Assessing the economic losses of destructive events: an analytical framework combining production and consumption perspectives

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Abstract

This study proposes an analytical framework to assess economic losses from destructive events in a world characterized by increasing uncertainties and risks. This framework, based on a multi-regional input-output model, incorporates production and consumption channels and feedback income-driven demand contractions. A retrospective study on the 2022 spring COVID-19 epidemic in Shanghai estimated a GDP loss of 153.8 billion yuan, with a 3.6% error rate. The framework's application across various Chinese regions highlights their diverse economic profiles. The effectiveness of disaster mitigation policies was investigated under varied scenarios. This comprehensive, accurate, and adaptable approach aids in effective policy making.

Keywords: destructive events; economic impact assessment; multi-regional input-output model; production; consumption

1. Introduction

The global pandemic COVID-19 had unprecedented impacts on the world over the past years (Delardas et al. 2022, Ke and Hsiao 2022). Countries worldwide implemented lockdown measures for over a year and repeatedly enforced similar restrictions in response to the emergence of new COVID-19 variants (Allen 2022). The pandemic and the associated lockdown measures limited people's mobility, including business activities, shopping, and travel, leading to a substantial decline in economic activities that affected both consumers and producers (Barro, Ursúa and Weng 2020, Zhang et al. 2022, Bonato et al. 2020). Moreover, the impact was further propagated through the production network to upstream and downstream industries and regions, generating more secondary effects (Inoue and Todo 2020, Gao et al. 2021, Gao, Hewings and Yang 2022).

In addition to the pandemic, the global community faces escalating geopolitical and climate risks, leading to more frequent and unpredictable natural and man-made events. Examples include the 2022 Russia-Ukraine conflict and the 2023 Turkey earthquake. These destructive events could cause stagnation of production and daily consumption, and shock the economy following a similar mechanism. Confronting larger uncertainties and challenges, a critical issue for authorities and institutions is to assess the short-term and long-term economic impacts of such destructive events in a timely and accurate manner. Based on the assessments, proper policies can be implemented as soon as possible. After all, “If you can measure it, you can manage and improve it.”

This study proposes an analytical framework for a comprehensive assessment of economic losses resulting from destructive events. The framework is based on a multi-regional input-output (MRIO) model and incorporates both production and consumption perspectives. Compared with existing literature, this framework makes two major contributions to the methodology. Firstly, on the production side, this framework goes beyond the traditional input-output (IO) models by incorporating downstream production losses resulting from the interruption of intermediate product supply. This is achieved by introducing the concept of raw material inventory days on hand into the model. Secondly, on the consumption side, the framework encompasses the notion of non-rigid consumption to capture the reduction in household spending resulting from the event, as well as the long-term feedback demand contraction generated by income loss.

The proposed analytical framework enabled us to conduct both retrospective and prospective analyses of various destructive events. In the empirical part, we first performed a retrospective analysis of the Shanghai lockdown in the spring of 2022 and evaluated its impact on China's economy due to the strong data availability of the case. Further, we conducted simulations to assess the potential impacts of similar events occurring in other regions of China as an empirical example for a prospective analysis. Moreover, we performed a series of what-if analyses to explore the effectiveness of different types of disaster-mitigation policies. The results indicate that our analytical framework is an accurate estimator for assessing the economic losses from destructive events with high flexibility and applicability, and can shed light on the differentiated characteristics and roles of different regions in the national economic system.

The article is organized as follows. Section 2 reviews the economic impact analysis of destructive events such as COVID-19. Section 3 presents the modelling processes of the analytical framework. Section 4 provides the data and parameters required by the framework. Section 5 presents the results and discusses the empirical analysis. Section 6 concludes.

2. Literature Review

Destructive events have the unique feature of being unable to find similar cases and build models that rely solely on historical data. Economic models with detailed transmission mechanisms are usually employed to evaluate these events. To comprehend the potential impact of destructive events on the economy, researchers have identified various plausible mechanisms and developed multiple quantitative methods (Brodeur et al. 2021), which establish a solid foundation for our analytical framework.

In terms of impact channels, destructive events usually cut off supply and shrink demand, generating disruptions in both production and consumption (Tanaka 2022). On the production side, destructive events can disrupt production and trigger cascading effects (Barrot and Sauvagnat 2016). Taking COVID-19 as an example, Brinca et al. (Brinca, Duarte and Faria-e-Castro 2021) found that lockdowns led to negative labor supply shocks and reduced working hours. Baldwin (Baldwin 2020) described its economic impact in a circular flow framework and pointed out that the breakdown of supply chains would generate cascading effects. The impact on production will ultimately be reflected in economic indicators, such as gross domestic product (GDP) (Céspedes, Chang and Velasco 2020, Elenev, Landvoigt and Van Nieuwerburgh 2022). Bonadio et al. (2021) found that the impact of the pandemic was transmitted through the global supply chain, leading to a decline in world GDP growth.

On the consumption side, researchers have found that destructive events restrict residents' daily lives, affect their behavior and change their income structure and consumption patterns, thereby imposing a negative effect on the economy. According to Baker et al. (2020), in the early period of COVID-19, household spending increased in specific sectors, such as retail and food, but overall spending subsequently decreased. Clemens and Veuger (2020) found that COVID-19 caused a substantial decline in consumption levels, and led to a significant decrease in sales and income tax revenues. Furthermore, disasters can cause a vicious cycle in which people's income decreases, poverty rates rise, and further affect consumption (Martin et al. 2020). A study in Vietnam showed that natural disasters led to 6.9% and 7.1% decreases in per capita income and expenditure of Vietnamese households, respectively (Bui et al. 2014).

As for quantitative models for disaster analysis, the computable general equilibrium (CGE) and IO models are widely applied because of their ability to capture interdependencies among economic sectors (Okuyama and Santos 2014, McKibbin and Fernando 2021, Eppinger et al. 2020). For instance, Walmsley et al. (2023) constructed a disaster economic consequence analysis framework by implementing the CGE model, Duan et al. (2021) studied the impact of COVID-19 on China's economy by building a quarterly CGE model, and Guan et al. (2020) conducted scenario simulations of COVID-19 with an enhanced adaptive regional input-output model. The advantage of the CGE model lies in its integration of the relevant relationships among multiple economic agents within the framework of general equilibrium theory. However, most CGE models are for long-term equilibrium analysis and potentially provide lower impact estimates, partly because the causations in models are not all unidirectional and functional relationships tend to counteract each other (Koks et al. 2016). In addition, with a larger extraordinary shock, the CGE models might fail to find the optimal solutions within their theoretical settings owing to the large deviations of the variables from their initial points. In comparison, the IO-based model is more flexible and better suited for capturing the impact of sudden exogenous shocks on the economy (Tian et al. 2022), and the hypothetical extraction method (HEM) is the most notable approach (Dietzenbacher and Lahr 2013, Los, Timmer and De Vries 2016). Los et al. (2017) employed HEM to evaluate the economic risks related to Brexit, and Hu et al. (2021) assessed the impacts of the US-China trade decoupling. Researchers have also used it to analyze the impact of disasters (Wen, Li and Song 2022). Tian et al. (2022) adapted the HEM and calculated the economic exposure to regional value chain disruptions due to city lockdowns. Nevertheless, the assessment results of HEM are highly dependent on the "hypothetical extraction" part (see Section 3.1). With improper or incomplete "hypothetical extraction", this method cannot accurately assess the impact of external shocks on the economic system (Dietzenbacher, van Burken and Kondo 2019).

