How do Manufacturing Plants Respond to Large Physical Shocks?

The Kobe Earthquake as a Natural Experiment

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Abstract

Using the 1995 Kobe earthquake as a natural experiment, we examine the impact of a large exogenous physical shock on the survival of manufacturing plants, their post-shock economic performance, and the birth of new plants. More specifically, we use geo-coded plant location and unique building-level surveys to identify for the first time the damage caused by a natural disaster to each plant. Our results show that damage significantly affects a plant's likelihood of failure and this effect persists for up to seven years. The plants most likely to fail as a result of earthquake damage are relatively unproductive, small, young and employing low-skilled workers. Surviving plants suffered a reduction in total employment and value added as a result of damage. However, surviving plants also experienced a temporary increase in productivity following the earthquake. Severe damage in an area appears to have fostered new plant births.

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1. Introduction

Earthquakes, like all natural disasters, can have a devastating impact on infrastructure, households, and firms in the affected areas. Moreover, with the rise of megacities such as Tokyo, Mexico City, and Tehran in areas of high seismic risk, the severity of such damage is likely to increase in the future. Thus, in the immediate aftermath of an earthquake, rapid government and international action is required to provide humanitarian support. However, to discern how funds can be most efficiently allocated it is important to understand the relationship between these natural disasters and economic activity. Moreover, from the perspective of post-disaster reconstruction, a policy-maker arguably needs to identify the short, medium, and long term consequences of the event.

In this paper we take a microeconomic approach to examine the impact of the 1995 Kobe earthquake on plant performance for the period 1995-2008 using an exhaustive panel data of manufacturing plants and a plant specific measure of damage.[1] As our study is at the plant level, one of the most technically challenging aspects of the paper and one of the main contributions was to generate a measure of the damage at the individual building level in the earthquake zone. To do this we used geo-coding techniques and building level surveys from the Japanese and Kobe City governments. Combining this damage proxy with a 16 year exhaustive panel of plants that covers the period before and after the earthquake means we are able to examine the impact of precisely measured plant-specific damage on the various phases of a plant's life cycle. More specifically, we use the example of the Kobe earthquake to investigate plant survival, plant performance and plant births in the aftermath of the earthquake.

The Kobe earthquake was one of the most severe earthquakes in modern history, with a magnitude of 7.2 on the Richter scale and estimated to have caused $100 billion in damage (approximately 2.5% of Japan's GDP at the time). Given the relatively benign long term macroeconomic effects of the Kobe earthquake for Japan as a whole (in terms of growth, inflation and interest rates) as noted by Horwich (2000), we argue that the Kobe event provides an ideal experiment to examine whether the aggregate figures mask more serious short and medium term effects at the local level. Importantly, for our study, Kobe is an area of Japan which was originally believed to be relatively safe from

[1] Although officially known as the Hanshin-Awaji Great Earthquake it is also known as the Hanshin or Kobe earthquake. In this paper we follow Horwich (2000) and refer to it as the Kobe earthquake.

earthquakes and hence little preparation and anticipatory behaviour was in place before the event in 1995. Thus, from an empirical point of view it was a truly exogenous shock.[2]

Our paper can also be considered as a contribution to the literature on the `cleansing effect' of recessions. Specifically, while a number of theoretical studies, such as Caballero and Hammour (1994) and Ouyang (2009) have suggested that it is the least productive and the youngest firms which fail as a result of a recession, the empirical evidence on how cost shocks induced by recessions may hasten the demise of unproductive firms has been rather mixed (see, for example, Griliches and Regev 1995 and Barlevy 2002). In this regard, our study can be viewed as a natural experiment where a large number of firms are subject to a substantial exogenous shock (with both the supply side and demand side implications) that was unrelated to their productivity prior to the event.[3]

It is important to note that the approach we take in this paper is in contrast to the majority of existing studies that have tended to take a cross-country macroeconomic approach to determine the impact of a disaster on country level growth.[4] The results from these studies have been rather mixed. On the one hand, because natural disasters are often associated with significant physical damage and human suffering, intuitively one would expect a disaster to have a large negative effect on economic activity and growth or as Felbermayr and Gröshel (2013) call it "naturally negative". On the other hand, fiscal expenditure and foreign aid that stimulate the locally affected area can result in an overall positive effect (Albala-Bertrand 1993) driven by a disaster response that may result in the development of more effective infrastructure or an increased productive effort in the unaffected areas of a country. Likewise, when more capital is destroyed than labor, the return to capital increases resulting in short-term growth. Local workers may also be incentivised to work

