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Assessing the business interruption costs from power outages in China

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ABSTRACT

With the increasing frequency of extreme weather events, cyber attacks and natural disasters, power system reliability is facing unprecedented challenges. To contribute to a more targeted electricity reliability policy in China, this study develops a Dynamic Inoperability Input-output Model to assess the business interruption costs (BICs) from a provincial extremely big electricity outage event. The time-varying inoperability is first simulated for different sectors over the recovery period with consideration of the sectoral interdependencies. Then, the BICs are estimated for different sectors and the most vulnerable sectors to power outages are identified. At last, the impacts of four influencing factors on the estimated BICs are explored in the sensitivity analysis section. Our major findings are that: (1) The total BIC of an outage event is about 1.44 billion yuan, and the first 24 h of the recovery period account for about 70% of the total BICs. (2) 2% of a sector's inoperability caused by power outages will, on average, be transmitted to other sectors due to their interdependencies. (3) The chemical sector has the biggest economic losses from power outages, while water supply sector has the largest peak inoperability from power outages.

1. Introduction

Electricity supply system is a lifeline for all economies around the world, whose failures can result in large-scale economic losses and serious social disruptions. Power failures can have various negative macroeconomic and microeconomic impacts, such as the weakened economic competitiveness, deteriorated investment attractiveness, reduced firm productivity and increased social unrest (Elliott et al., 2021; Hashemi, 2021; Yuan et al., 2021). Since the electricity system is a large-scale, hierarchical and interconnected critical infrastructure, ensuring the continuous security and reliability of power system is becoming more and more challenging with the increasing electrification rates and the higher penetration of intermittent renewable energy (Adefarati and Bansal, 2017; Chen et al., 2021; National Academies of Sciences, 2017; Steele et al., 2021; Vasconcelos and Carpio, 2015). Due to the natural disasters, cyber attacks and climate change, large-scale blackouts are happening more frequently than before (Koks et al., 2019). The recent big blackout events include Ukaraine outages induced by fierce cyber attacks in 2016, Taiwan electricity outages due to human operation errors in 2021, Texas outages caused by extreme climate events in 2021.[1] To provide guidance for the electricity system protection and also to minimize the economic consequences from power failures, there is an increasing need to better understand the impacts of power interruptions on the economy.

It is necessary to know the components of outage impacts before quantifying them. According to the previous studies, the major impacts of electricity outages on the socio-economic systems can be classified into three categories as (1) **Direct damage cost**, which refers to the production facility and infrastructure damages, the mortality and the injury, etc. (Liu et al., 2021). (2) **Emergency response and clean-up cost**, which indicates the cost associated with the electricity supply during the recovery process, such as the start-up of emergency

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[1] The Taiwan blackouts can be seen from https://k.sina.com.cn/article_1887344341_707e96d5020012pl6.html. The information of Texas outages can be seen from https://gisuser.com/2017/06/global-outage-tracker-powered-by-machine-learning-datacapable-adds-global-power-outage-maps-to-esris-arcgis-marketplace/. The Ukaraine outages can be seen from https://www.zdnet.com/article/us-report-confirms-ukraine-power-outage-caused-by-cyberattack/

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generators, the substitution cost for replaceable goods and services, and the production rescheduling cost (Rose and Lim, 2002). (3) **Business Interruption Cost (BIC)**, which represents the direct production losses of the electricity sector and the ripple/multiplier effects of other sectors due to their interdependencies (Poudineh and Jamasb, 2017; Rose et al., 2007). Moreover, interdependency effects become more significant with longer interruptions, because higher order and induced effects can cause additional costs (Yusta et al., 2011). The first two categories are more engineering-based cost and are usually estimated by bottom-up approaches, while the BIC is a more economic-based cost and is often assessed by top-down methods (Küfeoğlu and Lehtonen, 2016). Most of the current media news about the power outage losses only cover the direct physical damage cost and emergency response cost, few of them have taken into account the BICs (Morrissey et al., 2018; Sanstad, 2016). However, underestimation of the total cost of power outages could lead to insufficient infrastructure investment, threatening the security of electricity supply (De Nooij et al., 2007; Wijayatunga and Jayalath, 2004). Therefore, the BICs need to be well integrated into the cost-benefit and risk analysis, so as to reduce the future power outages.

Estimating the BICs of power outages is a challenging task. First, the costs of other sectors caused by power outages are difficult to quantify due to the complex interconnectedness and interdependencies of different sectors (Poudineh and Jamasb, 2017). Second, the BICs of power outages have significant dynamic characteristics and pattern, neglecting the dynamic characteristics will be insufficient for providing optimal responses to recover the electricity supply or even result in a bias in the damage estimation (Lian and Haimes, 2006). Third, the estimation of BIC is also challenging due to the limited data availability of electricity outages at an event level, resulting in difficulty for robustness check and comparison among different estimation results (Reichl et al., 2013).

China has the largest electricity consumption in the world, but its System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) is significantly higher than that of other developed countries (Chen et al., 2021). It is necessary to analyze the impacts of power outages in China, thus providing guidance for the cost-benefit analysis of optimal outage recovery and infrastructure investment. With these motivations, we plan to develop a Dynamic Inoperability Input–output Model (DIIM) to assess the time-varying disruptions of power outages on China's economic systems, aiming at answering the following three questions.

(1) How will China's power system recover over time after power outages? Which sector is the most susceptible to the power outages?
(2) What are the BICs of power outages?
(3) How will the estimated economic losses be affected by different influencing factors?

The remainder of this paper is organized as follows: Section 2 presents the literature review. Section 3 describes the methodology and data. Section 4 provides the empirical results. Section 5 summarizes the conclusions and proposes some policy implications.

