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自然災害の生産効率性へのダメージと回復:確率的フロンティア分析

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Institute for Economic Studies, Keio University 2-15-45 Mita, Minato-ku, Tokyo 108-8345, Japan ies-office@adst.keio.ac.jp 1 March, 2020 自然災害の生産効率性へのダメージと回復:確率的フロンティア分析 Preeya Mohan、大久保敏弘、Eric Strobl IES Keio DP2020-006 2020 年 3 月 1 日 JEL Classification: Q54, R11, O47 キーワード:確率的フロンティア分析;自然災害;生産の効率性;地震;非効率性スコア

【要旨】

本論文では確率的フロンティア分析により、自然災害が生産効率性にどのように損失を与え、 回復していくのかを分析した。日本の製造業(とくに機械産業と繊維産業)の都道府県レベルの 生産に関して、大規模自然災害が頻発した戦間期をサンプルに推計した。

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Natural Disasters and Industrial Production Efficiency Evidence from Prewar Japan

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Abstract

In this paper, we investigate whether destruction due to natural disasters induces industries to increase their production efficiency using the case of prewar Japan, a period of frequent disasters and technological upgrading. To this end, we compile a regional sectoral data set of natural disaster destruction and production for machinery and textiles during the period. We then employ a stochastic frontier analysis (SFA) approach to estimate the role of disaster events on changes in production efficiency. Our results show that earthquakes led to increases in efficiency for both machinery and textiles, although they were substantially greater for textiles due to recovery persisting longer. In contrast, climate-related natural disaster events played no role in production efficiency.

Keywords: Stochastic Frontier Analysis (SFA), Natural Disasters, Production Efficiency, Earthquakes, Inefficiency Scores **JEL:** Q54, R11, O47

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1. Introduction

Natural disasters can cause tremendous damage in terms of both human and physical assets, which can have considerable implications for the affected economies. While a priori the immediate direct effect of resulting damage on economies will clearly be negative, the direction of more medium- or long-term effects in terms of growth is unclear (Botzen et al., 2019). The underlying intuition in terms of the negative impact is straightforward: the destruction of human and/or physical capital, if sufficiently large, will lead to pushing economies downward from their growth path.² In contrast, a positive effect is feasible if the loss of capital results in the replacement of more productive and modern technologies or production methods that will push the economy to a newer, more efficient and higher growth path. This is known as the 'build back better' hypothesis.³ Related to this, there could also be 'creative destruction' in the Schumpeterian sense, in that less efficient firms damaged by natural disasters are driven out of the market.

Since the seminal study by Albala (1993), numerous researchers have set out to quantify the economic impact of natural disasters. Their results are reviewed in Cavallo and Noy (2011), Klomp and Valckx (2014), van Bergeijk and Lazzaroni (2015), Noy (2018), and Botzen et al. (2019). While these reviews emphasize the large differences in data and methods across existing studies, they also seem to reach the consensus that the literature points to a negative rather than a positive impact of natural disasters on economic wealth and/or growth, thus suggesting that natural disasters do not lead to any technological upgrading in response to the destroyed, human or

² The uncertainty regarding such a negative impact is whether this will only manifest itself over the short term, that is, whether economies will recover quickly back to their equilibrium growth trajectory, or whether recovery will only be gradual.

³ From a theoretical modeling perspective, the predictions in this regard rest in part crucially on the choice of economic growth model. Models based on neoclassical growth theory are generally only able to predict a negative impact because they assume rather than try to model technical change; in contrast, endogenous growth models can facilitate higher technology growth after natural disasters.

physical capital.⁴ However, it should be noted that there are two issues in most of the existing studies that may result in not empirically identifying a possible technological upgrading. First, most current papers look at the macroeconomic rather than regional effects of natural disasters. Because most natural disasters are very localized by nature, at least in terms of their damage, aggregate data may not be able to identify any technological upgrading that may occur. Second, almost all previous studies draw conclusions regarding an increase in efficiency through its translation into higher growth or income wealth, rather than examining changes in efficiency or technology directly.⁵

In this paper, we reexamine the issue of whether the destruction due to natural disasters can lead economies to become more productive by investigating how such events have affected regional production efficiency in two major industries, the textile and machinery industries, during the 1920s in Japan. Arguably, this period provides a particularly suitable context within which to study this question, that is, involving (1) technology destruction and recovery from natural disasters, and (2) development through technological progress. For this first aspect, frequent natural disasters might affect technology. Japan in the 1920s and 1930s experienced an exceptionally high number of large-scale natural disasters. On September 1, 1923, an earthquake of magnitude 7.9 hit the Greater Tokyo area (the Great Kanto Earthquake). The total number of dead and missing was estimated to be over 100,000 and the destruction of assets is estimated to be over 35% of GNP (Imaizumi, et al. 2016); the Great Kanto Earthquake shit Hyogo prefecture in 1925 (430 dead and 1,300 collapsed buildings) and in 1927 (3,000 dead and 12,500 collapsed

⁴ Pelli and Tschopp (2017) found that countries switch to exporting industries in which they have a comparative advantage after natural disasters.

⁵ One exception is Okazaki et al. (2019), who studied the upgrading of machine horsepower after an earthquake.

buildings), and Shizuoka prefecture in 1930 (420 dead and 1,300 collapsed buildings). A tsunami earthquake hit Iwate and Miyagi prefectures in 1933 (3,000 dead and 5,800 collapsed buildings). Turning to storms, large-scale typhoons hit Tokyo and Osaka in 1917 (1,300 dead and 38,800 collapsed buildings) and hit many regions in 1921 (700 dead and 7,400 collapsed buildings), in 1927 (440 dead and 2,200 collapsed buildings), and in 1932 (250 dead and 13,700 collapsed buildings). More serious was the Muroto typhoon in 1934, which caused high tides and serious damage in the Greater Osaka area. The total number of dead and missing was estimated at over 3,000 and the number of totally collapsed buildings at over 92,000 (Central Meteorological Observatory, 1935).

In the literature, there is already some evidence that natural disasters may have led to economic growth and helped firms upgrade during this period. Imaizumi et al. (2016) reported that after the 1923 Great Kanto Earthquake, there was a recovery process of manufacturing output growth in Tokyo City, which lasted around 6-7 years. From a sample of manufacturing firms in Yokohama City after the 1923 Great Kanto Earthquake, Okazaki et al. (2019) found a substantial upgrading of machine technology and an increased survival of efficient firms.

For the second aspect, development through technological progress, the 1920s also witnessed large technological and industrial structural change. After World War I, the Japanese economy managed to upgrade its industrial structure and technology in spite of harsh international competition and a prolonged depression. Previous studies highlight three main structural changes. First, this period saw substantial technological progress, which had led to the dramatic growth of heavy manufacturing industries. Abe et al. (2017) note that the share of manufacturing was less than 30% in 1900, but this had risen to 44% by 1925. Furthermore, labor productivity increased in manufacturing sectors, and industries such as textiles, mining, construction, and heavy

manufacturing (chemical and machinery) doubled their productivity in this period. Second, urbanization increased substantially with over 20% of the population living in urban areas by 1925 (Abe et al., 2017). In parallel, industries also concentrated geographically in specific regions in the 1920s, and this high degree of concentration fostered agglomeration economies and increased income in cities (Yuan et al., 2009; Fukao and Settsu, 2017). Finally, the Japanese economy experienced a motive power evolution from the steam engine to the electric/gas motor during this period (Minami, 1976).⁶ In the 1920s, most small and medium-size factories and traditional sectors shifted to machines with electric motors,⁷ which boosted their technology growth (Fukao and Settsu, 2017).