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[2] The unanticipated nature of the shock is nicely summed up by a quote from Kaji Hideki (UNRCD Director) who stated that "*The news that Kobe was directly hit by an earthquake had major repercussions throughout Japan, particularly because of the enormity of the damage and, at the same time, due to the fact that Kobe could be struck by an earthquake. During the 1,500 years that earthquake occurrence has been recorded in Japan, not once has Kobe been directly hit by an earthquake and it has always had the image of being a city safe from earthquakes". Similarly, Ederington (2010) states that "Few businesses or private households held earthquake insurance. Indeed, most losses were uninsured: only 3% of property in the Kobe area was covered by earthquake indemnity*". Hence, we are confident that this was a truly exogenous shock and that plants of all sizes and performance will have been equally taken by surprise by the events of the early hours of January 17th 1995.

[3] The exogenous shock can be thought of as a traditional cost shock (the cost of rebuilding the plant and/or replacing workers who may have been killed or migrated from Kobe) or a demand and supply shock. On the demand side, disruption to customers as a result of the earthquake may mean delays to the purchase of intermediates. On the supply side, plant production may be delayed whilst repairs are undertaken which, for a given plant, may lead to a loss of market share to undamaged competitors elsewhere in Kobe or further afield both within Japan and internationally.

[4] For example, Rasmussen (2004), Loayza *et al.* (2009), Hochrainer (2009), Hallegatte and Dumas (2009), Noy (2009), Strobl (2012) and Ahlerup (2013).

harder to compensate for inter-temporal losses (Melecky and Raddatz 2011).[5] The result is that existing studies provide no clear pattern, with findings suggesting a short-term negative, a short-term positive, or no effect at all.[6]

By taking a detailed micro plant-level approach we hope to better understand what is driving the seemingly contradictory findings in the literature concerning the impact of natural disasters. A brief review of the literature shows that a common trait of most existing studies is that they have tended to use data that is aggregated across disaster type, sectors, and space. Other research has raised concerned about the aggregation effect. Loayza *et al.* (2009) for example, show that the type and magnitude of a natural disaster can determine the sign and size of the estimated effect. Spatially, Strobl and Bertinelli (2013), Strobl (2011) and Elliott *et al.* (2015) show that for hurricanes and typhoons, national level regressions can mask much of the impact at the local regional level. Similarly, Fisker (2012) finds that although there were no observable country-level effects, an earthquake does have a significant negative impact at the local level. This may be particularly important for earthquakes as their local impacts tends to differ even within a relatively small geographical areas in that the extent of damage to a location depends on the magnitude, depth, and distance to the epicentre but also on local geological conditions, that can differ across just meters, and the architecture of the buildings.[7] Finally, and perhaps most importantly for our paper, is that one of the main impediments to accurately measuring the impact of a natural disaster has been the lack of a precise proxy of the damage incurred. That is, studies have almost exclusively resorted to using (possibly systematic) measurement error prone post-disaster cost estimates (most of the macro-economic studies have relied on the EMDAT database which collects information on losses due to natural disasters at the country level from publicly available sources) or, more recently, potential destruction proxies derived from physical characteristics of the event. This is a potential shortcoming that we attempt to overcome by the use of detailed building level damage data.[8]

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[5] Davis and Weinstein (2002) and Brakman *et al.* (2004) examine the effect of allied bombing during the second world war on city size in Japan and Germany, respectively. They find the effects of such bombing to be short term with long run city size unaffected.

[6] The absence of a consensus on the average effects of natural disasters is illustrated by the results of two recent studies by Cuaresma *et al.* (2008) and Cavallo and Noy (2010) who argue that on average natural disasters have a positive and negative impact, respectively. See Felbermayr and Gröshel (2013) for a recent review of the literature.

[7] The analysis is complicated by the heterogeneous nature of earthquake damage which can include landslides, fires, soil liquefaction, floods and tsunamis. Two important geological factors are the softness at the ground site and the total thickness of the sediment which can vary widely even within several meters of an area.