2. Literature review

Estimating the impacts of power outages has become an intense research topic. Many factors can affect the BICs, such as the scale of affected economies, the resilience of the electricity system and recovery time length, the interdependencies among different sectors, etc. (Munasinghe and Sanghvi, 1988; Poudineh and Jamasb, 2017; Sanstad, 2016). A proper methodology which takes all these factors into account is needed in estimating the BICs. Some pioneering studies have estimated the BICs of outage events caused by various reasons, such as terrorism, climate change, human errors, etc. (Larsen et al., 2018; Rose et al., 2007; Wing and Rose, 2020). The previous studies can be classified into two categories based the methodologies used in the estimation.

The first category is an Inoperability Input-output Model (IIM) based approach. IIM is developed from Input–output models, which are effective tools for investigating the inoperability and recovery of interdependent infrastructure system (Haimes et al., 2005a). IIM approach can be divided into static IIM and dynamic IIM by whether the dynamic recovery trajectories are simulated. There are several reasons why IIM based approach is popular in estimating the economic impacts of power outages. First, IIM takes a holistic view of the whole economy and also takes the interdependencies between different sectors into account (Anderson et al., 2007). Moreover, the IIM enables us to distinguish between the economic losses and the inoperability of power outages (Lian and Haimes, 2006). In addition, most traditional methods neglect the dynamic nature of power cuts, but the DIIM allows for intertemporal analysis and can model how the outage costs change with interruption durations (Lian and Haimes, 2006). Several studies have applied IIM approach to analyze the business interruption impacts of power outages. Rose et al. (1997) employed an Input-Output based model to estimate the economic impacts of power interruptions on the regional economy in metropolitan Memphis. Poudineh and Jamasb (2017) used a DIIM model to estimate the BICs of power outages in the Scotland in 2009. Haimes et al. (2005b) developed an Inoperability Input-Output Model to estimate the impacts of high-altitude electromagnetic pulse (HEMP) attack on the electricity system.

The second category is Computable General Equilibrium (CGE) based approach. Based on the neoclassical economic theory, CGE can be used to analyze the power outage shocks to economic systems by simulating the behavior changes of producers, average-cost pricing, and household demands (Hwang and Lee, 2015). The interlinks among different sectors can be well integrated into the CGE models in modeling the impacts of power outages. Moreover, CGE models allow for much more flexibility due to their non-linearity modeling of the substitution effects. Several studies have used CGE models to analyze the BICs of power outages (Sanstad, 2016). Wing and Rose (2020) employed a CGE model to analyze the impacts of a two-week power outage on California's Bay Area economy. Rose et al. (2005) utilized a CGE model to assess both the direct and indirect losses from electricity outages in Los Angeles.

As mentioned by Thissen (2004), IIM based approaches are good at estimating the short-term event effects, while CGE-based approaches are more promising in modeling the long-term effects that require more price flexibility. Furthermore, CGE model is more complex and needs more elasity parameters, while the data required by IIM can be easily obtained (Sanstad, 2016). In addition, IIM can provide a disaggregate information on the economic impacts of power outages at sectoral levels (Santos, 2006). Considering the characteristics of power outage events and the data availability, this study chooses to use a DIIM model to estimate the BICs of power outages. Compared with existing studies, we make two contributions to the literature. First, this study has considered the electricity system resilience brought by the energy substitution effects in measuring the sectoral inoperability, which can improve the accuracy of the estimation results. This improvement can help policy makers to make better investment decisions in the resiliency enhancement. Second, most of the existing outage cost estimations are for the developed countries, few studies have been conducted for the developing countries. This study bridges the gap and use China as a case study, which can provide important suggestions for the electricity policies in the developing countries. Moreover, this study has analyzed the impacts of different factors on the BICs, thus providing richer information for understanding the power outage cost.

3. Methodology

3.1. DIIM model

A DIIM model is developed to assess the BICs of different sectors from power outages, which is established by introducing the concept of inoperability to the traditional I-O analysis. The term inoperability indicates a system's dysfunction level and is expressed as a share of its "as planned" production capacity, see eq. (1).

$$Inoperability = \frac{As\ Planned\ Production - Degraded\ Production}{As\ Planned\ Production} \tag{1}$$

The sectoral inoperability q_i can be achieved by introducing degraded production $\widetilde{x}_i$ and 'as planned' production x_i of sector i, see eq. (2). The value of sectoral inoperability has a range of [0,1]. Taken the electricity sector as an example, an inoperability of 1 means that the electricity system is totally out of work, while an inoperability of 0 means that there is no disruption on the electricity supply.

$$q_i = \frac{x_i - \widetilde{x}_i}{x_i} \tag{2}$$

To establish the DIIM, we start with the original Leontief I-O eq. (3).

$$x = Ax + c \tag{3}$$

where $x = [x_1, x_2, \dots, x_n]^T$ represents the total production of different economic sectors; $c = [c_1, c_2, \dots, c_n]^T$ indicates the demand vector; $A = [a_{ij}]_{n\times n}$ shows the technology coefficient matrix.

Then, we combine the Leontief formulation for the 'as planned' production and the degraded production, see eq. (4).

$$x - \widetilde{x} = A(x - \widetilde{x}) + (c - \widetilde{c}) \tag{4}$$

Let $\widehat{x}$ be the diagonal matrix of the production vector x and introduce it to eq. (4).

$$\widehat{x}^{-1}(x - \widetilde{x}) = \widehat{x}^{-1}A(x - \widetilde{x}) + \widehat{x}^{-1}(c - \widetilde{c}) \tag{5}$$

It can be shown that Eq. (5) is equivalent to the IIM equation, see eq. (6).