The wave of globalization also pushed forward technology progress in some manufacturing sectors, in particular textile and machinery sectors. In the cotton textile industry, one of the main export sectors, Abe et al. (2017) note that many cotton spinning firms during the Great Depression adopted new technology (e.g., high draft) and new machines (e.g., automatic looms) and some of them established affiliates in China. Their technology matured and they competed with UK firms in the international market. Exports of cotton textiles and artificial silk dramatically increased due to the yen depreciation and tariff reforms, as well as some industrial policies (see Nishikawa, 1987 for more details). In the machinery sector, foreign machine companies with advanced technology directed foreign direct investment to Japan and/or established joint ventures with Japanese domestic firms, which contributed greatly to technological progress (Fujiwara, 1973; Udagawa, 1987; Fukao and Settsu, 2017). For example, in the mid-1920s, Ford and GM built new factories in Tokyo and Osaka and produced automobiles as new products using imported parts and

⁶ Using Japan's Census of Manufacture data, Minami (1976) illustrated the evolution of motive power and emphasized how this evolution contributed to industrialization.

⁷ After World War I, the indigenous industries stagnated for a time, which led to a "dual structure" of large productive firms and small unproductive firms (Nakamura, 1971).

components from the USA. Additionally, Tokyo Electric Co. (*Tokyo Denki*) and Nippon Electric Co.(*Nippon Denki*) entered into capital and technological cooperation with General Electric Co. and Western Electric Co., respectively, making electrical products such as electric bulbs and new products such as radios and telephones in response to the surge in demand for these new machines. Furthermore, a number of patents were registered (Nishimura, 2003).

This paper focuses on two industries, textile and machinery industries due to following reasons. First, these two sectors were major industries in Japan. According to the Census of Manufacture, shares of output in all manufacturing sectors is 42% for textile (the largest) and 16% for machine sector (the second largest) as of 1920. Second, these two sectors intensively used machines and saw substantial technological progress in the 1920s, as mentioned above.

To examine the issue at hand, we construct regional level data on outputs and inputs in the textile and machinery industries from 1919 to 1928 for Japan from historical official statistical sources; in addition, we build a database on the number of deaths from earthquakes and climatic disasters from historical documents. Using the industry input and output panel data set, we first estimate technical inefficiency for regional textile and machinery production using a stochastic frontier analysis (SFA).⁸ We then combine our measures of regional inefficiency with the natural disaster data to investigate whether natural disasters during this period can explain changes in the efficiency of these regional industries.⁹ Our results show that in the machinery sector, climate-related disasters had no effect on technical efficiency, while earthquakes provided an immediate

⁸ SFA was previously employed to study the technical inefficiency of Japanese regional industries in Otsuka et al. (2010) and Otsuka and Goto (2015).

⁹ A similar approach was taken for Caribbean countries with regard to hurricanes and their impact on country technical efficiency by Mohan et al. (2019), who found there was a short efficiency boost for these islands. Arguably, this approach is more suitable to the context here, since we are explicitly comparing efficiency across regions for the same sector within the same country where it is much more likely that technologies and inputs are similar. In contrast, comparisons at the national level, as in Mohan et al. (2019), must inherently assume that feasible countries can achieve the same technological frontiers regardless of differences in resources and sectoral structures.

boost. In the textile industry, while climate disasters also do not appear to have made regions more efficient, the boosting effect of earthquakes with respect to technical efficiency appears to have lasted for at least 5 years after any event.

The remainder of the paper is organized as follows. In Section 2, we describe the context of natural disasters and their likely effect on textile and machinery production in Japan during the 1920s using secondary evidence. Section 3 describes our data sets and provides some summary statistics. The empirical methodology underlying our econometric analysis is outlined in Section 4. Results of our econometric analysis are presented and discussed in Section 5. Concluding remarks are offered in Section 6.

2. Background

2.1 Earthquakes

To provide a greater understanding of the context of our study in terms of the impact of earthquakes on the textile and machinery sectors at the time, we use anecdotal evidence on a specific earthquake during our sample period, namely the Great Kanto Earthquake, which occurred on September 1, 1923 with a magnitude of 7.9. It is considered the most serious natural disaster that Japan has ever experienced. The total number of dead and injured was estimated at over 100,000. Table 1 shows that Tokyo and Kanagawa prefectures in particular experienced serious damage, where around 40% of buildings completely collapsed and 2% of the prefectural population were dead or missing. The destruction of Japan's capital counted for around 35% of GNP (Imaizumi et al., 2016). Moreover, the damage extended to several neighboring prefectures. Just after the earthquake, the government immediately established *Teito Hukkou-in* (the Imperial Capital Reconstruction Department), which undertook new urban planning and large-scale

infrastructure projects for the cities of Tokyo and Yokohama. By 1930, all planned recovery projects were completed and a celebration ceremony was held in March of that year in Tokyo's Imperial Palace Park (Tokyo City Government, 1932). Overall, recovery took several years.

Figure 1 shows the total output and number of employees in the manufacturing sector in Tokyo prefecture. Although there was clearly a sharp decline in the number of employees and output immediately after the earthquake, recovery was quite fast. In parallel to these stylized facts, Imaizumi et al. (2016) econometrically estimated the impact of the recovery process on industrial workers in Tokyo prefecture (15 wards and 5 counties) à la Davis and Weinstein (2002). It was found that while the earthquake caused mean downward shifts in the shares and numbers of industrial workers, these shifts disappeared by the early 1930s. Thus, Imaizumi et al. (2016) concluded that recovery took around 6-7 years.

Next, we decompose our data by manufacturing sector. Figure 2 plots output by sector in Tokyo prefecture. Output in the machinery sector drastically declined after the earthquake but recovered immediately. In 1925, the output level already exceeded the pre-earthquake level in 1922. Imaizumi (2014) argues that the reasons for the quick recovery and growth of the machinery sector involve not only the demand for industrial recovery but also the large demand for new products such as automobiles and electronic devices. In contrast, the textile sector barely recovered after the earthquake. This long-run stagnant growth in the textile sector was caused by the shutdown of some large damaged factories in central Tokyo.

It is insightful to examine some specific companies and how they were affected by the 1923 earthquake; we do this for Nippon Electric Co., a machine company, and Fuji Gas Spinning Co. (*Fuji Gasu Bouseki*), a textile company. Both of them were old, big and leading companies with advanced technology and large-scale production. Nippon Electric Co. was founded in 1899

as joint venture company with Western Electric Co. in the United States and produced telecommunication devices with advanced technology. Fuji Gas Spinning Co., founded in 1896, was one of the largest spinning factories in the world as of 1920. It had over 6,000 employees and several modern factories across regions.