[8] Other studies that attempt to capture the impact of a natural disaster with include Strobl (2011) who uses a wind field model to measure the potential destruction of hurricanes, Fisker (2012) who proxies the destruction of earthquakes with

There are a handful of other papers that use firm or plant-level data. For example, Craioveanu and Terrell (2010) consider the impact of storms on firm survival using elevation above sea level as a measure of flooding damage during Hurricane Katrina and find that large firms and those with less damage are more likely to survive. More surprisingly, they also discover that sole proprietorships are more likely to reopen than chain-stores. De Mel *et al.* (2011) conduct a post-disaster field study of surviving enterprises and workers following the Sri Lanka tsunami and find that aid helps retailers, but not manufacturing firms, to recover. Leiter *et al.* (2009) examine European firms that have been affected by floods using broad regional data on damages and find that firm employment growth is higher in regions that experienced major floods. Examining the impact of damage to transportation infrastructure due to the Northridge earthquake, Boarnet (1996) finds that nearly half of the firms surveyed experienced losses. Hosono *et al.* (2012) investigate the effect of banks' lending capacity on firms' capital investment using the Kobe earthquake as an exogenous shock but measure damage only broadly in terms of affected areas. Finally, Tanaka (2015) examines the short-term economic impact of the Kobe earthquake but does so by assuming that all plants within Kobe suffered the same damage. He finds that the earthquake had a significant short term impact on employment and value added.[9]

In terms of methodology, given our detailed damage data, we first employ a proportional hazards modelling approach to estimate the impact of plant-level damage on plant survival over time.[10] To briefly highlight our results we find that plants that experienced building damage were less likely to survive than those residing in less damaged buildings, as might have been expected. However, this effect lasts up to seven years after the earthquake and thus suggests that plants can continue to suffer from the negative effects of a natural disaster for much longer than the conventional

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earthquake intensity, Okazaki *et al.* (2009) who use broad geographical damage indicators to examine the 1923 Great Kanto earthquake and Felbermayr and Gröshel (2013) who build a database of disaster events and intensities from primary geophysical and meteorological information.

[9] There have also been a small number of case studies examining US disasters such as Dorfman *et al.* (2007) who look at the employment and wage effects of Hurricane Katrina and Smith and McCarty (1996) who examine the demographic impact of Hurricane Andrew. In a related literature, Skoufias (2003) provides a survey of household coping strategies in the face of disasters and aggregate shocks. For example, Carter *et al.* (2007) consider poverty traps and natural disasters in Ethiopia and Honduras, whilst Ferreira and Schady (2009) study the impact aggregate shocks on child schooling and health. A second strand of the literature examines the impact of earthquakes on the housing market following an earthquake (Beron *et al.* 1997 looking at the 1989 Loma Prieta earthquake and Deng *et al.* 2013 looking at the 2008 Wenchuan earthquake). More recently a literature has begun to emerge examining the impact of hurricane Katrina and other large storms on individuals in the US (see e.g. Groen *et al.* 2013 and Deryugina *et al.* 2013) and firms (Baskar and Miranda 2012).

[10] A large literature examines different aspects of firm survival. Argawal and Gort (1996 and 2002) examine firm survival within the context of a product life cycle framework. Audretsch and Mahmood (1995) use a hazard function to examine new firm survival rates while Mata and Portugal (1994) look at the duration of new firms.

macroeconomic evidence would suggest where the rebound effect is thought to be relatively quick. We find that the risk of death as a result of earthquake damage is highest for those plants that are the least productive, the smallest, the youngest and those with the lowest wages (which we interpret as being low skill plants), and thus we find evidence supportive of a cleansing effect of large cost shocks.

In the next stage we take a panel fixed-effects approach to evaluate the post-earthquake economic performance of surviving plants in terms of employment, value added, and productivity. We find that a negative effect on value added and employment, albeit with a fairly rapid recovery (of the survivors). Interestingly, when we consider the impact of the earthquake on productivity we find a positive short-term effect, which could be considered to be tentative evidence for forces of creative destruction. Finally, when considering the effect of the earthquake on new plant births, our results suggest that low to moderate levels of earthquake damage in a relatively small geographical areas generally deter such births, while more severe damage appears to have acted as a positive stimulus for new plant creation.

The reminder of this paper is organised as follows. Section 2 reviews the literature and presents the background to the Kobe earthquake. Section 3 describes our data while section 4 outlines our methodological approach. Section 5 presents the results and section 6 concludes.