$$q = A^* q + c^* \tag{6}$$

where

$$q = \widehat{x}^{-1}(x - \widetilde{x}) = \begin{bmatrix} \frac{1}{x_1} & 0 & \cdots & \cdots & 0 \\ 0 & \ddots & \ddots & \ddots & \vdots \\ \vdots & \ddots & \frac{1}{x_i} & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & \frac{1}{x_n} \end{bmatrix} \begin{bmatrix} x_1\text{-}\widetilde{x}_1 \\ \cdots \\ x_i\text{-}\widetilde{x}_i \\ \cdots \\ x_n\text{-}\widetilde{x}_n \end{bmatrix} \tag{7}$$

$$A^* = \widehat{x}^{-1}A\widehat{x} = \begin{bmatrix} a_{11}\left(\frac{x_1}{x_1}\right) & \cdots & a_{1j}\left(\frac{x_j}{x_1}\right) & \cdots & a_{1n}\left(\frac{x_n}{x_1}\right) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ a_{i1}\left(\frac{x_1}{x_i}\right) & \ddots & a_{ij}\left(\frac{x_j}{x_i}\right) & \ddots & a_{in}\left(\frac{x_n}{x_i}\right) \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ a_{n1}\left(\frac{x_1}{x_n}\right) & \cdots & a_{nj}\left(\frac{x_j}{x_n}\right) & \ddots & a_{nn}\left(\frac{x_n}{x_n}\right) \end{bmatrix} \tag{8}$$

$$c^* = \widehat{x}^{-1}(c - \widetilde{c}) = \begin{bmatrix} \frac{1}{x_1} & 0 & \cdots & \cdots & 0 \\ 0 & \ddots & \ddots & 0 & \vdots \\ \vdots & \ddots & \frac{1}{x_i} & \ddots & \vdots \\ \vdots & 0 & \ddots & \ddots & 0 \\ 0 & \cdots & \cdots & 0 & \frac{1}{x_n} \end{bmatrix} \begin{bmatrix} c_1\text{-}\widetilde{c}_1 \\ \cdots \\ c_i\text{-}\widetilde{c}_i \\ \cdots \\ c_n\text{-}\widetilde{c}_n \end{bmatrix} \tag{9}$$

By introducing the dynamic characteristics of sectoral interdependency and resiliency, the IIM model can be further extended to a DIIM, as shown in eq. (10).

$$q(t+1) = q(t) + K[A^* q(t) + c^*(t) - q(t)] \tag{10}$$

where K is a resilience matrix; t is the time period. As can be seen from the eq. (10), the inoperability is a sum of inoperability in the previous period and an adjustment of inoperability due to resiliency.

The eq. (10) can be approximated by a differential equation as below.

$$\dot{q}(t) = K[A^* q(t) + c^*(t) - q(t)] \tag{11}$$

The general solution to the differential eq. (11) is shown as in eq. (12).

$$q(t) = e^{-K(I-A^*)t} q(0) + \int_0^t K e^{-K(I-A^*)(t-z)} c^*(z) dz \tag{12}$$

With a stationarity assumption of final demand, $c^* = 0$, the solution eq. (12) can be further simplified as follows.

$$q(t) = e^{-K(I-A^*)t} q(0) \tag{13}$$

where $q(0)$ represents the initial inoperability caused by the power outages. The sectoral inoperability will fade off with time, as can be seen from the term $e^{-K(I-A_*)t}$.

An important feature of DIIM is the elements of resilience matrix (K), which shows how sectors respond to the inoperability shocks of other sectors. Assuming that the sectoral resiliency solely relies on itself and not on the other sectors, the inoperability of sector i in time t can be calculated by eq. (14).

$$q_i(t) = q_i(0) e^{-k_i\left(1-a_{ii}^*\right)t} \tag{14}$$

Therefore, the element values of the resiliency matrix can be obtained as follows.

$$k_i = \frac{ln[q_i(0)/q_i(T)]}{T_i(1 - a_{ii}^*)} \tag{15}$$

where $q_i(0)$ is the initial inoperability of sector i imposed by the power outage shocks; $q_i(T_i)$ is final inoperability level after a recovery time of T_i;a_{ii}* is the element of A* that can be calculated based on the Leontief coefficient matrix A.

Under the DIIM framework discussed above, the BICs from power outages of both an individual sector and for the whole economy can be obtained from (eqs. (16), (17)) respectively.

$$BIC_i = x_i \int_{t=0}^{t=T} q_i(t)\ dt \tag{16}$$

$$TBIC = \sum_{i=1}^{n} \left(x_i \int_{t=0}^{t=T} q_i(t)\ dt \right) \tag{17}$$

3.2. Data

To illustrate the applications of DIIM, this study estimates the impacts of a provincial power outage event on the national economy in

Table 1
Recovery time of different types of provincial electricity outage events.

Outage events	Small events	Medium events	Big events	Extremely big events
Initial inoperability	[5%, 10%]	[10%, 13%]	[13%, 30%]	[30%,100%]
Recover time (h)	44	86	120	127
Number of outage events caused by different disasters	Flood (55)	Flood (1)	Flood (3)	Flood (1)
	Snowstorm (32)	Snowstorm (3)	Snowstorm (2)	Snowstorm (3)
	Thunderstorm (47)	Thunderstorm (0)	Thunderstorm (0)	Thunderstorm (1)
	Hail (43)	Hail (2)	Hail (2)	Hail (0)
	Earthquake (26)	Earthquake (1)	Earthquake (7)	Earthquake (6)
	Typhoon (33)	Typhoon (4)	Typhoon (8)	Typhoon (5)

Notes: The four types of provincial outage events are classified based on the range of the initial inoperability, which is drawn from No.134 Notice of the general office of the State Council on printing and distributing the national emergency plan for large area blackout [2015], see http://www.gov.cn/zhengce/content/2015-11/26/content_10352.htm. The recovery time of the four types of outage events is the average value of all the samples after excluding the maximum and minimum values.

China. The major input parameters for the DIIM model are the initial inoperability, the recovery time, the final inoperability, the interdependency matrix **A*** and the sectoral economic outputs. We will explain them and their sources individually as below.

There are four types of provincial outage events according to the definitions from State Council of China, which classifies the outage events based on the ranges of their initial inoperability (see Table 1). This study selects an extremely big outage event for empirical analysis in the Business as Usual (BAU) scenario, while the results of other types are discussed in the sensitivity analysis section. In the BAU scenario, the lower bound (30%) of a provincial extremely big outage event is set as the initial inoperability of the electricity sector. Therefore, the average initial inoperability of the national electricity sector can be set as 0.97% (0.97% = 30%/31) considering the number of provinces.[2] The initial inoperability of other sectors is calculated by benchmarking their reliance on electricity in their economic activities with the electricity sector.[3] This is because there are substitution effects among different energy resources with the occurrence of power outages, and a sector with higher reliance on the electricity will have larger initial inoperability (Rose and Lim, 2002). In this study, the share of electricity in a sector's total energy consumption is used to represent the reliance level. The electricity consumption of different sectors is drawn from China Electricity Statistical Yearbook, while the amount of energy consumption is obtained from China Energy Statistical Yearbook.