In summary, in the existing literature, researchers have studied the economic impacts of destructive events through multiple mechanisms using quantitative models. When establishing quantitative models, it is necessary to consider the comprehensive impacts of external events. The analytical framework developed in this study is based on the IO model and HEM while simultaneously considering multiple feedback transmission channels, including both production and consumption perspectives. Therefore, this framework combines the advantages of CGE models in terms of comprehensiveness and IO models in terms of real-time adaptability and flexibility. In the empirical stage, we took COVID-19 in Shanghai as an example to demonstrate the accuracy of our framework's estimation results.

3. Model and Methods

The economic impacts of destructive events are divided into two main parts in the analytical framework: the current impact and the subsequent impact. The current impact refers to the economic losses caused by production shutdowns and restricted household consumption activities triggered by destructive events, such as lockdowns during pandemics, wars, and natural disasters. For instance, during the COVID-19 pandemic, strict control measures in certain areas led to the shutdown of industrial production, which caused a significant reduction in production capacity. This loss in capacity would spread through the production network, affecting other industries and regions both upstream and downstream, referred to as "upstream loss" and "downstream loss". Meanwhile, social activities such as shopping, traveling, and various services were severely limited or even suspended due to disruptions in social mobility and logistics, leading to a reduction in household consumption, referred to as "consumption loss". The subsequent impact refers to the feedback effects that occur after a destructive event has ended. As socioeconomic activities were sluggish during the event, falling household income tightens consumer demand, resulting in consequential impacts on the economic system. The analytical framework is illustrated in Figure 1. The remainder of this section elaborates on the model and assessment methods for the corresponding parts.

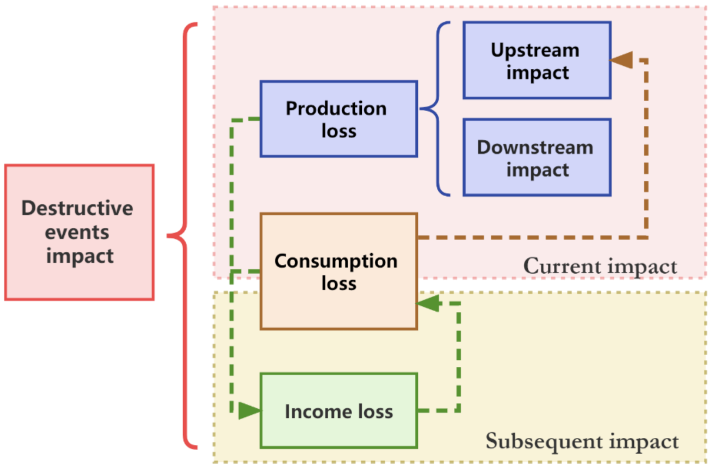

Figure 1. Analytical framework for assessing the economic losses of destructive events

3.1. Multi-regional input-output model and hypothesis extraction method

We built an analytical framework based on the MRIO model, as shown in Table 1, and HEM approach. The MRIO model allows us to conduct region-level analyses by considering interregional linkages in goods and services.

Table 1. Multi-regional input-output (MRIO) table

Flows		Intermediate demand					Final demand					Export	Total output
		R1	⋯	Rr	⋯	Rn	R1	⋯	Rr	⋯	Rn		
Domestic intermediate input	Region 1	$\boldsymbol{Z_{11}}$	⋯	$\boldsymbol{Z_{1r}}$	⋯	$\boldsymbol{Z_{1n}}$	$\boldsymbol{f_{11}}$	⋯	$\boldsymbol{f_{1r}}$	⋯	$\boldsymbol{f_{1n}}$	$\boldsymbol{ex_1}$	$\boldsymbol{x_1}$
	⋮	⋮	⋱	⋮	⋰	⋮	⋮	⋱	⋮	⋰	⋮	⋮	⋮
	Region r	$\boldsymbol{Z_{r1}}$	⋯	$\boldsymbol{Z_{rr}}$	⋯	$\boldsymbol{Z_{rn}}$	$\boldsymbol{f_{r1}}$	⋯	$\boldsymbol{f_{rr}}$	⋯	$\boldsymbol{f_{rn}}$	$\boldsymbol{ex_r}$	$\boldsymbol{x_r}$
	⋮	⋮	⋰	⋮	⋱	⋮	⋮	⋰	⋮	⋱	⋮	⋮	⋮
	Region n	$\boldsymbol{Z_{n1}}$	⋯	$\boldsymbol{Z_{nr}}$	⋯	$\boldsymbol{Z_{nn}}$	$\boldsymbol{f_{n1}}$	⋯	$\boldsymbol{f_{nr}}$	⋯	$\boldsymbol{f_{nn}}$	$\boldsymbol{ex_n}$	$\boldsymbol{x_n}$
Import intermediate		$\boldsymbol{IM_1}$	⋯	$\boldsymbol{IM_r}$	⋯	$\boldsymbol{IM_n}$							

Value added	$\boldsymbol{w_1}$	$\cdots$	$\boldsymbol{w_r}$	$\cdots$	$\boldsymbol{w_n}$	
Total input	$\boldsymbol{x'_1}$	$\cdots$	$\boldsymbol{x'_r}$	$\cdots$	$\boldsymbol{x'_n}$	

Within the framework of input-output analysis, there is an equilibrium relationship between production and consumption, expressed as $\boldsymbol{Zu} + \boldsymbol{f} = \boldsymbol{x}$, where matrix $\boldsymbol{Z}$ gives the values of the domestic intermediate input, vector $\boldsymbol{f}$ is the final demand for products in each sector, vector $\boldsymbol{x}$ is the total output, and $\boldsymbol{u}$ is the summation vector. We further define the matrix $\boldsymbol{A} = \boldsymbol{Z}\widehat{\boldsymbol{x}}^{-1}$ as the direct input coefficient matrix reflecting the intersectoral linkages, and the element $\boldsymbol{A}_{rs}$ of $\boldsymbol{A}$ represents the amount of input from region *r* directly required to produce one unit of output in region *s*. This yields the equation $\boldsymbol{x} = \boldsymbol{Zu} + \boldsymbol{f} = \boldsymbol{Ax} + \boldsymbol{f}$, which can be reformulated as:

$$\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{f} = \boldsymbol{Bf} \tag{1}$$

This is the core formula of the Leontief input-output model, where $\boldsymbol{I}$ is an identity matrix and matrix $\boldsymbol{B} = (\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the Leontief inverse matrix, which indicates the total amount of direct and indirect inputs required to produce one unit of final demand. $\boldsymbol{w}$ denotes the value-added vector in the table, and let $\boldsymbol{v} = \boldsymbol{w}\widehat{\boldsymbol{x}}^{-1}$ be the value-added coefficient vector, where $\boldsymbol{v}_r = \boldsymbol{w}_r\widehat{\boldsymbol{x}}_r^{\ -1}$ represents the value-added included in one unit of production in region *r*. Then:

$$\boldsymbol{w} = \widehat{\boldsymbol{v}}\boldsymbol{x} = \widehat{\boldsymbol{v}}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{f} \tag{2}$$

We adopted the HEM proposed by Los et al. (2016) to calculate the value-added in a certain part of the output (denoted as $\{P\_hy\}$). After extracting the corresponding flows from both the intermediate (matrix $\boldsymbol{A}$) and final products (vector $\boldsymbol{f}$), the direct input coefficient matrix of the remaining part is denoted as $\boldsymbol{A\_hy}$, and the remaining final product vector is denoted as $\boldsymbol{f\_hy}$. Then, the value-added generated by $\{P\_hy\}$ (in other words, the economic loss due to the cut-down of $\{P\_hy\}$) can be calculated as follows:

$$\boldsymbol{w\_hy} = \widehat{\boldsymbol{v}}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{f} - \widehat{\boldsymbol{v}}(\boldsymbol{I} - \boldsymbol{A\_hy})^{-1}\boldsymbol{f\_hy} \tag{3}$$

3.2. Assessment of the current impact of destructive events

According to the analytical framework shown in Figure 1, the current impact of a destructive event comprises two parts: losses caused by production disruptions and household consumption restrictions.