2. The Kobe Earthquake

We now provide a brief overview of the Kobe earthquake, paying particular attention to the damage to infrastructure and economic activity that occurred against a background of a stagnating Japanese economy. In the ten years following the earthquake the Japanese economy grew very little and Kobe faced considerable challenges from a reliance on traditional industries such as steel and shipbuilding.[11]

[11] Much of the factual information below is from Edgington (2010), who examines the reconstruction of Kobe and the geography of the crisis at a very detailed level, and a report from UNRCD (1995) entitled the "Comprehensive Study of the Great Hanshin Earthquake". During the 1990s Japan was in a period of stagnation following the boom of the late 1980s. In Kobe the damage from the earthquake coupled with an industrial structure that relied on the traditional heavy industries meant that recovery in certain sectors was challenging. This also meant that the City of Kobe had to incur considerable debt to pay for the city's reconstruction. Johnston (2005) points out that by the end of 2005 the City of Kobe had more than 3 trillion Yen in municipal bonds outstanding and was effectively bankrupt. Since firms also took

The earthquake that shook the Hanshin region of Western Japan that includes the city of Kobe occurred on the 17th January 1995 at 5.46am and lasted for a little under one minute with a strength of 7.2 on the Richter scale. Kobe is located 430 km southwest of Tokyo and at the time was an important port city with a population of close to 1.5 million contributing around 10% of Japan's total GDP (Orr 2007). The epicenter was 25 km from central Kobe and this was the first major earthquake to strike a Japanese urban area since the end of World War II. As a port city Kobe was home to a large number of working class and immigrant communities as well as a middle class involved in the shipping and industrial sectors. As an older city Kobe had a very high population density with between 6,000 and 12,000 people per square kilometre (Orr 2007).[12]

The massive scale of the destruction was caused by two key factors in addition to the magnitude, depth and timing of the earthquake. First, the soil in many areas of the city was soft and water saturated which led to landslides and structural damage as a result of liquefaction. This meant that damage was concentrated in a narrow area of soft soil 30km long and just 2km wide (Orr 2007). Second, Kobe itself is located on a narrow strip of land between the Rokko mountains and Osaka Bay which meant that city lifelines were easily cut not least because they were almost all installed prior to more recent building codes. Hence, immense damage was caused to infrastructure including the expressway and numerous high-rise buildings. In addition, tunnels and bridges were destroyed and train tracks buckled. Figure 1 presents a map of the greater Kobe region and includes the major fault lines of the earthquake and the different wards affected by the earthquake.

[Figure 1 about here]

Importantly for this study, houses and commercial premises were destroyed and large parts of the city were affected by fires. Firestorms were a particular problem in the narrow streets of the older districts where the traditional wooden houses were still prevalent. The older districts were also the areas where the older residents and students tended to live, often in low-cost housing, while the middle classes tended to live outside of the centre in higher quality and newer homes (Shaw and Goda 2004).

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on considerable borrowings following the earthquake they too came under financial pressure due to the relative slow growth of the Japanese economy. Hence, the effects of natural disasters can be prolonged and affect the chances of plant survival long after the event itself.

[12] The housing in the older areas of Kobe tended to be constructed using heavy roof tiles and light frames and were designed to withstand storms but were not well suited for earthquakes (Orr, 2007).

It is useful to provide some background statistics on the impact of the earthquake. According to the City of Kobe (2012) a total of 4,571 people lost their lives in Kobe city with a further 14,687 injured. A notable 59% of those who died were over the age of 60, the majority of whom died due to crushing related injuries. By the end of the month of January there were nearly 600 shelters operating which, at their peak towards the end of 1995, were being used by 236,899 citizens. The damage to buildings was considerable. The number of fully collapsed buildings was 67,421 and partially collapsed 55,145. Fire damage caused the complete destruction of 6,965 structures with many others being partially burned (covering a total area of 819,108 m^2). Utilities were also severely impacted. In addition to city-wide power and industrial water failure, 25% of phone lines were down and 80% of gas supplies no longer operated. The total value of the damage was estimated to be around 6.9 trillion Yen.