Nippon Electric Co. was one of the largest electric machine companies at the time and was located in Mita, Shiba ward in Tokyo. All of its factory buildings collapsed as a result of the earthquake and 105 employees died. The total physical damage was estimated to be around 1,670 thousand yen, of which 790 thousand yen were for buildings, 390 thousand yen for machines, and 240 thousand yen for raw materials and parts. The total amount of damage accounted for 17% of total annual sales (Nippon Denki Co., 2001, p. 115). In spite of this serious damage, Nippon Electric Co. immediately drew up a recovery plan and rebuilt several new advanced factories in Mita, for instance, including earthquake-fireproof instruments. Just 34 days after the earthquake, production restarted and all business resumed after 15 weeks (Nippon Denki Co., 2001, p. 116). It should be stressed that Nippon Electric Co. supplied many of the electrical products that were required for recovery. In addition, after the Great Kanto Earthquake, new high-technology electric machine products were developed, for example, radio and automatic telephone switchboards. Radio broadcasts started in Japan in 1925 while the automation of telephone exchange systems commenced in 1926. Thus, due to the huge public demand for telephone exchanges and radio stations, Nippon Electric Co. steadily increased sales (in particular telephone exchange machines) with the help of its US joint venture company (Western Electric Co.) and sought to catch up using the latest technology (Nippon Denki, 2001, pp. 115-121). To put these developments into perspective, Figure 3 shows the company's total profits and return on assets (ROA). In spite of the earthquake, profits increased, keeping up a high level of ROA.

Fuji Gas Spinning Co. was one of Japan's largest cotton spinning companies in the 1920s. It had several modern factories in Shizuoka, Kanagawa, and Tokyo prefectures, all of which were seriously damaged areas. Three factories were completely burnt down. One of them, Oshiage factory in Tokyo city, was finally sold without reconstruction in 1924. According to records, the Great Kanto Earthquake resulted in the death of 770 employees and many machines (174,000 spindles, i.e., 30% of all spindles) were also destroyed (Fuji Boseki Co., 1947, pp. 210–211). Indeed, the damage experienced by Fuji Gas Spinning Co. was the most serious in the whole cotton textile industry (Tokyo Nichi Nichi Shimbun, September 25, 1923) and was estimated at more than 13 million yen (Yakura, 1997). As shown in Figure 4, the company's ROA and profits decreased after the earthquake over time without recovery.

2.2 Typhoons

On September 21, 1934, a large typhoon struck western Japan, in particular Osaka, Japan's second largest city and manufacturing area. The storm, named Muroto, was one of the largest typhoons that Japan had experienced, with a minimum pressure of 911.6 hPa, the third lowest pressure on record in Japan, and with a maximum wind speed of 60 m/s. The typhoon first made landfall in Kochi prefecture and then went through the bay of Osaka. Causing a storm surge of more than 4 m in height, it flooded Osaka as well as the cities of Amagasaki and Kobe. Around 1,900 people drowned and many buildings and factories were flooded. In total, more than 3,000 people died or went missing and over 15,000 people were injured (Table 2). The damage extended to six other prefectures around Osaka.

After the typhoon, several industrial associations and firms in Osaka city cooperated to recover by themselves. The flooding due to the storm was particularly damaging because seawater

corroded the machines in factories, particularly the industrial cluster area of Amagasaki city in Hyogo prefecture, facing Osaka Bay. While some factories needed only 3–4 days to recover from the disaster, many factories took up to 1 month (Osaka City, 1953, vol. 6, p. 600). Heavy manufacturing firms took relatively longer to recover, one of the main reasons being subsidence that had already occurred before the typhoon. Specifically, the pumping of too much groundwater in the manufacturing area caused considerable subsidence in Amagasaki city. While this subsidence had already started in the 1910s, it became more substantial and very serious in the 1930s. The southern manufacturing area of Amagasaki city was flooded by the Muroto typhoon reaching a high tide of over 3 m. In 1935, 1937, and 1938, widespread flooding caused by high tides continued to occur, largely due to subsidence (Amagasaki City, 1970, vol. 3, p. 570).

Again, we also examine the experience of two particular companies: Dai-nihon Spinning Co. (*Dai-nihon Bouseki*), a large producer of cotton textiles, and Sumitomo Copper and Steel Co. (*Sumitomo Shindo Kokan*), a major producer of metal wire. On September 21, 1934, many of Dainihon Spinning's plants were damaged by the Muroto typhoon. In particular, factories in Amagasaki and Settsu cities in Hyogo prefecture were seriously affected. Their operation machinery as well as raw materials and final products were submerged, and recovery took 1 month (Nichibo Co., 1966, pp. 211–212). At Sumitomo Copper and Steel Co., the damage to plants was also very serious, with many machine motors under 2–3 m of seawater. Buildings had collapsed or had their chimney stacks blown off (Sumitomo Kinzoku Kogyo Co., 1977, p. 111).

3. Data

3.1 Industry Data

Our unit of analysis is Japan's 47 prefectures, which is the highest administrative geographical unit. We note that the spatial delineation of prefectures has not changed since 1890. A map of the prefectures can be seen in Appendix Figure 1. The size of prefectures ranges from 1,876.72 km² (Kagawa) to 83,424.31 km² (Hokkaido).

Our data for the machinery and textile industries at the prefecture level are taken from the annual Census of Manufacture, from the Ministry of Agriculture and Commerce. The data cover all manufacturing plants with more than five employees. The data include output, the number of employees, the number of factories, and the total horsepower of employed machines. Overall, we were able to compile data for the two industries from 1919 to 1928.¹⁰ We note that horsepower data are only available at sector level for this period. Output data are deflated to be in 1920 yen values.

We provide summary statistics for the textile and machinery sectors in Tables 3 and 4, respectively. Table 3 shows that the average total output in textiles is about 58 million yen, but with considerable variation across prefectures; the largest producer is Nagasaki prefecture, employing 128,361 workers on average, and the smallest is Yamanashi prefecture with a workforce of 53. On average, each prefecture has 708 factories and annually uses 5,790 kWh of horsepower to produce their textile products. Table 4 shows that the total output value and number of persons employed in the machinery sector is about one-quarter that in the textile sector. However, the relative ratio of factors is only about one-third, and horsepower a little more than one-half in the machinery sector relative to the textile sector. This attests to the fact that production

¹⁰ Unfortunately, information on the number of factories with machines and the amount of horsepower is unavailable for a few prefectures in 1922 due to technical reasons at the statistical office. The Great Kanto Earthquake in September 1923 destroyed the statistical office building and the government lost the data for 1922 in the process of compiling the data.

in the machinery sector is, unsurprisingly, relatively more capital-intensive than that in the textile sector.

3.2 Natural Disaster Data

We build an earthquake damage data index based on the number of persons killed per prefecture. To do so, we used *Nihon Saiagai-shi Jiten 1868–2009* (Historical Encyclopedia of Natural Disaster in Japan 1868–2009) from Nichigai Associates (2010), and *Showa Saigai-shi Jiten* (Historical Encyclopedia of Natural Disaster in Showa Period of Japan) from Nichigai Associates (1993). Based on the information in these data sources, we additionally consulted newspaper articles for some more detailed information. This allows us to cover all earthquakes above one person killed and thus construct the total number of persons killed per earthquake in each prefecture. Using population data from the Population Census (Ministry of Internal Affairs), we then constructed an annual regional measure of the number of deaths per capita (where population is measured in thousands).

We also constructed a parallel index capturing deaths due to climatic disasters from *Nihon Teikoku Tokei Nenkan* (Imperial Japan Statistical Yearbook), the annual publication by the Cabinet Office. Although climatic events are generally classified in these sources as being either due to (i) floods and water, (ii) high tides, (iii) typhoons, or (iv) heavy rain and storms, it was not always clear whether those due to (i), (ii), or (iv) were not simply also part of a typhoon striking or some separate event. We thus simply grouped all of these together as a 'climatic' disaster group.