As to the recovery time of electricity outages, there is no publicly available statistical information at the event level. Therefore, we collect them by ourselves from the historical provincial outages caused by natural disasters from news websites (Chen and Chang, 2021). 285 historical outage events, occurred from 2005 to 2021, are gathered based on the data availability, which are caused by six types of natural disasters (Earthquake, Flood, Ice and Snow, Thunderstorm, Hail and Typhoon). The average recovery time after excluding the maximum and minimum values are 127 h for an extremely big event, see Table 1. Moreover, we assume all the sectors have the same recovery time in this study.

As to the final inoperability, all the sectors are set as 10^{-8} with reference to Poudineh and Jamasb (2017) and Gong (2018). This indicates that all sectors are assumed to become almost operable at the end of the recovery period.

As to the interdependency matrix, it is calculated based on the 2018 national Input-Output (I-O) table published by National Bureau of Statistics (NBS). For simplicity, the final version of I-O table used in this study only contains 42 sectors, which are aggregated from 153 sectors in the original 2018 I-O table. The sectoral aggregation scheme is referred to Zhang et al. (2017), see the supplementary material.

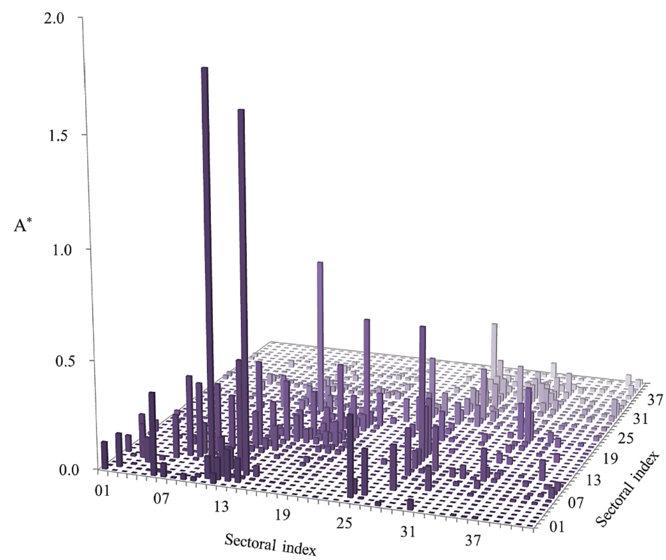

Fig. 1. The value of A* matrix elements. Notes: the sectoral index can be seen from the appendix.

As to the economic output of different sectors, there is no statistical information at the hourly level. For simplicity, this study assumes that national economy are evenly distributed throughout the year in the BAU scenario, so the hourly economic outputs of different sectors are obtained by dividing the annual outputs from the national I-O table by 8760 h. However, the impacts of occurrence time of power outages are explored in the sensitivity analysis section.

4. Results and discussions

4.1. Dynamic changes of sector inoperability over the recovery period

Before we analyze the dynamic changes of sector inoperability over the recovery period, we first show the values of A* matrix in Fig. 1. The elements (a_{ij}) in the A* shows the interdependencies among different economic sectors, and more attention should be paid to the higher values in A*to reduce the power outage impacts. This is because a bigger value of a_{ij} indicates that sector i's inoperability will have larger impacts on sector j. As seen from the height of the pillars, the Top three values of A* elements are the Petroleum and Natural Gas Extraction sector on the Petroleum and Natural Gas Processing sector (1.80), the Metal Ores sector on the Smelting and Pressing of Metals sector (1.62), and the Waste Resources sector on the Smelting and Pressing of Metals sector (0.73). Furthermore, most sectors are interconnected between each other because more than 60% of the a_{ij} elements are bigger than 0.001.

[2] Only 31 provinces are considered in this study due to the data unavailability of Taiwan, Hong Kong and Macao.

[3] The formulation of initial inoperability of sector i is calculated by the equation $q_i = q_0 \cdot \frac{u_i}{u_0}$, where $q_i$is the initial inoperability of sector *i* as a result of q_0 shock to the electricity industry; u_i is the share of electricity in the total energy consumption of industry *i*; u_0 is the share of electricity in the total energy consumption of the electricity sector.