Most importantly for this paper is the effect on industry. According to the City of Kobe (2012) report, many large manufacturers suffered damage to their main factories and had production lines interrupted. For small and medium sized enterprises the damage was extensive. The examples given in the City of Kobe (2012) report note that 80% of factories in the non-leather shoe industry were damaged and 50% of the Sake breweries were severely impacted. In addition, the tourism and agriculture and fishing sectors were damaged. It is interesting to note that although the overall mining and manufacturing production index in September 2007 was 119.8% of the September 1994 figure, the values for non-leather shoes and Sake Breweries were only 78.8% and 40.4% respectively suggesting a significant de-agglomeration effect (see e.g. Maejima 1995, Sumiya 1995 and Shimizu 1997). This impact on local industry is often masked by the aggregate Japanese GDP figures which had surpassed the 1994 value by 1998. Chang (2001) points out that this was mainly a result of construction induced economic stimulus. In terms of the local economy, tourism fell by over 50% between 1994 and 1995 while retail spending in the main department stores fell by more than 45% with 2,281 stores remaining closed (Takagi 1996).

One concern for the Kobe city government was the potential for a decrease in gross production as a result of companies moving some or all of their production to other parts of Japan. The concern was that once production had moved it would not return following the period of reconstruction.[13] Problems were also exacerbated by the displacement of shipping from the port of Kobe to nearby

[13] Ashitani (1995) highlights the example of Sumitomo Rubber Industries which closed and relocated a plant that had been operating since 1909 to Aichi and Fukushima prefectures, taking with them 840 employees.

ports in China and South Korea many of which did not return even after the Port reconstruction. Further difficulties were caused by the collapse of the Hyogo Bank in Kobe following business and individual bankruptcies from the bank's borrowers which in turn lead to a fall in local land prices and hence further bad loan difficulties (Edgington 2010).

The one mitigating factor that helped the larger companies was their membership of wider conglomerates (Keiretsu) which had access to funds to enable rapid recovery. Examples include Kobe Steel, Kawasaki Steel and Mitsubishi Heavy Industries. However, small and medium sized enterprises were less fortunate. Edgington (2010) cites a Kobe Chamber of Commerce survey that found that for the first one or two years following the earthquake large numbers of businesses and retailers were operating out of tents and prefabricated buildings with many others suffering continued financial problems that often resulted in the closure of the business (HERO 1998). Moreover, the small and medium sized firms found it difficult to benefit directly from the large construction projects that were often lead by Tokyo headquartered corporate companies. According to Saito (2005) the most affected firms were those that were reliant on local demand and those who faced lost cost competition from China. Likewise, after 1997 when the construction phase was largely complete there was a further round of business failure as construction related money dried up.

One important aspect of the damage not yet discussed is the heterogeneous nature of the destruction across the nine major wards of Kobe. Of the eleven wards, the most damage occurred in Nagata, Higashi Nada and Nada respectively. The geographical clusters of firms in certain areas meant that certain sectors were severely damaged whilst others experienced only minor damage. In terms of infrastructure and utilities, within seven days of the quake electricity had been restored and within 100 days restoration of industrial water, gas and telephone lines had been completed. By the end of 1995 all railway and bus lines were fully operational with roads and nearly all bridges fully restored by the end of September 1996.

Finally, it is important to discuss the reconstruction efforts that were implemented following the earthquake. Given the heterogeneous nature of the reconstruction expenditure both politically and geographically it is important to have an understanding of the decision making process. Although considerable effort was targeted at house building, neighborhood community reconstruction projects and health care, in this paper we are primarily concerned with economic revitalization. The main objectives according the City of Kobe (2012) were to secure job opportunities through early recovery, to promote local industries that were perceived to be central to urban restoration, to create new businesses and to encourage growth industries to move to Kobe which would result in a more sophisticated industrial structure. Much of this work came under the Hansin-Awaji Economic Revitalization Organization which operated between December 1995 and March 2005. One specific policy that we are able to capture is where Kobe city nominated a number of areas (for three years) that tended to be larger than individual chomes that were severely damaged in the quake but were perceived as being in strategically important areas of the city (Kobe City Office report "The emergency development regulation for earthquake disaster reconstruction").[14]

Emergency measures provided by the government to firms included an emergency loan system (ended 31st July 1995) which provided 94.9 billion Yen in loans in 5,979 cases and a further 23.2 billion Yen in 4,129 cases for unsecured loans. In addition, 170 new temporary factories were built. Between 1998 and 2005 it was also possible to receive targeted loans and business guidance on how to re-open a business in Kobe. Similarly, certain tax reductions were available for rebuilding businesses and publically operated factories were also built that could be rented (1996-1999) and still housed 98 businesses in 2008. Other initiatives included a rental assistance scheme to operate in private factories and interest subsidies for small and medium sized businesses that wanted to invest in new equipment. Finally, to help attract new industries and international trade, the Kobe Enterprise Zone was approved in January 1997 which had attracted 374 firms by 2006.[15]