3.2.1. Losses caused by production disruptions

When a destructive event occurs in a certain region, the local industrial production sectors face the risk of shutting down and suspending production. We denote the set of affected regions as E, and the set of production sectors as M. Define the proportion of recovered production of sector *i* in region *r* at time *t* in its total production as $\rho_{ri}(t)$. Then, the "equivalent shutdown duration" of sector *i* in region *r* is calculated as:

$$D_{ri} = \int_0^T \big(1 - \rho_{ri}(t)\big)dt \tag{4}$$

In this equation, 0 represents the time point when the event occurs and production is halted, *T* refers to the end of the assessment period. Therefore, D_{ri} indicates the equivalent duration of being completely shut down for sector *i* in region *r* owing to the impact of the destructive event. The suspension of production activities in the affected region will result in a reduction in output as well as a decrease in demand for intermediate products; thus, its impact will propagate to upstream regions and sectors through the production network. The ratio of production loss of production sectors in the affected region is represented by the vector $\boldsymbol{LossP}_{up} = (LossP_{up_{s,i}})$:

$$LossP_{up_{s,i}} = \begin{cases} \frac{D_{si}}{365}, & s \in E,\ i \in M \\ 0, & others \end{cases} \tag{5}$$

In addition, in the domestic production network, various regions and sectors are highly interrelated and interdependent. Owing to shutdowns and insufficient production, the involved regions/sectors are limited in delivering intermediate goods to downstream regions and sectors in time. For downstream enterprises that rely heavily on intermediate products from the affected regions/sectors, their raw material inventory can partly mitigate the impact of insufficient supply. However, if the supply does not recover after the inventory is exhausted, these firms face challenges in finding reliable alternative sources in the short term, resulting in capacity gaps. Suppose that the raw material inventory of sector i in region s can sustain normal production in the case of a supply shortage for a duration of C_{si}. The set of sectors in each region with a high degree of dependence on intermediate products from the affected regions is denoted as I, and the set of intermediate inputs from region r in the production of sector i in region s is denoted as $\{j|r,s,i\}$. Thus, the ratio of total production loss in production sectors, including both upstream and downstream, is represented by the vector $\boldsymbol{LossP} = (LossP_{s,i})$:

$$LossP_{s,i} = \begin{cases} \frac{D_{si}}{365}, & s \in E \\ \frac{\max_{j\in\{j|r,s,j\},r\in E} D_{rj} - C_{s,i}}{365}, & s \notin E, i \in M, C_{s,i} \le \max_{j\in\{j|r,s,j\},r\in E} D_{rj} \\ 0, & others \end{cases} \tag{6}$$

3.2.2. Losses caused by household consumption restrictions

Destructive events could lead to a substantial decline in household consumption levels since residents' activities would be disrupted. To capture the impact of destructive events on household consumption, we decomposed it into two parts: endogenous and exogenous consumption. Endogenous consumption is mainly determined by current household income. Exogenous consumption, also known as rigid consumption (including basic necessities, such as food, healthcare, and housing), is determined by other factors and remains relatively stable. This decomposition approach is consistent with the modern consumption theory.

We denote β_i^* as the rigid consumption coefficient, that is, the relatively stable proportion of household consumption of product or service i, while $1-\beta_i^*$ represents the non-rigid consumption coefficient, which is the proportion of consumption of product i excluding rigid consumption. After a destructive event occurs, non-rigid consumption is usually more severely affected. Let T_r represent the duration of living restrictions for residents in region r, and P_r represent the proportion of the population affected by the event in region r. Thus, the ratio of household consumption loss in the affected region r is represented by the vector $\boldsymbol{LossC^r} = (LossC_i^r)$:

$$LossC_i^r = \frac{T_r P_r}{365}(1-\beta_i^*) \tag{7}$$

3.2.3. The current impact of destructive events

We combine the above two parts of losses, that is, losses in production and losses in household consumption, to estimate the current impact caused by the destructive event. In the MRIO framework, we subtract the proportion of non-rigid consumption from the household consumption vector in the regions affected by destructive events, including commodities and services. Given the close interconnectivity of the domestic economic system, insufficient local demand for products can be supported by other regions. Therefore, we compare the capacity loss of local production with the loss of non-rigid consumption. If the remaining capacity of local production is insufficient to meet the local rigid consumption needs, the shortfall is proportionally allocated according to the consumption structure by region.

We denote the household consumption vector of the affected region r ($r \in E$) as $\boldsymbol{C^r} = \left(c_{s,i}^r\right)$, where $c_{s,i}^r$ represents the consumption of product *i* from region *s* by consumers in region *r*. $LossP_{s,i}$ and $LossC_i^r$ are the ratio of production and household consumption loss in region *r*, calculated in Equation (6) and (7) respectively. Thus, using the HEM based on the MRIO model, the current impact $\boldsymbol{im}_{current}$ is[1]:

$$\boldsymbol{im}_{current} = \hat{\boldsymbol{v}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{F} - \hat{\boldsymbol{v}}(\boldsymbol{I}-\boldsymbol{A\_hy}_{current})^{-1}\boldsymbol{F\_hy}_{current} \tag{8}$$

$$\boldsymbol{A\_hy}_{current} = \left(\boldsymbol{I}-\widehat{\boldsymbol{LossP}}\right)\boldsymbol{A} + \widehat{\boldsymbol{LossP}}\widehat{\boldsymbol{A}_{rr}} \tag{9}$$

$$\boldsymbol{F\_hy}_{current} = (\boldsymbol{I}-\widehat{\boldsymbol{LossP}})(\boldsymbol{F}-\textstyle\sum_{r\in E}\boldsymbol{C^r}) + \textstyle\sum_{r\in E}\boldsymbol{C^r}(\boldsymbol{u}-\tilde{\boldsymbol{t}}^{\boldsymbol{r}}) \tag{10}$$

in which $\boldsymbol{u}$ is a vector consisting of ones, and $\tilde{\boldsymbol{t}}^r = \left(\tilde{t}_{s,i}^r\right)$ is:

$$\tilde{t}_{s,i}^r = \begin{cases} LossP_{s,i}\,,\ s,i \in F^r, i \in M \\ \max\left\{0, LossC_i^r - \dfrac{(1-LossP_{s,i})\sum_{q,k\in F^r}\left(LossP_{q,k}-LossC_k^q\right)c_{q,k}^r}{\sum_{p,j\notin F^r}\left(1-LossP_{p,j}\right)c_{p,j}^r}\right\}, s,i \notin F^r, i \in M \\ LossC_i^r\,,\ i \notin M \end{cases} \tag{11}$$

where F^r is a set defined as:

$$F^r = \left\{s,i \middle| LossP_{s,i} > LossC_i^r,\ i \in M\right\} \tag{12}$$

Moreover, according to the analytical framework presented in Figure 1, the current impact of destructive events is divided into three components that can be calculated separately. Owing to the disruptions of production in the affected areas, the impact on the production sector itself and its upstream sectors is referred to as "production loss - upstream", which is calculated as follows:

$$\boldsymbol{im}_{upsteam} = \hat{\boldsymbol{v}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{F} - \hat{\boldsymbol{v}}\left(\boldsymbol{I}-\boldsymbol{A\_hy}_{upsteam}\right)^{-1}\boldsymbol{F\_hy}_{upsteam} \tag{13}$$

where:

$$\boldsymbol{A\_hy}_{upsteam} = \left(\boldsymbol{I}-\widehat{\boldsymbol{LossP}}_{up}\right)\boldsymbol{A} + \widehat{\boldsymbol{LossP}}_{up}\widehat{\boldsymbol{A}_{rr}} \tag{14}$$

$$\boldsymbol{F\_hy}_{upsteam} = \left(\boldsymbol{I}-\widehat{\boldsymbol{LossP}}_{up}\right)\boldsymbol{F} \tag{15}$$

The impact caused by the disruption of intermediate product supply in the affected sectors, leading to production shutdowns in downstream sectors dependent on these intermediate products, is referred to as "production loss - downstream". The calculation method subtracts the upstream loss from the total loss on the production side:

$$\boldsymbol{im}_{downsteam} = \boldsymbol{im}_{product} - \boldsymbol{im}_{upsteam} \tag{16}$$

where:

$$\boldsymbol{im}_{product} = \hat{\boldsymbol{v}}(\boldsymbol{I}-\boldsymbol{A})^{-1}\boldsymbol{F} - \hat{\boldsymbol{v}}\left(\boldsymbol{I}-\boldsymbol{A\_hy}_{product}\right)^{-1}\boldsymbol{F\_hy}_{product} \tag{17}$$

$$\boldsymbol{A\_hy}_{product} = \left(\boldsymbol{I}-\widehat{\boldsymbol{LossP}}\right)\boldsymbol{A} + \widehat{\boldsymbol{LossP}}\widehat{\boldsymbol{A}_{rr}} \tag{18}$$

$$\boldsymbol{F\_hy}_{product} = \left(\boldsymbol{I}-\widehat{\boldsymbol{LossP}}\right)\boldsymbol{F} \tag{19}$$

Finally, the loss caused by restricted household consumption due to destructive events is

1 $\widehat{\boldsymbol{A}_{rr}}$ is the block diagonal matrix with sub-matrices $\boldsymbol{A_{11}}, \cdots, \boldsymbol{A_{nn}}$. That is, to avoid the issue of large-scale double counting, we hypothetically extract the production losses of final products and interregional intermediate products in the affected regions.

called “consumption loss”, which can be calculated as the difference between the total current impact and the loss on the production side:

$$\boldsymbol{im}_{consump} = \boldsymbol{im}_{current} - \boldsymbol{im}_{product} \tag{20}$$

3.3. Assessment of the subsequent impact of destructive events

Destructive events usually limit social and economic activities and decrease household income, resulting in a decrease in endogenous (non-rigid) consumer demand for goods and services. We denote α_i^* as the income elasticity coefficient of consumption of product or service i. Suppose that after a destructive event, the reduction in disposable income in region s is Δinc_s, then the corresponding decrease in consumption demand of region s is $\Delta inc_s \widehat{\boldsymbol{\alpha}}^* \boldsymbol{C}^s$. The total subsequent impact is the sum of the subsequent impacts of all areas affected by the event:

$$\boldsymbol{im}_{sub} = \sum_s \widehat{\boldsymbol{v}}(\boldsymbol{I} - \boldsymbol{A})^{-1} \Delta \boldsymbol{f}_s = \sum_s \widehat{\boldsymbol{v}}(\boldsymbol{I} - \boldsymbol{A})^{-1} \Delta inc_s \widehat{\boldsymbol{\alpha}}^* \boldsymbol{C}^s \tag{21}$$

4. Data and Parameters

4.1. Chinese multi-regional input-output table

The input-output table used in this study is the Chinese MRIO table in 2017 compiled by Li et al.(Li et al. 2022), which includes data on transactions between 42 sectors in 31 provincial administrative regions in China (excluding Hong Kong, Macao, and Taiwan). This table is non-competitive and can avoid overestimation issues. We used the value-added and direct input coefficients drawn from the MRIO table, which reflect production technology rather than economic scale. On the other hand, to better match the volume of the simulated economy with the real one, we updated the final demand matrix using the categorized national GDP growth rates based on the expenditure approach statistics from 2017 to 2021, published by China’s National Bureau of Statistics (NBS). The final demand matrix includes three categories: consumption expenditure, changes in inventories, and gross capital formation. In addition, the export vector was updated using the growth rate of China's total export of goods and services from 2017 to 2021. All data were nominal to ensure comparability between the quantitative results and the real-world GDP loss in the empirical case of Shanghai.

The formula is as follows, where $s = 1,2,3$ represents the three categories of final demand:

$$\boldsymbol{fd}_s^{update} = \boldsymbol{fd}_s \times \frac{GDP_s^{2021}}{GDP_s^{2017}}, s = 1,2,3 \tag{22}$$

$$\boldsymbol{ex}^{update} = \boldsymbol{ex} \times \frac{EXP^{2021}}{EXP^{2017}} \tag{23}$$

4.2. Income elasticity coefficient and rigid consumption coefficient

According to household consumption decomposition theory, we decompose it into two parts: endogenous consumption, which is determined by current household income, and exogenous consumption (rigid consumption), which remains relatively stable. We adopted the decomposition method and the corresponding results proposed by Chen et al. (2016), and introduced the consumption decomposition formula as follows:

$$\begin{cases} c_{it} = \alpha_{it} x_t + \beta_i c_{i(t-1)} + \varepsilon_{it}, & \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \\ \alpha_{it} = \alpha_{i(t-1)} + \mu_{it}, & \mu_{it} \sim N(0, \sigma_\mu^2) \end{cases} \tag{24}$$

where c_{it} is the household consumption of product (or service) i in period t, and x_t is the household income in period t. This formula decomposes household consumption into endogenous consumption, $\alpha_{it} x_t$ and rigid consumption, $\beta_i c_{i(t-1)} + \varepsilon_{it}$. The parameter β_i can be regarded as the rigid consumption coefficient, that is, the relatively stable proportion of the consumption of product i, and is not significantly influenced by current income, while $1-\beta_i$ represents the non-rigid coefficient. α_{it} is the endogenous consumption coefficient of product i, and is assumed to follow a random walking process that varies over time.

The decomposition formula can be estimated using the maximum likelihood estimation method with a Kalman filter applied to the time-varying parameter model. The data used were annual data on the per capita disposable income of households and expenditures on eight consumption categories, including food, clothing, housing, home equipment, facilities and services, health and medical care, transportation and communication, education, cultural and recreational services, and miscellaneous goods and services. The sample data were from 1989 to 2008. To ensure the comparability of the data from different years, the expenditure of each consumption category was deflated using the corresponding consumer price index, and the household income was deflated using the aggregate consumer price index. Based on the processed data, a time-varying parameter model was estimated separately for each consumption category using the maximum likelihood estimation method with a Kalman filter. Table 2 lists the rigid consumption coefficients for each category.