Summary statistics of the number of deaths per thousand people by prefecture are shown in "EQ" and "CL" of Tables 3 and 4. As can be seen, annually the number of deaths due to climaterelated disasters (CL) is much smaller than that due to earthquakes (EQ), i.e., about 5%. At face value, one would expect about five deaths per million for climatic events as opposed to 104 for earthquakes in each prefecture each year. The largest earthquake event (the Great Kanto Earthquake) killed up to 21,467 per million in one prefecture (Tokyo prefecture).

We also depict the distribution of the average per capita deaths for earthquakes and climatic events in Figures 5 and 6, respectively (See Appendix Figure 1 for prefecture names). We note that the maps use average values over sample period for each prefecture. In parallel to the previous discussion, the most serious earthquake was Kanto Great Earthquake of 1923, which damaged Tokyo, Kanagawa, Chiba, Saitama, Yamanashi, Shizuoka, and Yamanashi prefectures (Figure 5 and Table 1). There were some other earthquakes mainly in West Japan during this period, although only 11 prefectures were damaged. In contrast, the distribution of deaths by climatic events is much more evenly distributed across prefectures. In particular, prefectures in West and Central Japan facing the Pacific Ocean had serious damage as, for example, Kochi and Kumamoto prefectures.

4. Methodology

To investigate the impact of natural disasters on regional technical efficiency in Japan for the machinery and textile sectors, we adopt a two-stage approach, following Otsuka et al. (2010).¹¹ First, we derive a measure of technical efficiency using an SFA model. Next, we regress the estimated technical inefficiency scores on the number of deaths per capita caused by earthquakes and climatic disasters.

¹¹ A similar approach was taken by Otsuka et al. (2010) who examined whether agglomeration economies, market access, and public fiscal transfers affected Japanese regional industries. The authors found that while agglomeration economies and greater market access increased efficiency, public fiscal transfers had a negative effect.

4.1 Stochastic Frontier Analysis (SFA) Approach

In traditional nonfrontier approaches to productivity analysis, all economic agents are assumed to be homogeneous units of production, and productivity growth takes place as a movement of the production frontier (Solow, 1957). A producer is technically efficient if he/she produces maximum output, for a given technology, from a given amount of inputs, and operates on the production efficiency frontier (Coelli et al. 2005). However, empirical studies demonstrate that in reality some production units are more efficient and operate on the technological frontier and are technically efficient, while others lag behind (Caves, 1989). In line with this, the SFA model is underpinned by the theoretical notion that production agents may behave suboptimally and produce below the ideal "frontier" leading to technical inefficiency. This approach accounts for possible inefficient behavior by measuring inefficiency as the potential increase in the observed value of production against the maximum technically achievable value defined by the production frontier. Estimation of this frontier is based on the notion that a maximum achievable output exists, but is constrained by available inputs, and inefficiencies decrease production below the frontier. Technical inefficiency scores are thus calculated as the distance from current output to the frontier.

Statistically, the SFA is a parametric approach where the form of the production function is assumed to be known and allows other parameters of the production technology to be estimated. As such, it specifies a regression model characterized by a composite error term that can be decomposed into two parts. The first error component is assumed to follow a symmetric distribution and is a standard error term, while the second component captures technical inefficiency. Technical inefficiency scores are therefore free from distortion and statistical noise. The SFA also allows for the measurement of inefficiency and random shocks outside the control of the producer to affect output (Wadud, 2003; Coelli et al., 2005).

To apply the SFA model it is necessary to impose an a priori functional form and to specify distributional assumptions to separate the two components of the error term. We assume a general regional Cobb–Doulas production function as follows:

$$\log(OUTPUT_{it}) = \beta_0 + \beta_1 \log(EMPLOYMENT_{it}) + \beta_2 \log(FACTORY_{it}) + \beta_3 \log(HORSEPOWER_{it}) + \mu_i + \lambda_t + V_{it} - IE_{it}$$
(1)

where *OUTPUT* is output (yen) deflated to 1920 prices produced, *EMPLOYMENT* is the number of persons employed in production, *FACTORY* is the number of factories, and *HORSEPOWER* is the power for production machines in factories measured by horsepower in prefecture *i* in year *t*; μ and λ are country fixed effects and time dummies respectively, while *V* is a nonnegative random variable accounting for technical inefficiency in the production function and *IE* is the usual error term where both are independently distributed for all production units (*i*=1, 2, ..., *N*). Importantly, *IE*_{it} stands for time-varying technical inefficiency scores in prefecture *i* in year *t*. If *IE*_{it} is equal to zero, then prefecture *i* in year *t* is defined as being totally technically efficient and is at its maximum output level given the inputs used and technology available. If *IE*_{it} is greater than zero, then prefecture *i* in year *t* is defined as being technically inefficient. We estimate Eq. (1) for the machinery and textile sectors separately.

To estimate the impact of natural disasters through deaths and injuries on technical efficiency, we utilize the inefficiency scores obtained from the SFA model in Eq. (1) and run the following general regression equation:

$$IE_{it} = \alpha_0 + \sum_{j=0}^{J} \alpha_{EQ,t-j} EQ_{i,t-j} + \sum_{j=0}^{J} \alpha_{CL,t-j} CL_{i,t-j} + \rho_i + \tau_t + \varepsilon_{it}$$
(2)

where EQ is the number of deaths per 1,000 people caused by earthquakes and CL is the number of deaths per 1,000 people due to climate-based natural disasters (high tide, floods, and typhoons), and ρ and τ represent prefecture and year dummies.

5. Estimation Results

5.1 Production Function

We estimate Eq. (1) for the machinery and textile sectors separately, and the results for these are shown in Table 5, where the estimated coefficients can be straightforwardly interpreted as elasticities. For both sectors, all three inputs significantly predict output. In the machinery sector, the elasticity with respect to employment is highest while that due to horsepower is lowest. While the labor elasticity is also highest in the production of textiles, regional output in contrast reacts more elastically to the amount of horsepower than to the number of factories in the prefecture. Comparing coefficients across sectors, the elasticity with respect to employment in machineries is 43% higher. Regional machinery production is also more susceptible (38%) to changes in the number of factors as inputs. In contrast, the elasticity with respect to horsepower is 7.7 percentage points higher in the textile sector.