However, as Horwich (2000) points out, whilst the non-interest loans and subsidies for factory construction certainly helped, not all firms could get access to these funds leading to further bankruptcies. It must be remembered that whilst these loans were welcomed by business, and in

[14] In addition to the city-wide Ten Year Reconstruction Plan published on March 27, 1995 and finalised on June 9th 1995, there was a much more extensive redevelopment plan for Hyogo prefecture called the "Hyogo Phoenix Plan". The third goal of the Phoenix plan was "the creation of a society where existing industries grow and new industries flourish". Together the plans involved over $132 billion to be spent in the years following the earthquake. The industry promotion measures included in the plan were as follows: A plan for a new city centre in eastern Kobe; the development of a new Kobe start-up zone; A China/Asia exchange zone; and the development of a base for next-generation telecommunications research (City of Kobe 1995). See Beaumann (1998) for further discussion.

[15] In a related development the Port of Kobe had largely been redeveloped by the end of March 1997. However, the number of containers handled by the Port of Kobe in 2007 was still only 84.8% of the 1994 figure, although the total value of imports in 2007 was 106.4% of the 1994 value and exports were 95.3% of the 1994 value.

many cases enabled the business to continue trading, the resultant increased debt burden was to lead to many bankruptcies over the following 10 years (Edgington 2010).[16]

3. Data

3.1 Panel Data of Manufacturing Plants

We utilise the Japanese Manufacturing Census (Japanese Ministry of Economy, Trade and Industry) and the Establishment and Enterprise Census (Japanese Ministry of Internal Affairs and Communications) to create a database of 1,846 manufacturing plants in Kobe city from 1992. We are able to follow these plants until their death or until the end of our sample period in 2007. Importantly, the Manufacturing Census and the Establishment and Enterprise Census are exhaustive and do not have a minimum size requirement for inclusion. As such, we do not have the problem of plants leaving the sample simply because their size has dropped below a minimum threshold. We are therefore able to identify precisely when a plant closed down in Kobe. One caveat is that although we know when a plant closes and reopens elsewhere in Kobe, we cannot distinguish between those plants that closed permanently and those that moved elsewhere within Japan. However, since the focus of this paper is on the local impact of the Kobe earthquake, this distinction is not crucial. Whether a plant dies or relocates outside of Kobe, its activities within Kobe have ceased. In terms of characteristics of the plants, the censuses provide, amongst other things, information on the exact address, sector of activity, age, wages, employment, and value added.[17]

3.2 Earthquake Damage Data

3.2.1. Plant-Level Damage

[16] The long term impact on firms is shown by Edgington (2010) who points out that even by 2006 manufacturing output in Kobe was only 83% of its 1991 level and retail sales only 86%. Furthermore, in 2005 69% of small firms reported that their profits had not returned to pre-quake levels (Nikkei Weekly 2005).

[17] In Japan an address usually consists of five elements starting with a prefecture (*ken*) which is the largest division of the country. Next comes the municipality or city (*shi*). Each city consists of a number of wards (*ku*) which may be further divided into *machi* or *cho*. Below this are the detailed address information which is the city district (*chome*) followed by the city block (*banchi*) and finally the building number (*go*).

In order to accurately identify the level of damage suffered by each plant we utilise the 'Shinsai Hukkou Akaibu' (archive on the damage of the 1995 Hyogo-Awaji earthquake) by Kobe City Office and Toru Fukushima (University of Hyogo), together with 'Zenrin's Residential Map, Hyogo-ken Kobe city 1995' from Toru Fukushima (University of Hyogo). These sources provide a highly detailed map of Kobe and assign one of five colors to each building to categorise the damage incurred. More specifically, shortly after the earthquake each registered building (registered prior to the earthquake) was surveyed with respect to the damage incurred and then classified into one of five categories:

- Green: No damage (damage was not more than 3 per cent of the building's total value).
- Yellow: Partially collapsed (damage was between 3-20% of the building's value).
- Orange: Half collapsed (damage was between 20-50% of the building's total value; typically this constituted partial damage to the principal structures such as walls, pillars, beams, roof and stairs).
- Red: Fully collapsed (damage was between 50-100% of the building's total value; typically this constituted damage to the principal structures such as walls, pillars, beams, roof and stairs).
- Pink: Fire damage (damage was between 50-100% of the building's total value).

