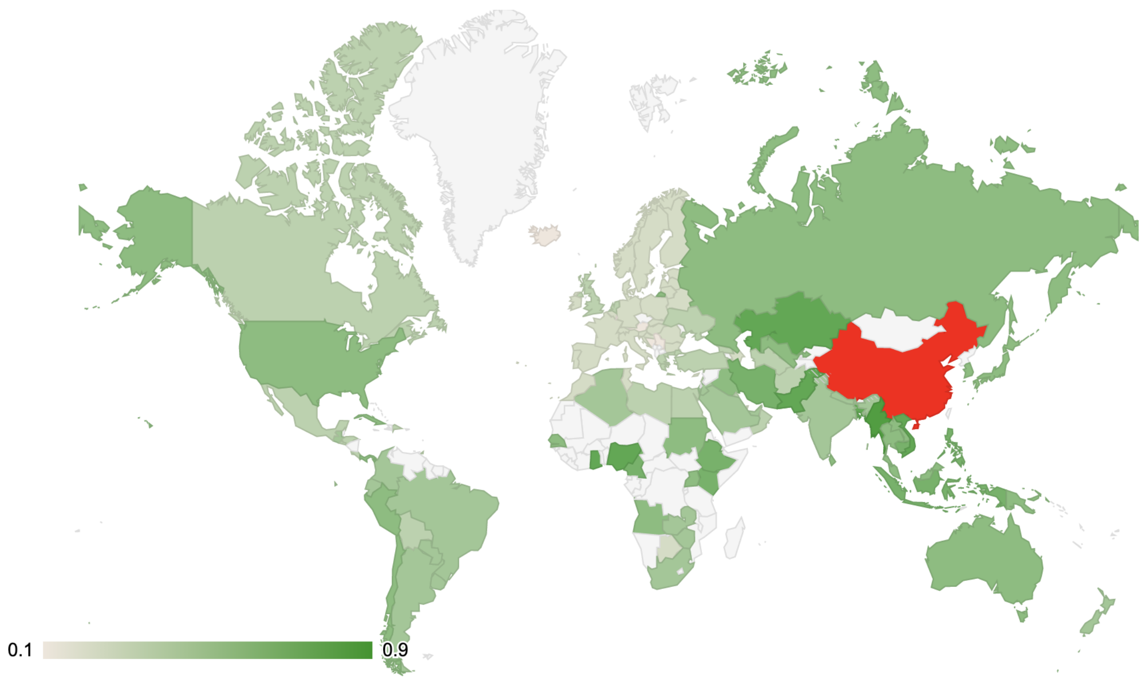


Figure 5: Aggregate Impact and Sensitivity Analysis



Note: The first four bars present the response of China GDP. The last four bars present the response of Global GDP. Error bar: Total labor loss $L^{Hubei\to} = [0.5 * 619m, 1.5 * 619m]$.

Figure 6: Global Impact Illustration - version 1 z^{Labor}



Note: Unit is in percentage point decrease. China is in orange and has a reduction of 4%. Light grey color: not included due to lack of data.