5.2 Distribution of Inefficiency Scores

After estimating Eq. (1), we obtain the technical inefficiency scores from the production frontier. Tables 3 and 4 contain summary statistics on basic regional technical inefficiency scores for the machinery and textile industries, respectively. The mean inefficiency score is higher in the textile than in the machinery sector, but less variant. We also depict the distribution of the mean regional scores over time for both sectors in Figures 7 and 8 (see Appendix Figure 1 for prefecture names). Inefficiency scores are positively correlated with disaster damages shown in Figures 5 and 6. For the machinery sector (Figure 7), there are some notable patterns of concentration in terms of inefficiency. Specifically, there appears to be a geographical centralization of inefficiency in the industry. Indeed, eight of the 10 most inefficient machinery producing prefectures are in core with big machine production (Tokyo, Osaka, Hyogo, Aichi, Kanagawa, Kyoto, Fukuoka, and Nagasaki prefectures), where Tokyo is the most inefficient and had the biggest machine production. The Great Kanto Earthquake seriously damaged Tokyo and Kanagawa. For the textile sector (Figure 8), while the Osaka is the most inefficient region and had the biggest textile production¹², there are also some inefficient textile prefectures as for instance, Tokyo, Nagano, Hyogo, Kyoto, Gifu, and Gumma. All of them are big textile producers, and many of them were seriously damaged by earthquakes or climate events. On the other hand, the most efficient producers in both sectors are located at the most southern part of Japan, namely Okinawa, south islands, where earthquakes are much less likely to happen and typhoons hit but there is always small damage due to their large resilience. Here, we note that the inefficient score is to measure the deviation from technological frontier, and thus we must interpret that Okinawa tends to be on the technological frontier due to less damage of natural disasters. In both sectors, producers are on average more efficient in the north-east and south-west of Japan, as indicated in Figures 7 and 8 by the greater concentration of yellow or orange shading in that part of the country. These regions have less damage of natural disasters and less manufacturing production. Therefore, prefectures, which have many producers and were seriously damaged by earthquakes and/or climate events, tend to have high inefficient scores. Natural disasters seriously damaged technology in big cluster

¹² The raw correlation between mean regional inefficiency across the two sectors is 0.57.

regions (Greater Tokyo and Greater Osaka). This is just consistent to our anecdotal evidences on the Great Kanto Earthquake, as mentioned above.

5.3 Inefficiency and Natural Disasters

Our results of regressing the prefecture inefficiency scores on our natural disaster indicators as in Eq. (2) are shown for the two sectors in Table 6, where we allow for up to five lags of the two natural disaster indices.¹³ For the machinery sector, depicted in the first column, climatic disasters have no contemporaneous or lagged effects on inefficiency in the industry. In contrast, earthquake damage, as measured by the number of deaths per capita in a prefecture, reduces inefficiency significantly, albeit as a one-time sudden shock. Taken at the mean nonzero value of EQ, the estimated coefficient suggests that an average damage-causing earthquake induces an efficiency gain of 0.3% relative to the mean, whereas the largest observed value induced a gain in efficiency in machinery production of 2.8%.

In contrast to the machinery sector, climate-related natural disasters appear to have had no effect on the technical efficiency of textile-producing firms in Japan during the 1920s. In contrast, earthquake damage resulted in a reduction in inefficiency in the industry, with creative destruction inducing much more persistent efficiency growth. Specifically, the significant negative effect of EQ in the textile sectors lasts up to at least 5 years after the event. Additionally, the estimated coefficient only drops marginally as time since the event passes. If we take into account the cumulative effect over our 5-year window, then the estimated coefficients imply that the efficiency gain is at least 0.9% for the average observed damage and 7.7% for the largest observed value of deaths per capita due to earthquakes.

¹³ Including further lags would have substantially reduced our sample.

5.4 Discussion

These results are consistent with the anecdotal evidence as well as stylized facts reported above. As confirmed by our anecdotal evidence and some previous studies (e.g., Imaizumi et al., 2016), earthquakes caused serious damage with a longer recovery time compared with typhoons, because of more complete destruction with the collapse of buildings and social infrastructure. As shown in Figure 2, earthquakes decreased output in all industries but the recovery process differed across industries. While recovery was rapid in the machinery sector, it was sluggish in the textile sector. In parallel, as suggested by our anecdotal evidence of Nippon Electric, a major machine company, the quick recovery in the machinery sector was caused not only by the demand for the recovery of the economy, but also by the large domestic demand for new technology and new products from the Industrial Revolution (Imaizumi, 2014; Abe et al., 2017). This boosted technology growth of the machinery sector, which can thus be seen as a kind of creative destruction. On the other hand, the textile sector was stagnant. The export of silk products, the major export product, was already in decline in the international market during World War I. The bubble of the World War I boom broke in 1920 and seriously hit the cotton spinning sector (e.g., Hashiguchi, 2011). In the 1920s, the cotton spinning sector faced rationalization of firm organization and stringent labor regulations introduced by revision of the Factory Acts (Nishikawa, 1974). This prolonged the recovery from natural disasters. Abe et al. (2017) and Abe (1995) note that during the Great Depression, the cotton sector eventually saw economic growth owing to the adoption of new technology and vertical integration from cotton yarn companies to trading companies. Exports dramatically increased as a result of yen depreciation and trade policy reforms,

and by the 1930s, Japan became the largest cotton textile producer in the world. This could explain why the textile sector took longer to recover.

In sum, it is clear that natural disasters seriously damaged technology, but the duration of recovery and technological progress after a disaster are heterogeneous across industries. Technological progress and market conditions in each industry mattered. Some industries such as the machinery sector saw quick recovery and technology growth with the help of substantial technological changes from the Industrial Revolution, the market entry of advanced foreign technology, and the demand for new products. On the other hand, for some industries such as the textile sector, recovery was lengthy due to the decline in exports with strong international market competition. We can say that serious physical damage resulting from natural disasters could create some space for the renewal of technology—given the collapse of the old facilities and replacement by new ones—although this depended on market conditions.

6. Conclusion

In this study, we used the case study of prewar Japan to investigate whether natural disasters could lead to greater production efficiency. We constructed a panel data set of regional inputs and outputs, as well as indicators of natural disaster damage, for the textile and machinery industries in the 1920s. Employing an SFA approach, we then estimated whether these natural events led to Japanese regions becoming more efficient in production in these sectors. Our results show that this was indeed the case, at least for earthquake-induced destruction, although the effect was substantially larger due to recovery persisting longer for the textile sector.

Our findings confirm the possibility that natural disasters can drive industries to become more productive as they change production technologies in response to damaged or lost physical and human capital. It might be suspected that this is a particular feature of the uniqueness of the historical Japanese setting that we examined. However, using firm level data after the 1995 Great Hanshin Earthquake, Cole et al., (2019) found that, for the manufacturing sector, the least productive firms were more likely to exit if they were damaged, survivors tended to experience a productivity boost after being damaged, and more firms were created in damaged areas around Kobe. Thus, despite generally overwhelming evidence at the aggregate level to the contrary, some industries may actually benefit in the long-run from natural disasters.

REFERENCES

- Abe,T (1995) "Mengyo: senkanki ni okeru bouseki kigyou no doukou wo chushin ni" (Cotton industry—cotton spinning companies during the interwar period), in H. Takeda ed. *Nihon Sangyou Hatten no Dainamizumu* (Dynamism of the Japanese industrial growth), Tokyo: Tokyo Univ Press. (in Japanese)
- Abe, T, T.Yuuki, and I. Shirai (2017) "Senkain-ki ni okeru Sangyo kozo no hensen to kokusai kyoso" (Transition of industrial structure and international competition in the interwar period), vol 4. Ch.4 in *Nihon Keizai no Rekishi* (History of the Japanese Economy), edit by K. Fukao, N.Nakamura, and M.Nakabhayashi, Tokyo: Iwanami Shoten. (in Japanese)
- Albala-Bertrand, J.M., (1993). Natural disaster situations and growth: A macroeconomic model for sudden disaster impacts. *World Development*, 21(9), pp.1417-1434.
- Amagasaki city, (1970) Amagasaki-shi shi (History of Amagasaki city), vol.3, Amagasaki: Amagasaki City Office.
- Botzen, W.W., Deschenes, O. and Sanders, M., (2019). The economic impacts of natural disasters: A review of models and empirical studies. *Review of Environmental Economics and Policy*, 13(2), pp.167-188.
- Cavallo, E. and Noy, I., (2011). Natural disasters and the economy—a survey. *International Review of Environmental and Resource Economics*, 5(1), pp.63-102.