In practical terms, the original maps consisted of 111 individual tiles in jpeg format covering the Kobe area. These had to be geo-referenced and the buildings and their corresponding colors extracted and cleaned to generate a full set of building polygons with their damage colors. We depict an example of part of the original tiles in Figures 2. Using the address of each plant we then identified the plant's location by latitude and longitude and thus were able to allocate each plant to its respective building.

[Figures 2 about here]

As a starting point we create a single variable damage index, *PlantDAM,* which proxies the percentage of loss in value of the building a plant was residing. More specifically, we assign a numerical scale to each building color type by using the median between the category thresholds (i.e. 11.5% loss of value for yellow, 35% for orange, and 75% for red), except for green buildings which we assigned a loss of value of 0%. In our robustness analysis we also experiment with other values for each category and plant.[18]

3.2.2. Chome-Level Damage

From the original map the local authorities also created summary measures of damages at the local chome-level, where a chome is a small administrative unit (city district) of which there are 3,179 in the Kobe-Hanshin area.[19] Since we have a proxy for building-level damage it means that we know the number of buildings for each chome categorized by damage color. This enables us to create a chome-level building damage indicator based on the percentage of damage to each building as given by:

$$ChomeDAM_j = \frac{(w_{pink} \times pink_j) + (w_{red} \times red_j) + (w_{orange} \times orange_j) + (w_{yellow} \times yellow_j) + (w_{green} \times green_j)}{total_j}$$

where the denominator*, total$_j$*, is the total number of buildings and *red, pink, orange, yellow,* and *green* are the number of buildings within chome *j* that are classified in these categories. The weights *w* are the loss in value associated with each color, where, as with our plant level damage variable, we assume that losses are the midway points between the thresholds (except for the green category where we assume no loss).

Figure 3 plots the distribution of our *ChomeDAM* index. One can immediately observe a wide variation in damages across individual chomes which is linked to geographical and building differences discussed in Section 2, as well as the unique ability of earthquakes to have very different impacts within narrowly defined areas. Cole *et al.* (2015) takes a closer look at a subset of individual chomes and reveals considerable heterogeneity in building damage even within a chome which

[18] One could also use the individual categories on their own and create a set of corresponding dummy variables. We opt for the ratio variable as our benchmark proxy for a number of reasons. First, as will be seen, we include time interactions in our analysis, making the interpretation of a single index more amenable to both presentation and interpretation. Second, this allows us to have an index that is more easily compared to our geographical damage index which is derived from a different data source (described below). Nevertheless, in our sensitivity analysis we do replace the single damage index with individual dummies for each damage level.

[19] Chomes can vary greatly in size, ranging from as small as a few hundred squared meters to several square kilometers. However, the majority of the manufacturing plants within Kobe are located in chomes that tend to be just a few hundred squared meters large. One should note that in order to confirm the accuracy of our geo-referencing of buildings and their damage type we overlaid our building shape-file with a shape-file of the chomes, calculated the number of buildings *per se* and per damage category per chome and compared this to the official aggregated data available and found these to agree almost perfectly.

demonstrates that assuming spatial homogeneity in earthquake damage even at the chome level, let alone the city level, as previous studies have done, would induce a considerable degree of measurement error and hence attenuation bias. To the best of our knowledge no previous study has been able to capture this degree of heterogeneity in the recorded damage of a natural disaster.

[Figures 3 about here]

3.2.2. Other Damage Indicators

Previous econometric studies that have tried to identify spatial differences in the damage due to earthquakes have often used certain physical characteristics of the event to do so. For example, to proxy location specific damage due to the Northridge earthquake Boarnet (1996) employed, amongst other things, the distance to the epicenter, while Garmaise and Moskowitz (2009) used an earthquake shake-map that distinguishes the peak ground acceleration across approximately 1 square mile areas. We thus create similar proxies to compare with our damage indicators. More specifically, the distance to the epicenter (*DISTEPI*) is simply calculated as the straight-line distance from the epicenter to the latitude and longitude of a plant's location. In our data the average plant is 18.6 km from the epicenter with a standard deviation of 13.5 kilometres. To obtain a measure of peak ground acceleration we used the gridded shake map generated by Fujimoto and Midorikawa (2002) to allocate peak ground acceleration values to each plant's building (*SHAKE*) which can be found in Cole et al. (2013). The main message is that the degree of shaking differs widely across Kobe.[20]

3.3 Other Data

While we know the level of damage of the building in which the plant is located, we have no building specific information on its architecture. However, local authorities did collate information on buildings at the chome-level. These include the number of buildings by year of construction and building construction types (brick, cement, wood and iron). We use these to calculate the average age and shares of building types within any given chome.