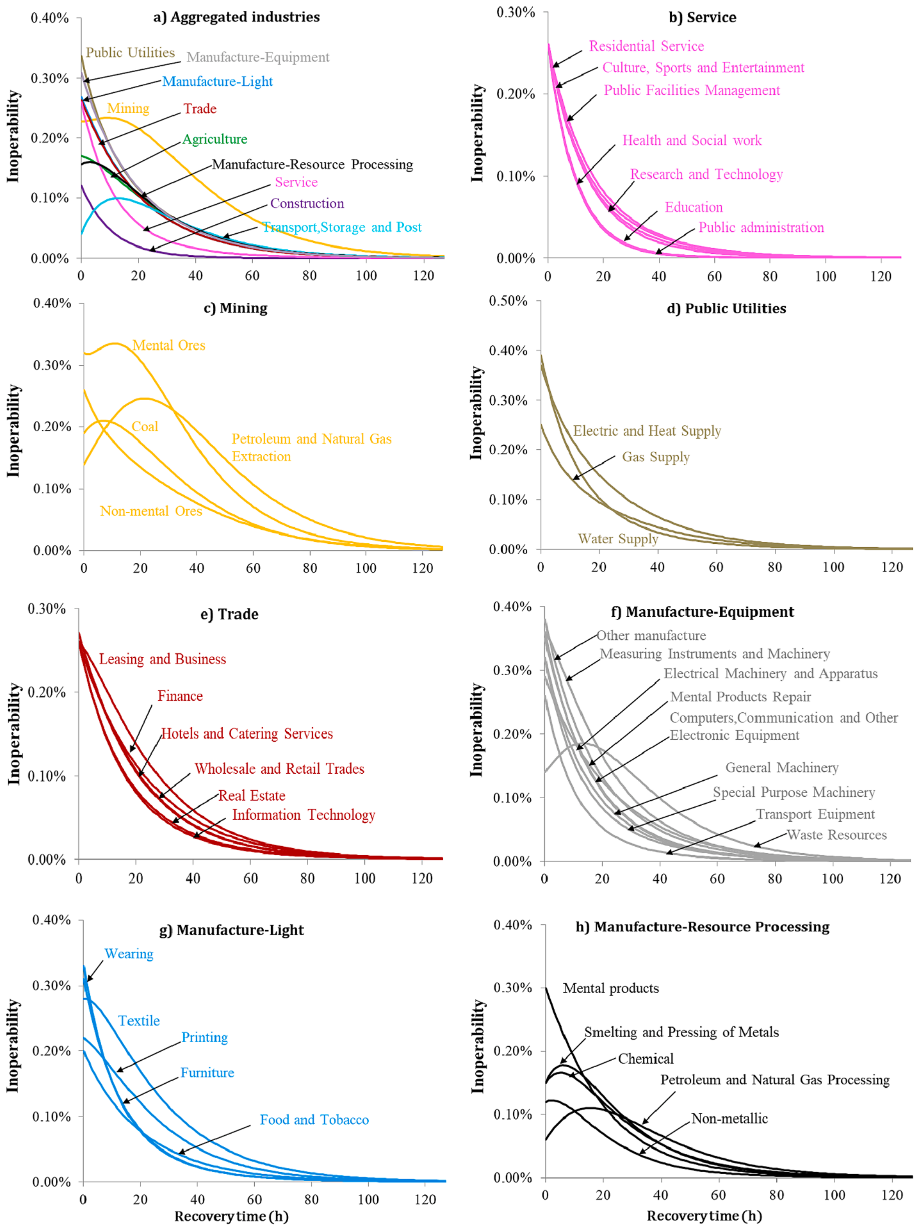

Fig. 2. the sector inoperability trajectories over the recovery period. Notes: All the sectors have been classified into eight categories. Figure a shows the curves of the aggregated sectors, while the remaining figures show the curves of different categories of sectors. Figure b to figure h shows the recovery trajectories of service industry, mining industry, public utilities industry, trade industry, equipment manufacture industry, light manufacture industry and resource processing manufacture industry.

The average value of a_{ij} is 0.02, indicating that 2% of a sector's inoperability will, on average, be transmitted to other sectors due to their interdependencies.

Using the DIIM model and the interdependency matrix, the dynamic inoperability recovery trajectory curves after power outages can be simulated, see Fig. 2. There are two types of sector inoperability trajectories over the recovery period. 79% of the sectors have a continuous downward shape of inoperability curves, such as the Electricity and Heat Supply sector, the Water Supply sector and the Furniture sector. However, 21% of sectors have inverted U-shaped inoperability recovery trajectory curves, such as the Petroleum and Gas Extraction sector. The pattern of inoperability changes can be used to guide the optimal response for mitigating the impacts of electricity outages. This is because different strategies can be used to mitigate the negative impacts from power outages. For example, peak inoperability shaving strategy can be used for the inverted U-shaped curves, while reducing the recovery time can be utilized for the continuous downward curves.

Furthermore, we have compared the peak inoperability and arrival time of different sectors. The average peak inoperability is 0.26% for all the sectors. Water Supply sector (0.39%) and Electric and Heat Supply sector (0.37%) and are the two sectors affected most by the electricity outages. The arrival time of peak inoperability vary substantially among different sectors. 33 sectors have peak inoperability at time when the power outage happens ($t = 0$), while the remaining rectors arrive at their peak inoperability within 22 h. Petroleum and Natural Gas Extraction sector has the longest time length (22h) to arrive at its peak inoperability.

4.2. Economic losses over the recovery period

Based on the inoperability recovery trajectories, the temporal distributions of BICs can be obtained, see Fig. 3. The total costs from a provincial extremely big outage event will be at least 1.44 billion yuan, representing 0.11% of the Gross Domestic Product (GDP) during the

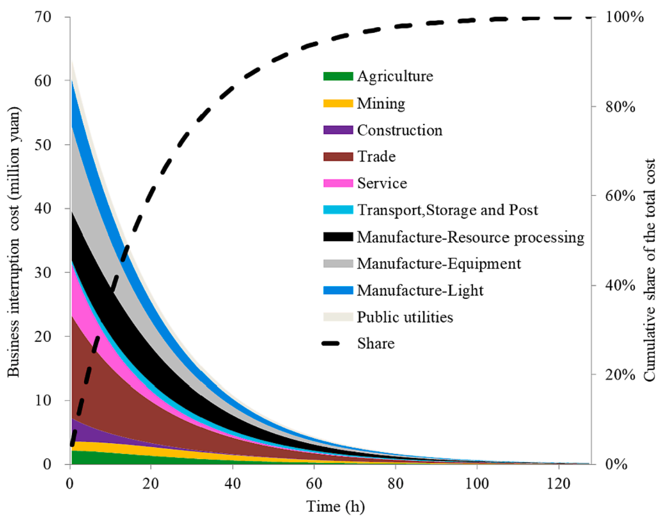

Fig. 3. The dynamic BICs of power outages. Notes: this figure only shows the aggregated sector results to save space and easy for clarification.