- Caves, R.E., (1989). Mergers, takeovers, and economic efficiency: foresight vs. hindsight. *International Journal of Industrial Organization*, 7(1), pp.151-174.
- Central Meteorological Observatory (1935) "Muroto Taihuu Chosa Houkoku" (Research report on Muroto Typhoon) Central Meteorological Observatory Report No. 9.
- Coelli, T.J., D.S.P. Rao, C.J. O'Donnell, and G.E. Battese. (2005). *An introduction to efficiency and productivity analysis*, 2nd ed. New York: Springer.
- Cole, M. A., Elliott, R. J., Okubo, T., and Strobl, E. (2019). Natural disasters and spatial heterogeneity in damages: the birth, life and death of manufacturing plants. *Journal of Economic Geography*, 19(2), 373-408.
- Davis, D. R., and Weinstein, D. E. (2002). Bones, bombs, and break points: the geography of economic activity. *American Economic Review*, 92(5), 1269-1289.
- Fuji Boseki Co.(1947) Fuji Bouseki Kabushiki Kaisha Goju nen shi (50 year history of Fuji Spinning Co), Tokyo:
 Fuji Bouseki, Co. (in Japanese)
- Fujiwara, S (1973) "Wagakuni Denki Sangyo nitaisuru Gaikoku Chokusetsu Toshi-1920 nen dai shoto no baai" (Inward foreign direct investment in the Japanese electric industry—case of early 1920s), *Keizai Ronshu*, 111(3) 204-222 (in Japanese).
- Fukao, K and T.Settsu, (2017) "Seicho to Makuro Keizai" (Economic growth and Macro Economy) vol 4. in Nihon Keizai no Rekishi (History of the Japanese Economy), edit by K. Fukao, N.Nakamura, and M.Nakabhayashi, Tokyo: Iwanami Shoten. (in Japanese).
- Hashiguchi, K. (2011) "1920 nen Kyoko Zengo no Nihon Mengyo" (Cotton industry during the recession of 1920), *Shakai Keizai-shi gaku* 77-3 pp.27-51 (in Japanese).
- Imaizumi, A. (2014) "Kanto Daishinsai-go no Tokyo niokeru Sangyo Hukko no Kiten" (Industrial Reconstruction after the Great Kanto Earthquake: Focusing on the Population and Demand for Labour in Tokyo), Shakai Kagaku Ronshu, vol. 142, p155-178 (in Japanese).
- Imaizumi, A., Ito, K., and Okazaki, T. (2016). Impact of natural disasters on industrial agglomeration: The case of the Great Kantō Earthquake in 1923. *Explorations in Economic History*, *60*, 52-68.
- Klomp, J. and Valckx, K., (2014). Natural disasters and economic growth: A meta-analysis. *Global Environmental Change*, 26, pp.183-195.

- Minami, R. (1976) "Insatugyou ni okeru Douryoku to Gijutsu Shinpo" (Motive Power and Technology in the Printing Industry), Keizai Kenkyu (Economic Review) 27(1), (in Japanese): 28-35.
- Mohan, P.S., Spencer, N. and Strobl, E., (2019). Natural Hazard-Induced Disasters and Production Efficiency: Moving Closer to or Further from the Frontier?. *International Journal of Disaster Risk Science*, 10(2), pp.166-178.
- Nakamura, T.(1971) Senzen-ki Nihon Keizai Seicho no Bunseki (Analysis of the Japanese Economic Growth in the Prewar Period), Tokyo: Iwanami Shoten.
- Nichigai Associates (1993) Showa Saigai shi Jiten (Historical Encyclopedia of Natural Disaster in Showa Period of Japan)
- Nichigai Associates (2010) Nihon Saiagai Shi Jiten 1868-2009 (Historical Encyclopedia of Natural Disaster in Japan 1868-2009)
- Nichibo Co. (1966) Nichibo 75 nen shi (75 year history of Nichibo), Osaka: Nichibo, Co. (in Japanese)
- Nippon Denki Co. (2001) Nippon Denki Kabushiki Kaisha Hyakunen shi Honpen (100 year history of Nippon Denki Co), Tokyo, Nippon Denki, Co. (in Japanese)
- Nishikawa, H. (1974) "1920 nendai no nihon menshi bouseki no gourika to dokusen taisei", (Rationalization and monopoly system in cotton spinning industries in the 1920s) *Tochi Seido Shigaku 16*(2), 17-35 (in Japanese).
- Nishikawa, H. (1987) *Nihon Teikoku Shugi to Mengyo* (Japanese Imperialism and Cotton Textile Industry), Kyoto: Mineruva Shobo. (in Japanese).
- Nishimura, S. (2003) "Senkanki ni okeru Tokyo Denki no Gijtsu Donyu to Gijutu Kaihatsu" (Technology introduction and development in Tokyo Denki Co. in the inter-war period), *Keizai Ronshu*, 172(4) pp. 20-42 (in Japanese).
- Noy, I., (2018). "The long-term consequences of disasters: What do we know, and what we still don't." *International Review of Environmental and Resource Economics*, *12*(4), pp.325-354.
- Okazaki, T., Okubo, T., and Strobl, E. (2019). "Creative Destruction of Industries: Yokohama City in the Great Kanto Earthquake, 1923". *The Journal of Economic History*, *79*(1), 1-31.
- Osaka City, (1953) Showa Osaka-shi shi (History of Osaka city in Showa period), vol.3, Osaka: Osaka City Office.

- Otsuka, A., Goto, M. and Sueyoshi, T., (2010). "Industrial agglomeration effects in Japan: Productive efficiency, market access, and public fiscal transfer". *Papers in Regional Science*, 89(4), pp.819-840.
- Otsuka, A. and Goto, M., (2015). "Regional policy and the productive efficiency of Japanese industries". *Regional Studies*, 49(4), pp.518-531.
- Pelli, M. and Tschopp, J., (2017). "Comparative advantage, capital destruction, and hurricanes". *Journal of International Economics*, 108, pp.315-337.
- Solow, R. (1957). "Technical change and the aggregate production function". *Review of Economics and Statistics*. 39 (3): 312–320
- Sumitomo Kinzoku Kogyo Co. (1977) *Sumitomo Kinzoku Kogyo saikin ju-nenshi : sogyo hachijisshunen kinen* (80 year history of Sumitomo Kinzoku Kogyo), Osaka: Sumitomo Kinzoku Kogyo Co. (in Japanese)
- Tokyo City Government (1925) Shinsai niyoru Nihon no Sonshitsu (damage to Japan by the Great Kanto Earthquake), Tokyo: Tokyo City Government.
- Tokyo City Government (1929) Saikin Tokyo Shi Kojo Yoran (Handbook on Factories in Recent Tokyo City), Tokyo: Tokyo City Government.
- Tokyo City Government (1932) *Teito Hukkou Saishi* (Celebration for Recovery of Imperial Capital City), Tokyo: Tokyo City Government.
- Udagawa, M. (1987) "Senzen Nihon no Kigyou keiei to Gaishikei kigyo", (Management and Foreign companies in pre-war Japan) *Keiei Shirin*, 24(1) 15-31 (in Japanese)
- van Bergeijk, P. and Lazzaroni, S., (2015). Macroeconomics of natural disasters: Strengths and weaknesses of meta-analysis versus review of literature. *Risk Analysis*, *35*(6), pp.1050-1072.
- Wadud, M.A. (2003). Technical, allocative, and economic efficiency of farms in Bangladesh: A stochastic frontier and DEA approach. *Journal of Developing Areas* 37(1): 109–126.
- Yakura, S (1997) "Kanto Daishinsai go ni okeru Fuji Gasu Bouseki kabushiki gaisya to Kanegahuchi Bouseki kabushiki gaisya no keiei ni tuite" (On the management in Fuji Gas Spinning Co. and Kanegafuchi Spinning Co. after the Great Kanto Earthquake), *Sangyo to Keizai* vol. 12(2) 53-69. (in Japanese)
- Yuan, T, T. Settsu, J-P. Bassino and K. Fukao (2009) "Senzen ki Nihon no Kennai Souseisan to Sangyo Kozo", (Prefectural GDP and Industrial Structure in pre-war Japan) *Keizai Kenkyu* vol. 60 (2) (in Japanese)