Table 2. Rigid consumption coefficient of each household consumption category

Household consumption category	Rigid consumption coefficient
Food	0.500
Clothing	0.395
Housing	0.708
Home equipment, facilities and services	0.282
Health and medical care	0.523
Transportation and communication	0.926
Education, cultural and recreational services	0.653
Miscellaneous goods and services	0.785

4.3. Estimation of the household income decline

To assess the full impact of destructive events, we estimated the magnitude of the subsequent income decline of regions Δinc_s by considering the current economic loss it suffered and the income level of residents in the region:

$$\Delta inc_s = \frac{\boldsymbol{lc}_s \widehat{\boldsymbol{w}}_s{}^{-1} \boldsymbol{im}_{current\_s}}{LC_s} \cdot \frac{w\_avg_s - w\_min_s \cdot 12}{w\_avg_s} \tag{25}$$

$\boldsymbol{lc}$ denotes the labor compensation vector in the IO table, whereas $\boldsymbol{lc}_s \widehat{\boldsymbol{w}}_s{}^{-1}$ represents the labor compensation included in one unit of value-added in region s, and LC_s is the total labor compensation in region s. w_avg_s and w_min_s represent the per capita disposable income per year in region s and the minimum wage standard per month in region s, respectively. Thus, the first half of the equation represents the magnitude of the decline in residents' incomes caused by the current impact of the destructive event; the second half represents the cushioning effect of guaranteed minimum income for residents.

4.4. Identification of affected downstream manufacturers

In this study, we assumed that downstream manufacturers with high dependence on intermediate products from regions affected by destructive events may not be able to find reliable alternative sources in the short term. As a result, they may face a production gap if their supply of raw materials is disrupted. First, we need to identify the dependent downstream sectors. We use data from the MRIO table to calculate the proportion of intermediate products used in production by each sector in each region from other regions. If the proportion of the affected region ranks in the top three among all sources, we consider the downstream sector to be highly dependent on intermediate products from the affected area. If the supply of intermediate products is not restored when the inventory of raw materials is exhausted, the production of these downstream sectors will be affected.

4.5. Assessment of raw material "days on hand"

For each production sector, we need to obtain the "days on hand" (DOH) for raw materials, which refers to the number of production days before all available raw materials are used. This is estimated using the raw material inventory turnover ratio, calculated by dividing the annual usage of materials by the year-end inventory balance. The DOH is then determined by dividing 365 days by this turnover rate.

The estimation method is as follows: First, we collected the annual ending raw material inventory and operating cost data of all listed companies in China from 2016 to 2018 from the Wind database and summarized them by the production sector to which they belong. Operating costs include raw material, labor, and fixed asset depreciation costs. Next, we used the intermediate input data, labor compensation data, and fixed asset depreciation data for each sector from the 2017 MRIO table to obtain the proportion of intermediate input (i.e., raw materials) in the operating costs for each sector. We used it to extract the raw material costs from the operating cost data. Then, we divided the full-year raw material costs by the ending raw material inventory to obtain the raw material inventory turnover rate for each sector from 2016 to 2018, and then divided the time period of 365 days by the turnover rate to obtain the raw material DOH. Finally, by taking the average of the estimated results for each sector over the three years, we can obtain the average raw material inventory DOH for each production sector.

5. Empirical Analysis

5.1. Retrospective analysis: empirical case of Shanghai in 2022

In mid-March 2022, Shanghai, one of the largest and most dynamic megacities in Asia, experienced a surge of the COVID-19 outbreak. To control the spread of the virus, the local government implemented a provincial-level lockdown policy that covered almost the entire city of Shanghai for the majority of the second quarter of 2022. This event eliminated the interference of other factors and generated comparable real-world economic statistical data (e.g., GDP growth) to validate the reliability and accuracy of our framework, thus making it a suitable case study.

In addition to the parameters introduced in Section 4, some essential input variables are required for the analysis framework. These variables include: 1) the equivalent shutdown duration of production sectors in the affected region D_{ri}, 2) the length of time during which residents' lives are restricted T_r, and 3) the proportion of the population affected θ. To estimate the equivalent duration of production shutdowns that determine the proportion of production losses, we used the monthly electricity-generating capacity data published by NBS. Specifically, we calculated the decline rate in Shanghai's electricity-generating capacity during the lockdown period from March to June 2022, compared with the same period in 2021. We assumed that this decline rate was equivalent to the monthly average production loss ratio. By multiplying the decline rate by the number of days in each month and summing them up according to Equation

(4), we obtained the equivalent shutdown duration of 32.8 days, which represents the production sector's loss[2].

Regarding the duration of residents' living restrictions and the proportion affected, the provincial-level lockdown policy was implemented from March 28th to May 31st, 2022, totaling 65 days. However, even in June, residents' daily lives only partially recovered. According to the Shanghai Transportation Industry Operation Briefing, the total number of urban transportation passengers in June decreased by 52.3% compared with the previous year. Therefore, we assumed that all residents in Shanghai were affected during the 65-day lockdown, and 52.3% of residents were affected in June[3].

Our results show that the current impact of the event, attributed to production and consumption losses, amounts to 533.5 billion yuan in value-added, of which Shanghai's loss is 153.8 billion yuan. According to statistics from the Shanghai Bureau of Statistics, the regional GDP of Shanghai in the second quarter of 2022, calculated at comparable prices, decreased by 13.7% compared with the same period last year, which is a loss of 148.3 billion yuan. This indicates that our estimated results have an error of only 3.6% compared to the actual data.

A more detailed categorization of the economic losses caused by this event is presented in Table 3. According to the analytical framework, the current impact can be divided into three components. Due to the production shutdown in the affected region, the impact on itself and the upstream regions and sectors providing intermediate products, referred to as "production loss - upstream", is 303.1 billion yuan in value-added, accounting for more than half of the total current impact. The loss caused by downstream sectors' shutdown due to the interruption of intermediate product supply, referred to as "production loss - downstream", is 142.0 billion yuan. The "consumption loss" caused by reduced household consumption is 88.4 billion yuan. Additionally, there is a potential loss of 51.3 billion yuan, which is the subsequent impact of the decline in household income and consumer demand[4].

Table 3. Economic losses caused by the destructive event in Shanghai

Economic impact category	Losses in VA (billion yuan)	Percentage (%)
Current impact	533.5	-
- Within Shanghai	153.8	28.8%
Production loss - upstream	303.1	56.8%
Production loss - downstream	142.0	26.6%
Consumption loss	88.4	16.6%
Subsequent impact	51.3	-
- Within Shanghai	16.2	31.6%

The impact of Shanghai's COVID-19 shutdown spread to other regions through the domestic production network. Using the proposed framework, we can further analyze the current

2 In this case, we identified the manufacturing and construction sectors as the affected industrial production sectors, with mining being unaffected.

3 The lockdown primarily took place in the second quarter, and its economic impact was mainly reflected in the second-quarter economic data. Therefore, we chose this time period as the research object and compared the estimated results with the actual data.

4 The subsequent impact takes time to manifest and therefore is not compared with actual data alongside the current impact.

impact of a destructive event by identifying the regions and sectors with the highest losses, as depicted in Figure 2. Among the most affected regions, aside from Shanghai itself, Guangdong, Jiangsu, and Zhejiang Provinces are economically developed areas with the highest GDP in China. They are also geographically close to Shanghai and have strong economic ties with the city. The Henan and Jilin Provinces are closely connected to Shanghai through the supply chain. They supply consumer goods and intermediate products to Shanghai, such as food and energy products, and also rely on products from Shanghai. The most affected sectors in these regions include transport equipment manufacturing, a key industry in Shanghai. This sector suffers the most significant loss and causes chain reactions in the same sectors in other regions. On the other hand, chemical products and wholesale and retail trades, which are essential to residents' lives, also experience large losses.