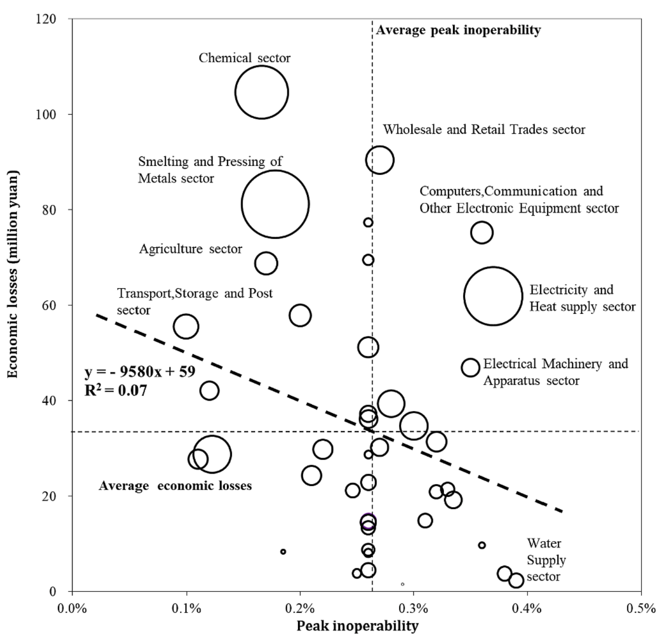

Fig. 4. the comparison between peak inoperability and economic losses. Notes: The average sectoral economic losses are 34 million yuan and the average peak inoperability is 0.26%. The bubble size represents the amount of sectoral electricity consumption.

sample period.[4] The hourly total electricity outage cost exhibits a declining trend during the recovery period. The economic losses during the first 24 h account for about 70% of the total economic losses. Therefore, effective and timely emergency response measures are valuable for reducing the impacts from power outages. In addition, the losses from electricity sector only accounts for a small share (~4%) of the total economic losses, indicating that neglecting the BICs of other sectors will strongly underestimate the impacts from power outages.

We have also analyzed the correlations between the peak inoperability and the BIC of the 42 sectors, see Fig. 4. There is a weak negative relationship between the peak inoperability and BIC of different sectors, which means that we cannot simply equate the rank of inoperability with that of BICs in comparing the impacts of power outages. Sectors with bigger inoperability do not necessarily mean that they have larger BICs. Taken the Chemical sector as an example, its peak inoperability is only 0.17% and below the average level, but its BIC is the highest. Therefore, an optimal reallocation of the emergency rescue resources after power outages should be based on a more comprehensive approach. The Chemical sector has the biggest economic losses from power outages (0.11 billion yuan), while the Water Supply sector has the largest peak inoperability from power outages (0.39%). An identification of the 'top-n' sectors that are perceived to suffer the greatest economic losses and biggest inoperability can narrow a policymaker's resource reallocations and optimal recovery.

In addition, the estimated BICs are also compared with the economic impacts from the actual power outage events in China, see Table 2. The information of economic impacts gathered from media news represents the total direct economic losses. In order to increase the comparability, we have calculated the average cost of one hour blackout. Several interesting results can be found from the results comparison. On the one hand, we can see that the estimation results of China's outage cost vary substantially among different events (0.06–5.14 million yuan/h), highlighting the necessity to conduct more estimations to increase the robustness of the estimated results. On the other hand, we can see that the BIC estimated in this study is relatively bigger than the average economic losses (direct damage cost) from 17 historical outage events (1.56 million yuan/h), indicating that neglecting the BICs will significantly underestimate the total economic impacts of power outages.

4.3. Sensitivity analysis

The estimated national BICs caused by provincial outages can be affected by many factors, so a sensitivity analysis is employed to analyze the potential changes due to the parameter variations. Four major influencing factors are considered in this study, including the occurrence time, the initial inoperability, the recovery period lengths and the occurrence places.

4.3.1. Occurrence time

The BICs can be affected by the time when the electricity outage events occurre. This is because the intensity of economic activities vary a lot during different time. Outage events happen during more economic-active period will result in larger damages. In this section, we will simulate how the outage events occurred in different months will affect the amount of BIC. Since the statistical GDP information is published by the NBS either annually or quarterly, we use the valued added share of industrial products to split the quarterly GDP to get the monthly GDP. The estimated BICs of extremely big outage events in different months are shown in Fig. 5. We can see that there are significant differences if the outage events are happened in different months, and the estimated BIC ranges from 1.21 billion yuan in February to 1.66 billion yuan in November.

4.3.2. Initial inoperability

The impacts of provincial initial inoperability on the national BICs are explored by modeling the provincial electricity interruption shares from 0% to 100%, see Fig. 6. We can see that the economic losses will increase with the levels of initial inoperability in all the four types of outage events. However, the increasing speed of BIC becomes slower as the initial inoperability increases. On average, the BIC will increase by 0.43 billion yuan when the initial inoperability of outage events increase by 10%. The simulated economic losses can be used for the cost benefit analysis of the resilience enhancement measures of the electricity system.

[4] According to the National Bureau of Statisticals, The annual GDP in 2018 is 91,928 billion yuan, so the GDP for 127 h is 1333 billion yuan (91,928/8760*127).

Table 2
the comparison of economic impacts of different electricity outage events.

No.	Province	Reason	Time	Durations	Economic Losses	Losses Per Hour
				days	Million yuan	Million yuan /h
1	Inner Mongolia	Snowstorm	Apr., 2006	0.62	4	0.27
2	Xinjiang	Sandstorm	Apr., 2006	2.00	3	0.06
3	Hubei	Hail	Jun., 2007	0.06	1	0.07
4	Hunan	Flood	Jun., 2007	17.00	1200	2.94
5	Hubei	Snow	Jan., 2008	18.00	86	0.20
6	Sichuan	Snow	Jan., 2008	4.00	13	0.14
7	Jiangxi	Flood	Jul., 2009	3.67	14	0.16
8	Jiangxi	Typhoon	Aug.,2009	3.61	220	2.54
9	Jiangsu	Typhoon	Aug., 2009	3.61	410	4.73
10	Hubei	Hail	Jan., 2009	0.90	111	5.14
11	Chongqing	Hail	May., 2010	0.75	1	0.06
12	Guangxi	Typhoon	Jul., 2014	2.04	7	0.14
13	Yunnan	Flood	Aug., 2015	1.00	3	0.13
14	Sichuan	Earthquake	Feb., 2018	2.97	320	4.49
15	Fujian	Typhoon	Aug., 2019	0.58	10	0.72
16	Anhui	Hail	Mar., 2019	0.46	46	4.17
17	Sichuan	Flood	Aug., 2019	0.81	12	0.62
18	Hypothetical provincial outage		2018	5.29	1444	11.37

Notes: the information of these historical outage events are drawn from various news websites, including Baidu (www.baidu.com), Yidianzixun (www.yidianzixun.com/), Sohu (http://news.sohu.com), etc. Most of the economic losses reported by news websites are the direct economic losses, such as the infrastructure damages, buildings collapse and product damages.