	Human da	amage	Physical damage		
Prefecture	Number of death and missing	Percentage to the population	Num of buildings completely burnt or destroyed	Percentage to the total buildings	
Total	104,619	0.89	464,909	20.4	
Tokyo	70,497	1.75	328,646	39.8	
Kanagawa	31,859	2.31	115,353	42.1	
Chiba	1,420	0.11	42,945	24.5	
Saitama	316	0.02	13,372	5.1	
Yamanashi	20	0.00	562	0.5	
Shizuoka	492	0.03	4,562	1.9	
Ibaraki	15	0.00	157	0.1	

Table 1: Damage by the Great Kanto Earthquake

Source: Tokyo City Government (1925), pp.160-163.

Table 2: Damage by Muroto Typhoon

	Human da	Physical damage			
Number of death and missing	Percentage to the population	Number of Injured	Percentage to the population	Number of buildings destroyed	Percentage to the total buildings
3,066	0.00	15,361	0.02	83,611	0.6
1,888	0.05	9,008	0.23	34,200	3.8
233	0.01	1,771	0.11	6,022	1.7
261	0.01	1,418	0.05	10,533	1.7
37	0.00	434	0.05	2,501	1.4
122	0.02	508	0.07	3,194	2.0
39	0.01	345	0.05	4,273	2.9
152	0.01	420	0.03	4,461	1.6
	death and missing 3,066 1,888 233 261 37 122 39	Number of death and missing Percentage to the population 3,066 0.00 1,888 0.05 233 0.01 261 0.01 37 0.00 122 0.02 39 0.01	death and missingto the populationInjured3,0660.0015,3611,8880.059,0082330.011,7712610.011,418370.004341220.02508390.01345	Number of death and missing Percentage to the population Number of Injured Percentage to the population 3,066 0.00 15,361 0.02 1,888 0.05 9,008 0.23 233 0.01 1,771 0.11 261 0.01 1,418 0.05 37 0.00 434 0.05 122 0.02 508 0.07 39 0.01 345 0.05	Number of death and missing Percentage to the population Number of Injured Percentage to the population Number of buildings destroyed 3,066 0.00 15,361 0.02 83,611 1,888 0.05 9,008 0.23 34,200 233 0.01 1,771 0.11 6,022 261 0.01 1,418 0.05 10,533 37 0.00 434 0.05 2,501 122 0.02 508 0.07 3,194 39 0.01 345 0.05 4,273

Source: Central Meteorological Observatory (1935, pp.276-279)

	Average	Std. Dev.	Min.	Max.
OUTPUT	5.83e+07	8.34e+07	64023	5.95e+08
EMPLOYMENT	21022	26690	53	128361
FACTORY	708.06	918.20	5	5564
HORSEPOWER	5790.70	16315.77	0	152446
EQ	0.104	1.372	0	21.467
CLI	0.005	0.022	0	0.317
INEFFICIENCY	17.096	0.842	13.743	18.989

Table 3: Summary Statistics (Textiles)

Table 4: Summary Statistics (Machinery)

	Average	Std. Dev.	Min.	Max.
OUTPUT	1.33e+07	3.47e+07	2227	2.12e+08
EMPLOYMENT	4810	11018	6	70194
FACTORY	207.05	541.16	2	4705
HORSEPOWER	3291.1	12460.8	0	155066
EQ	0.104	1.372	0	21.467
CL	0.005	0.022	0	0.317
INEFFICIENCY	14.162	1.427	10.807	17.902

Table 5: Stochastic Frontier Model

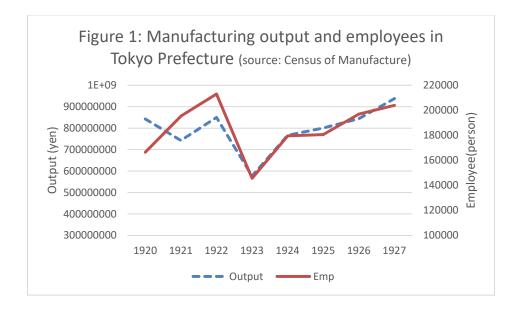
Variables	(1)	(2)
log(EMPLOYMENT)	0.503**	0.320**
	(0.060)	(0.048)
log(FACTORY)	0.189*	0.117*
	(0.095)	(0.056)
log(HORSEPOWER)	0.121*	0.198**
	(0.048)	(0.032)
SAMPLE:	MACHINERY	TEXTILES
Observations	417	417

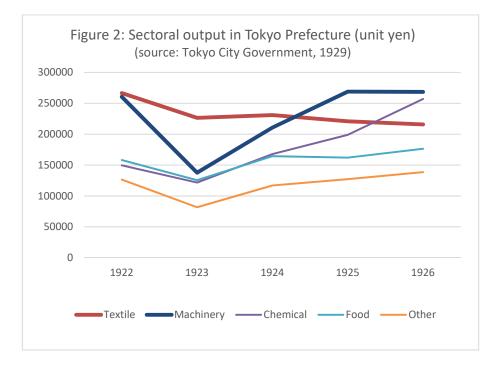
Notes: (i) Robust standard errors in parentheses, (ii) ** and * indicate 1 and 5 percent significance levels, (iii) Year dummies included but not reported.