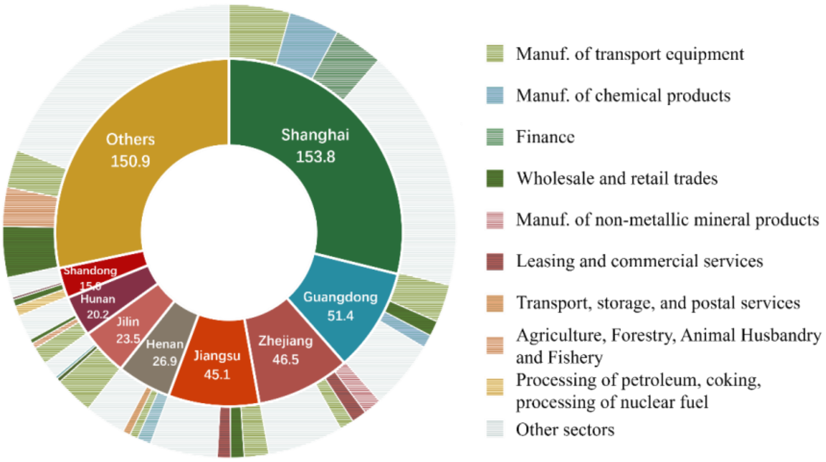

Figure 2. Regions that suffer the highest current impact of the destructive event in Shanghai and their corresponding sectors

5.2. Prospective analysis: simulations on destructive event risks in regions of China

As an empirical example of prospective analysis, we simulated the impact assuming a same destructive event occur in other regions (using the same input variables). The results shed light on the differentiated characteristics and roles of various regions in the national economic system.

The current impact of the destructive event in each region is ranked from high to low, and its three components are presented in Figure 3. If a similar destructive event were to occur in economically developed regions like Guangdong, Jiangsu, and Zhejiang, the resulting losses would be greater.

From the perspective of the three components, production disruption causes a high proportion of losses, with upstream losses being dominant. Meanwhile, in certain regions like Henan, Chongqing, and Jilin, the downstream losses caused by disruptions in intermediate product supply are relatively higher than those in other regions. This indicates that these regions act as crucial suppliers in the production supply chain, upon which many downstream regions and sectors depend. For example, in Henan Province, the main production sectors that downstream sectors depend on include food, textiles, clothing, and non-metallic mineral products. Chongqing is mainly relied upon by the surrounding regions of Yunnan, Guizhou, and Sichuan, while Jilin primarily influences the surrounding northeastern regions of Heilongjiang and Liaoning.

In addition, the percentage of losses attributed to consumption decline is relatively low.

Regions with higher proportions of consumption loss are mainly located in the less industrially developed western area of China, leading to a relatively smaller overall impact. Detailed estimation results are available in Appendix Table A1.

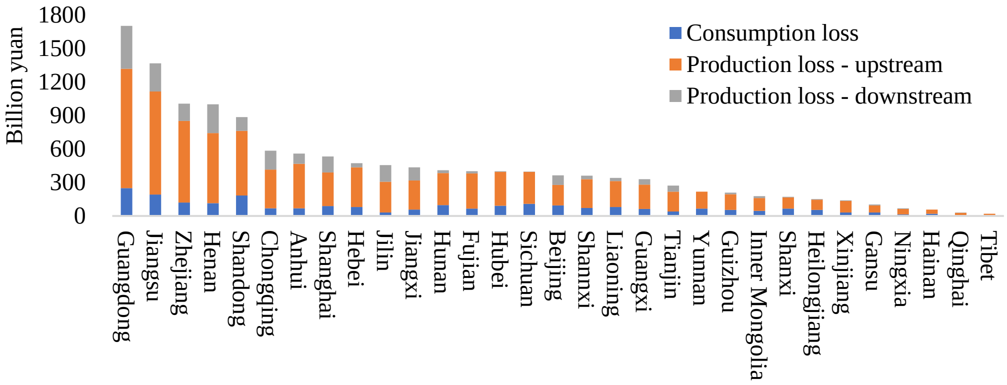

Figure 3. Ranking of current impact caused by destructive events in various regions

Figure 4 illustrates the distribution of the current impact of destructive events in each region. The horizontal axis represents where the event occurs, and the vertical axis represents the distribution of losses. On the diagonal line, the economic loss is undoubtedly highest in the region itself. In regions like Shandong, Hubei, and Hunan, the proportion of their own losses is higher, indicating that these regions are relatively self-sufficient in the production network. In some regions, the losses are widely distributed across different areas. This includes two situations: one where regions cannot be self-sufficient and rely on other regions for imports, like Hainan and Shaanxi, and the other where regions have extensive external connections in the supply chain, like Jilin and Henan. Hence, simulations of loss distribution resulting from destructive events can be used to assess economic connectivity between regions and evaluate associated economic risks.

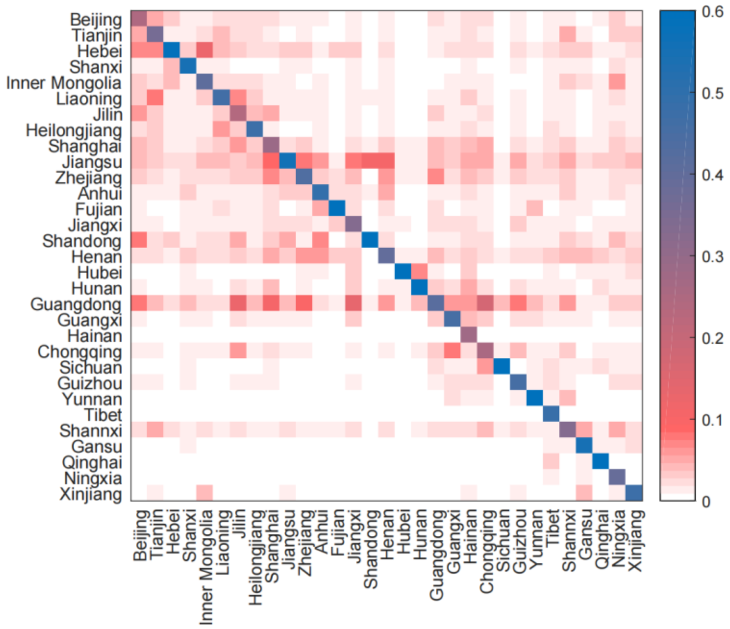

Figure 4. Distribution of current impact caused by destructive events in various regions

The ranking of the subsequent impacts caused by the destructive event in each region and the corresponding losses incurred within each region are shown in Figure 5. In regions with larger economic volumes, losses are still higher. Shandong Province has a notably high concentration of losses within the region, suggesting that its residents primarily buy locally produced consumer goods and services. By contrast, Henan, Shanghai, and Chongqing have relatively low percentages of losses within their respective regions, indicating that their residents buy more consumer goods and services from all over the country.