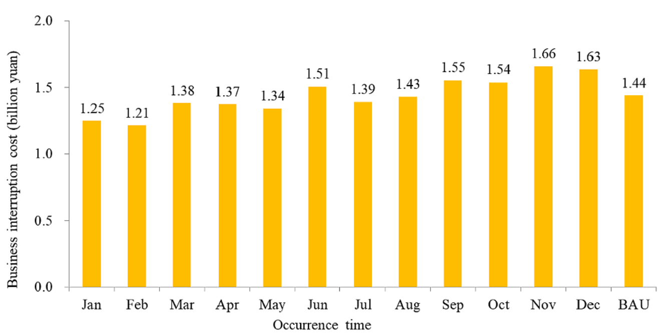

Fig. 5. The impacts of occurrence time on the national BICs.

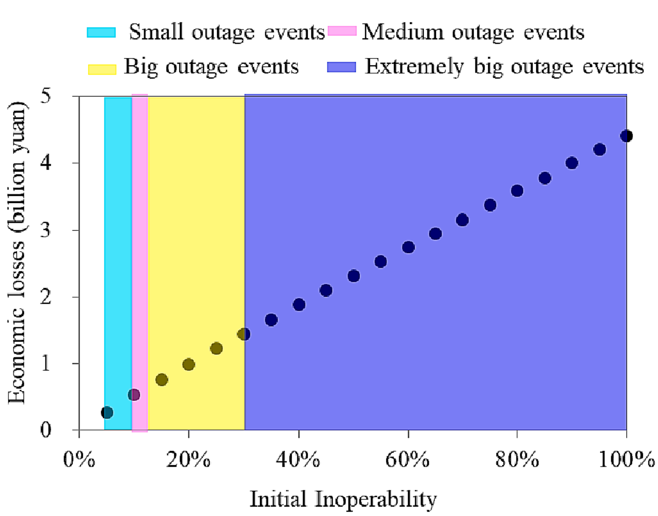

Fig. 6. the impacts of provincial initial inoperability on the national BICs.

4.3.3. Length of recovery period

The length of recovery period is also an important factor which affects the economic losses from power outages. Based on the recovery information from the historical outage events collected by Chen and Chang (2021), this study simulates the national BIC of a provincial outage event when the recovery time changes from 1 h to 200 h, with a step of five hours. The results are shown in Fig. 7. Similar to the results of the initial inoperability, the estimated BICs will increase with the length of the recovery period. The BICs will, on average, increase about 0.01 billion yuan when the recovery period increases by one hour. Therefore, cutting down the recovery time is an effective approach to reduce the BICs after power outages.

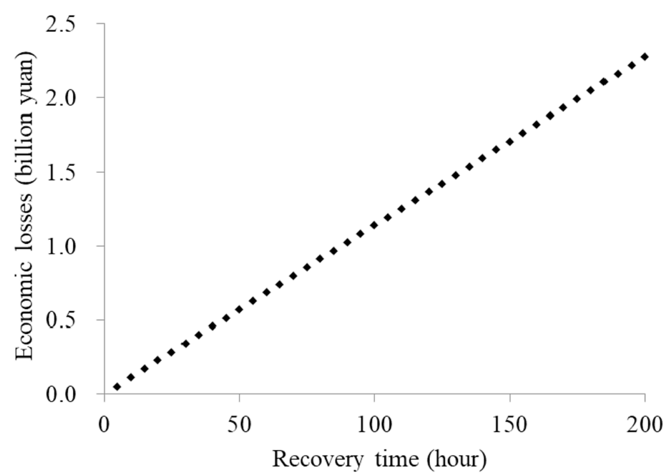

Fig. 7. the impacts of recovery time length on the national BICs.

4.3.4. Occurrence place

The occurrence places of provincial electricity outage events can also affect the economic losses. Although there are significant economic differences among provinces, the national Input-Output table is used in the sensitivity analysis instead of the provincial Input-Output tables. On the one hand, this study's research target is to investigate the impacts of provincial power outages on the national economy. A provincial extremely big outage event is selected as the source of impacts, but the assessed consequences of power outages are for the whole country economy. Moreover, the provincial I-O table is not available for the year of 2018 currently, which makes us difficult to conduct the estimation for different provinces. On the other hand, there is a large amount of electricity transmission between different provinces in China (Xu et al., 2020). Power outages in one province may simultaneously cause

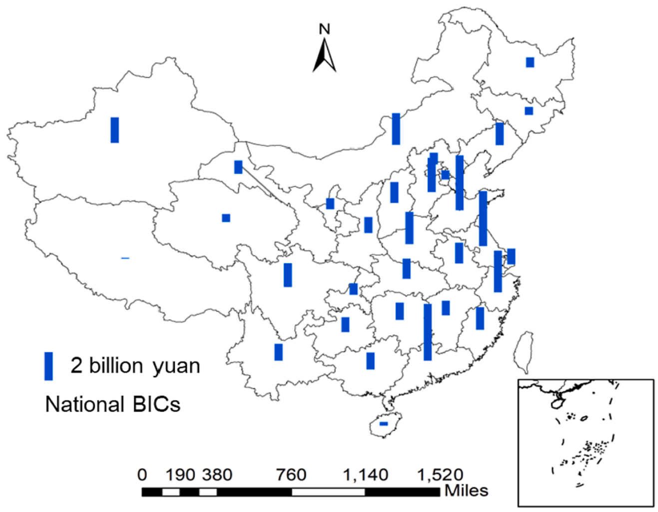

Fig. 8. the national BICs caused by extremely big outage events in different provinces. Note: the results of Taiwan, Hongkong and Macao are not estimated due to the data availability.