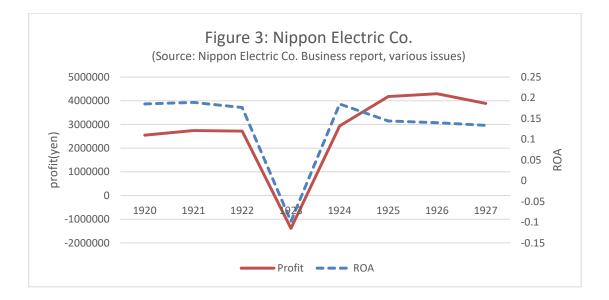
Variables	(1)	(2)
EQt	-0.0184**	-0.0114**
	(0.00474)	(0.00153)
EQ _{t-1}	-0.00407	-0.0106**
	(0.00535)	(0.00232)
EQ _{t-2}	-0.00862	-0.00937**
	(0.00624)	(0.00168)
EQ _{t-3}	-0.00234	-0.00932**
	(0.00485)	(0.00298)
EQ _{t-4}	-0.00145	-0.00937*
	(0.00638)	(0.00356)
EQ _{t-5}	-0.00245	-0.0108**
	(0.00541)	(0.00310)
CLIt	0.178	0.0594
	(0.802)	(0.214)
CLI _{t-1}	-0.680	0.0811
	(0.469)	(0.230)
CLI _{t-2}	-0.102	0.0130
	(0.891)	(0.246)
CLI _{t-3}	0.503	-0.0590
	(0.757)	(0.261)
CLI _{t-4}	0.489	-0.265
	(0.675)	(0.162)
CLI _{t-5}	0.218	-0.340
	(0.453)	(0.192)
SAMPLE:	MACHINERY	TEXTILES
Observations	413	408
R	0.5375	0.6364
F-stat	4187.40	8279.07

Table 6: Impact of Natural Disasters on Technical Inefficiency

Notes: (i) Robust standard errors in parentheses, (ii) ** and * indicate 1 and 5 percent significance levels, (iii) Year dummies included but not reported.







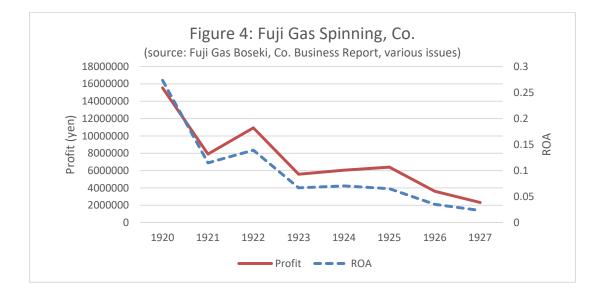


Figure 5: Earthquake damage

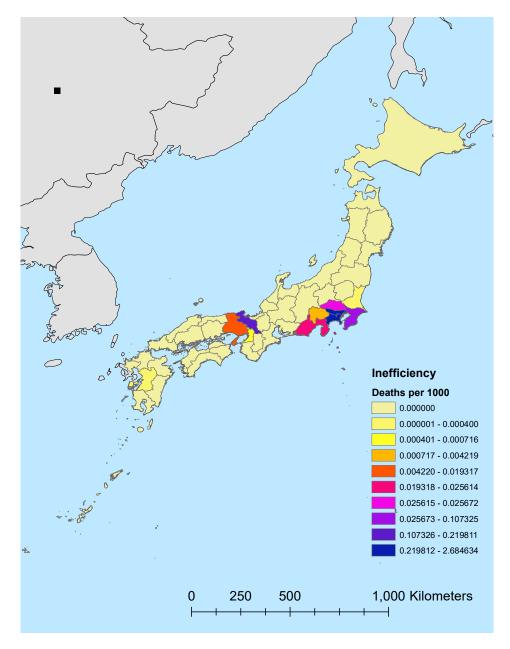
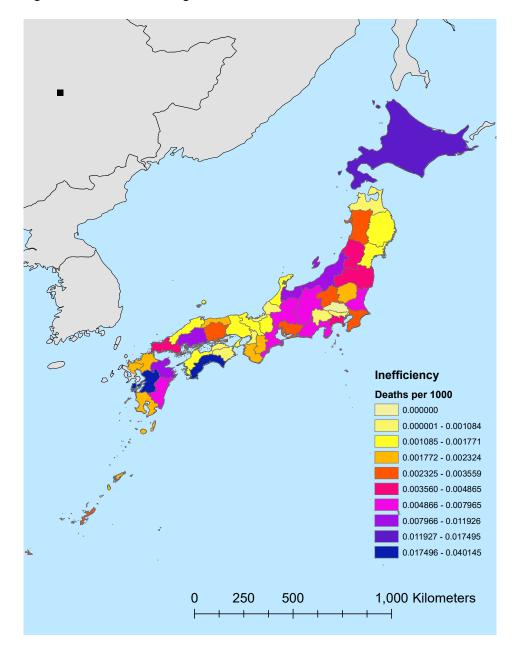


Figure 6: Climate damage



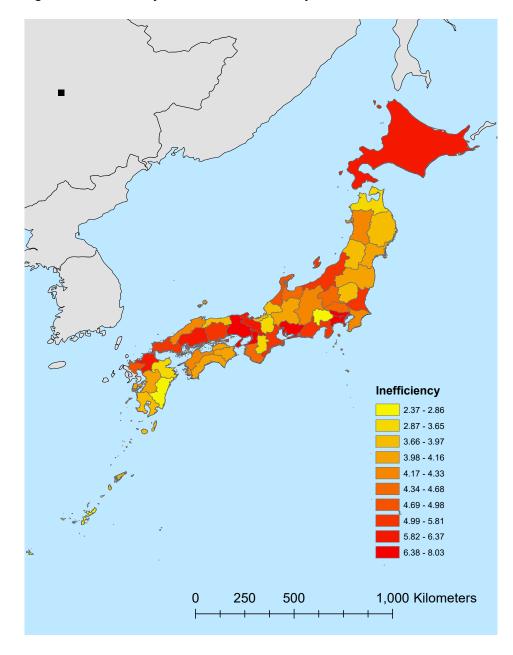


Figure 7 Inefficiency Scores for Machinery Sector

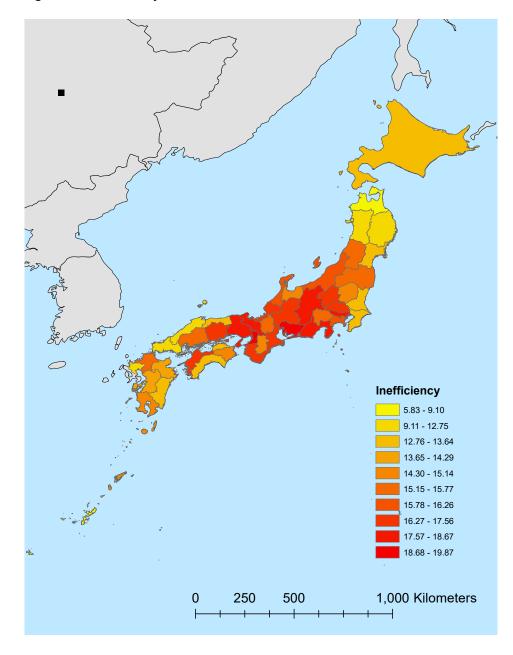


Figure 8 Inefficiency Scores for Textiles Sector

Appendix Figure 1: Map



1	Hokkaido	11	Saitama	21	Gifu	31	Tottori	41	Saga
2	Aomori	12	Chiba	22	Shizuoka	32	Shimane	42	Nagasaki
3	lwate	13	Tokyo	23	Aichi	33	Okayama	43	Kumamoto
4	Miyagi	14	Kanagawa	24	Mie	34	Hiroshima	44	Oita
5	Akita	15	Niigata	25	Shiga	35	Yamaguchi	45	Miyazaki
6	Yamagata	16	Toyama	26	Kyoto	36	Tokushima	46	Kagoshima
7	Fukushima	17	Ishikawa	27	Osaka	37	Kagawa	47	Okinawa
8	Ibaraki	18	Fukui	28	Hyogo	38	Ehime		
9	Tochigi	19	Yamanashi	29	Nara	39	Kochi		
10	Gunma	20	Nagano	30	Wakayama	40	Fukuoka		