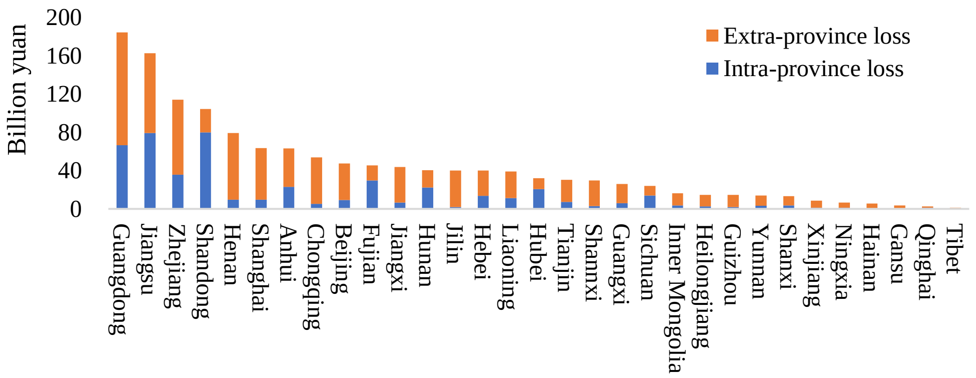

Figure 5. Ranking of subsequent impact caused by destructive events in various regions

5.3. What-if analysis: simulation of disaster mitigation policies

In this section, we present a series of what-if analyses based on the simulations in Section 5.2, to explore the effectiveness of various coping policies on mitigating the losses caused by destructive events. By adjusting the parameters and input variables in the analytical framework, we have the flexibility to assess the economic losses under different scenarios.

5.3.1. Effective production management measures

The implementation of measures such as safe passage and closed-loop management (minimizing factories' exposure to the outside to maintain smooth operation) can effectively reduce the duration of production shutdowns. Figure 6 presents the mitigated economic loss values and percentages for each region, achieved through a 10% reduction in production downtime from destructive events. This approach helps minimize the economic losses from production disruptions and ensures a more effective recovery process.

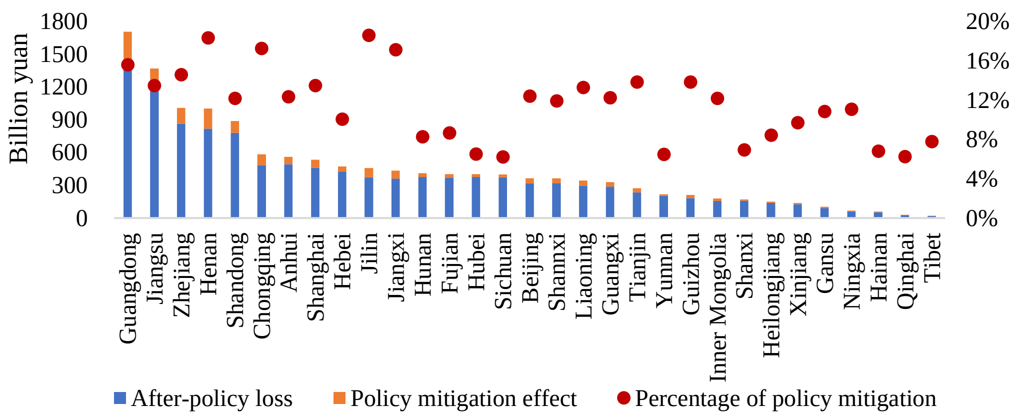

Figure 6. Policy mitigation effects of reducing production shutdown duration in various regions

5.3.2. Ensuring the household livelihoods

To minimize consumption losses, measures such as community group purchasing can be adopted to offer residents access to products and services other than necessities during destructive events. This ensures that household consumption is maintained at a certain level, thereby minimizing the impact on the overall economy. Figure 7 presents the percentage of economic losses that could be mitigated by a 10% reduction in consumption loss for each region.

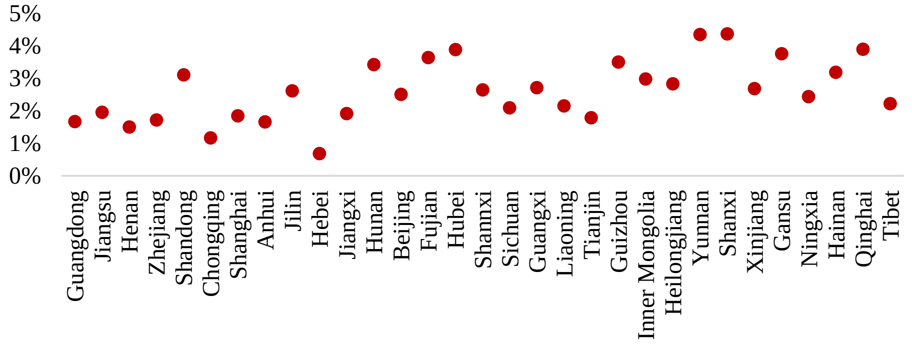

Figure 7. Policy mitigation effects of reducing consumption loss in various regions

5.3.3. Ensuring transportation and core supply chain resilience

By implementing security measures to protect transportation and critical supply chains in core industrial sectors, downstream disruptions can be minimized. This approach improves the overall resilience of production and supply networks and reduces losses in related sectors. Supply chain resilience is mainly reflected in manufacturers reducing their reliance on their prime suppliers. In this framework, the policy simulation is conducted by considering the downstream sector to be affected by the intermediate supply cutoff only if the affected area is the top one or top two sources of supply (instead of the top three, as originally set), referred to as Policy I and Policy II, respectively. This means that the downstream sectors are less vulnerable to the supply cutoffs. Figure 8 illustrates the economic losses that can be mitigated by these two types of policies, both in value and percentage.

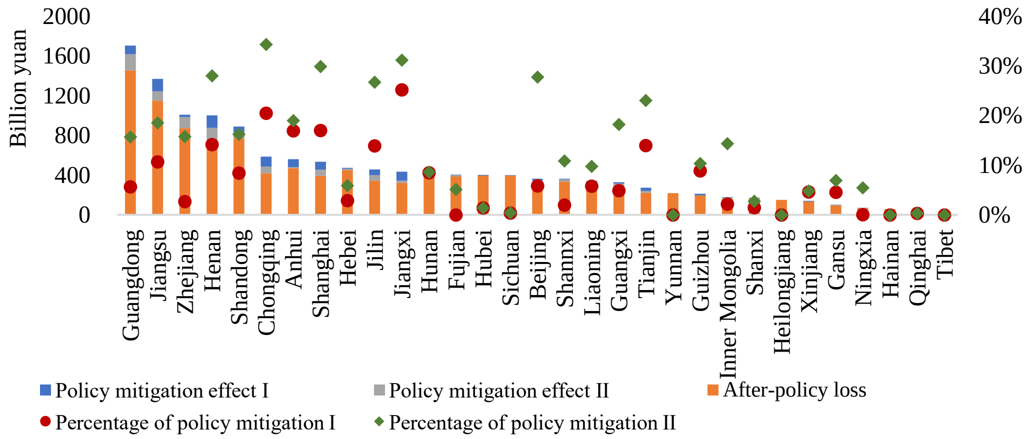

Figure 8. Policy mitigation effects of protecting critical supply chains in various regions

5.3.4. Implementing post-disaster recovery measures

Post-disaster measures, such as issuing shopping vouchers and subsistence subsidies, can be employed to stimulate consumption and mitigate the long-term economic impact of destructive events. Figure 9 presents the values and percentages of subsequent economic losses that can be mitigated through a 50% reduction in consumption loss resulting from income loss. The proactive measures that encourage consumption help expedite post-disaster recovery and prevent the vicious cycle where declining incomes lead to further reductions in consumption.