outages in other provinces, so the electricity transmission and commodity trading among different provinces can make it difficult and complex for us to estimate the impacts of outages on a provincial economy. However, a focus on the national economy can avoid these problems because China, as a whole, is almost self-sufficient in electricity. In estimating the national BICs caused by power outages in different provinces, the shares of provincial electricity consumption in the total electricity consumption in China are used in converting the provincial initial inoperability to national initial inoperability. The estimated national BICs caused by different provincial power outages are shown in Fig. 8. We can see that there are substantial differences among different provinces regarding the economic losses. Guangdong has the largest BIC (3.77 billion yuan), while Tibet has the smallest BIC (0.06 billion yuan). Therefore, regional differences should be well integrated into the reallocation of emergency rescue resources to minimize the economic impacts.

5. Conclusions and policy implications

5.1. Conclusions

With the increasing frequency of extreme weather events, cyber attacks and natural disasters, power system reliability is facing unprecedented challenges. In order to contribute to a more targeted electricity reliability policy, it is necessary to have a good understanding of the BICs from power outages. With this aim, this study employs a DIIM to assess the economic impacts from a provincial extremely big electricity outage event in China. First, the time-varying inoperability is simulated for different sectors over the recovery period with consideration of the sectoral interdependencies. Second, the BICs are estimated for different sectors and the most vulnerable sectors to power outages are identified. At last, the impacts of four influencing factors on the estimated BICs are explored in the sensitivity analysis section. During this process, we have obtained the following major conclusions.

(1) **Electricity outages can cause inoperability to all the economic sectors due to the interdependentcies, but the shapes of inoperability trajectory curves differ over the recovery period.** 79% of the sectors will have the highest inoperability at the time when power failures occurre, while 21% of the sectors exhibit inverted ‘U’ shape curves of the inoperability recovery. The average sectoral peak inoperability is 0.26% under a provincial extremely big outage event, and the dysfunction levels of Water Supply sector (0.39%), Electricity and Heat Supply sector (0.37%) are the highest caused by the electricity outages.

(2) **The total BIC of a provincial extremely big outage event is about 1.44 billion yuan, representing 0.04% of the national GDP during the recovery period.** The BIC of electricity sector only accounts for a small share (~4%) of the total economic losses, so neglecting the BICs of other sectors will strongly underestimate the impacts from power outages. Moreover, 70% of the economic losses will be caused in the first 24 h, indicating that timely emergency measures are very valuable in reducing the damages. In addition, the estimated BIC is about seven times of the average direct damage cost of the historical 17 outage events.

(3) **To set priorities for the risk management measures, the identification of the ‘top-n’ vulnerable sectors from power outages need be conducted separately in terms of inoperability and economic losses.** There is only a weak negative relationship between the peak inoperability and BICs of different sectors. The Chemical sector has the biggest economic losses from the outages, but the Water Supply sector has the largest peak inoperability from power outages. Therefore, more targeted measures and policies should be designed for different sectors to optimize the resource reallocations during the outage recovery.

(4) **The values of BIC from power outages can be affected by the occurrence time, the initial inoperability, the recovery period lengths and the occurrence places.** The BICs increase linearly with the initial inoperability and the recovery time. On average, the BICs will increase by 0.04 billion yuan when the initial inoperability increase by 1%, while the BICs will increase by 0.01 billion yuan when the recovery time increase by 1 h. In addition, there are significant differences in BIC from both the temporal perspective and the spatial perspective. With the occurrence of a provincial extremely big outage event, the estimated BICs will range from 1.21 billion yuan (Feburary) to 1.66 billion yuan (November) in different months, while they will also change from 0.06 billion yuan (Tibet) to 3.77 billion yuan (Guangdong) in different provinces.

5.2. Policy implications

Based on the above results and conclusions, this study proposes several policy implications to better reduce the economic impacts of power outages.

First, the estimation of BIC from power outages relies on the accuracy of critical parameters greatly, such as the initial inoperability, resilience, economic outputs and recovery period. However, a database which collects these information is still lacked, posing challenges for the parameter validation and results comparison. Therefore, it is necessary for the government to help establish proper platforms to collect and publicize the statistical information of historical outage events. These platforms can be served as useful tools to estimate the BICs and manage the risk holistically.

Second, the vulnerability varies substantially among different economic sectors in terms of both inoperability and economic losses. To achieve an efficient resource allocation in the outage recovery and reliability enhancement, it is necessary for the government to focus on the ‘Top-n’ sectors identified in this study. There are some policy choices that can be employed to mitigate the electricity outage risk, such as selecting the most critical sectors for resilience hardening, increasing preparedness to reduce the interdependency among critical sectors, providing early warning and enabling smart response to power outages.

At last, there is a trade-off between different measures in the resiliency enhancement investment, so the government can use the estimated BICs from this study to help designing the regulation policies for reliability improvement. The cost benefit analysis of different measures (hardening, redundancy and prevention) can achieve an economically optimal level of reliability. Moreover, the effectiveness of different reliability policies can also be evaluated with the estimated BICs.

Although this study has addressed several questions associated with the BICs from power outages, there are some places to be improved in future studies. On the one hand, it is necessary to use economic output data of smaller time resolutions (daily or hourly) to estimate the BICs, which can increase the accuracy of the estimation results. On the other hand, the results can be updated when the data of provincial Input-Output Table and hourly interregional electricity trading are available, which can obtain the BICs of power outages in different provinces. Moreover, the results can also be expanded to the total cost of power outages when more information of the direct damages and emergency responses are available. With these improvements, the results can be improved to provide better guidance for improving the measures in response to the power outages.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105757.

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