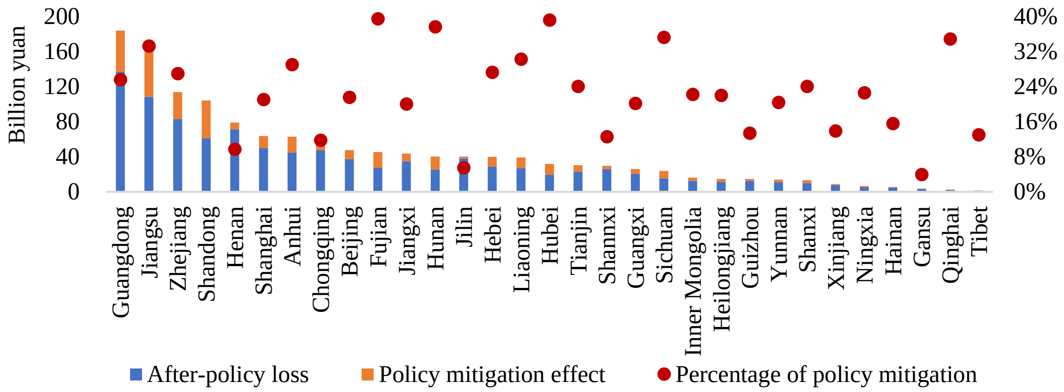

Figure 9. Policy mitigation effects of reducing subsequent consumption loss in various regions

6. Conclusion

As global uncertainties and threats persist, the occurrence of destructive events, whether natural or man-made, has the potential to disrupt production and consumption, leading to a significant impact on the overall economy. This study developed an analytical framework using the MRIO model and HEM to assess the economic losses from destructive events. The value of this framework lies in its unique combination of the production and household consumption perspectives. On the production side, we took into account both the upstream and downstream production loss due to the supply interruption. On the consumption side, we incorporated the concept of non-rigid consumption into the model and captured both short-term and long-term declines in household consumption. The proposed analytical framework advanced the set of tools available for accurately evaluating the potential economic damages of destructive events. Moreover, it can provide valuable insights for policy-making through simulations.

Using the updated 2017 Chinese MRIO table, we applied the analytical framework to assess the aggregate impact of the epidemic outbreak in Shanghai, China in 2022. We estimated that the epidemic crisis caused Shanghai to suffer a loss of 153.8 billion yuan in GDP value in the second quarter of 2022, with an error of only 3.6% compared to the actual data. Additionally, a prospective analysis was conducted to simulate the impact of such events in various regions of China. The results provide estimates of economic losses resulting from destructive events in each region, facilitating an analysis of the characteristics and roles of different regions within the national economic system.

The results show that regions characterized by larger economic scales, such as Guangdong, Jiangsu, and Zhejiang exert a more significant impact on the national economy in the event of such destructive occurrences. Regions with a higher self-reliance, such as Shandong, Hubei, and Hunan, exhibit a higher proportion of internally incurred losses. In contrast, regions with strong external economic connections, such as Hainan and Shaanxi, which heavily rely on provincial imported consumer goods, or Jilin and Henan, which have strong interregional links in the production supply chain, are likely to exert a greater influence on other regions. Furthermore, what-if analyses provide valuable insights into the effectiveness of various mitigation policies. By adjusting the parameters and input variables of the analytical framework, policymakers can effectively customize their strategies to address specific challenges and promote resilience in the face of uncertainty.

Our proposed methodology can be readily applied to analogous scenarios, such as evaluating the impacts of the Russia-Ukraine conflict on the global economy or the impacts of extreme weather events on China's regional or global economy. The limitation of this method inherits from its reliance on the IO method, as it does not consider the potential impact of price effects. However, the proposed double-sided approach indirectly captures the impact of price changes. After all, both the supply and demand sides are affected by prices. Another issue associated with the application of this method is the need for precise parameter calibration to ensure the reliability of the results. By carefully adjusting the parameters in this methodology, we can take into account the price effects and well picture the economic damages resulting from the destructive event. The proposed methodology sheds light on the risk management of emerging events. It enables the government to conduct stress tests for different destructive events and evaluate the corresponding economic risks and potential coping policies.

Acknowledgments

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Appendix

Table A1. Ranking of current impact caused by destructive events in various regions

Ranking	Province	Consumption loss		Production loss				Total loss
				upstream		downstream		
		Value	Proportion	Value	Proportion	Value	Proportion	
1	Guangdong	248.5	14.6%	1071.4	62.8%	384.9	22.6%	1704.8
2	Jiangsu	191.0	14.0%	925.7	67.7%	250.7	18.3%	1367.4
3	Henan	119.9	11.9%	732.2	72.6%	155.9	15.5%	1008.1
4	Zhejiang	113.3	11.3%	628.9	62.8%	259.2	25.9%	1001.3
5	Shandong	184.9	20.8%	577.8	65.1%	124.6	14.0%	887.3
6	Chongqing	67.9	11.6%	347.0	59.4%	169.1	29.0%	584.1
7	Shanghai	68.4	12.2%	398.5	71.1%	93.6	16.7%	560.4
8	Anhui	88.4	16.6%	303.1	56.8%	142.0	26.6%	533.5
9	Jilin	79.3	16.8%	355.5	75.1%	38.5	8.1%	473.3
10	Hebei	30.4	6.7%	275.5	60.4%	150.3	32.9%	456.3
11	Jiangxi	56.8	13.0%	262.6	60.3%	115.9	26.6%	435.3
12	Beijing	97.6	23.8%	286.2	69.8%	26.4	6.4%	410.1
13	Fujian	66.6	16.6%	314.1	78.2%	21.1	5.3%	401.8
14	Hunan	92.0	23.0%	304.9	76.0%	4.1	1.0%	401.0
15	Hubei	108.7	27.3%	287.8	72.4%	1.1	0.3%	397.6
16	Shannxi	94.8	26.1%	183.0	50.4%	85.7	23.6%	363.4

17	Guangxi	71.6	19.8%	258.9	71.4%	31.9	8.8%	362.4
18	Sichuan	79.3	23.2%	234.7	68.6%	28.3	8.3%	342.3
19	Liaoning	63.0	19.1%	217.0	65.9%	49.1	14.9%	329.1
20	Tianjin	40.4	14.8%	178.0	65.2%	54.6	20.0%	272.9
21	Guizhou	65.1	29.9%	152.5	70.1%	0.0	0.0%	217.6
22	Inner Mongolia	54.1	25.7%	139.7	66.4%	16.7	7.9%	210.5
23	Heilongjiang	45.7	25.7%	114.8	64.5%	17.6	9.9%	178.1
24	Yunnan	64.9	38.0%	102.5	59.9%	3.5	2.1%	170.9
25	Shanxi	54.4	36.1%	91.5	60.8%	4.7	3.1%	150.7
26	Xinjiang	32.4	23.2%	103.2	73.8%	4.2	3.0%	139.8
27	Gansu	31.4	30.7%	62.6	61.3%	8.1	8.0%	102.1
28	Ningxia	15.1	22.2%	49.0	72.1%	3.8	5.7%	68.0
29	Hainan	18.6	31.9%	39.8	68.1%	0.0	0.0%	58.5
30	Qinghai	8.3	27.7%	21.5	72.2%	0.1	0.2%	29.8
31	Tibet	4.2	21.1%	15.7	78.9%	0.0	0.0%	19.9