[20] We assumed that the age of building was the medium value between categorical thresholds. For example, buildings constructed between 1955 and 1965 were assumed to be 44 years old in 1994.

Other variables that we include in our analysis include a dummy variables to capture whether the plant belongs to a multi-plant firm (*MULTI*), whether the plant moved location within Kobe city during the sample period (*MOVE*) and whether or not the plant is in a designated reconstruction priority zone (*RECON*), discussed in section 2, in which urban reconstruction costs were heavily subsidized and planning schemes were implemented to improve urban living (new roads, parks etc.). Another possible determinant of survival might be due to agglomeration forces, where plants may have chosen to geographically cluster in order to benefit from positive externalities. To capture this we include the variable *ClusterFirms,* which measures the number of plants within the same industry and same chome.[21] Other standard variables that we include are the age of the plant (*AGE*) and the average wage within a plant (*WAGE*) as a proxy for the average skill level of the workforce. Finally, we include a measure of total factor productivity (*TFP*). However, as our dataset provides a measure of capital stock for only a subset of our sample, namely firms with over 30 workers, we follow Cui *et al.* (2012) and construct a measure of TFP that does not require a direct measure of capital.

3.4 Identifying Assumption

Before proceeding to our analysis it is important to state the identifying assumption behind our econometric specifications in the rest of the paper. Essentially, an unbiased estimate of the impact of our damage variables hinges on the assumption that after controlling for plant-level characteristics prior to the earthquake and the building types within chomes, any differences in damages experienced are not correlated with other unobservable determinants of plant performance. In this regard, the worry would be that some plants chose their location so as to reduce their exposure to seismic risk and that these plants are also characterized by other factors that would influence their survival regardless of whether an earthquake had occurred or not. As noted earlier, we are confident that the earthquake was unexpected, so that such anticipatory behaviour would have been unlikely. Nevertheless, even if this was not the case it could be by pure chance that those plants that were anyway more likely to survive happened to have been located in buildings that were more or less

[21] In unreported estimations we defined clusters as the number of other plants within the same industry as plant *i* within the same or neighboring chomes, the level of employment within the same industry as plant *i* within the same or neighboring chomes, and the level of employment within the same industry and same chome. These alternative measures of clusters provided almost identical results to the reported cluster variable. See Collins (2008) for a discussion of the post-earthquake biomedical cluster in Kobe.

earthquake proof or in areas with overall less or more damage. However, we believe that the number of plant-level explanatory variables that the census provides us with makes such a violation of the assumption unlikely. One aspect that we do not capture are the characteristics of the actual plant's building. Instead, as described above, we have chome level measures of building types, namely the age and construction material type. Reassuringly though, chomes tend to be fairly homogenous in their building type. For example, in 50% of all chomes the dominant building type constituted over 75% of all buildings with a standard deviation of 0.15 %. Similarly, while the average age of buildings for those built after 1945 was approximately 33 years, the standard deviation within chomes was only eight years. In contrast, there is clearly more within-chome heterogeneity in terms of damage type of buildings. For example, the most dominant building type constituted less (69%) than the distribution of building types and almost double the standard deviation (0.28%).

Nevertheless, to ensure that plant characteristics are not influencing the earthquake damage incurred by plants we estimate a cross-sectional regression expressing plant-level earthquake damage as a function of pre-earthquake plant-level characteristics age, size, wage, TFP and our cluster variable (the model also contains controls for industry, age of buildings in chome and type of buildings in chome.) None of these plant-level characteristics are statistically significant determinants of plant-level earthquake damage (even at 10% significance levels). The results are available from the authors upon request.

3.5 Data descriptives

We now provide a brief description of our data. In Table 1 we provide a summary of the industrial structure in Kobe as well as estimates of the average plant-level damage for each industry using the previously defined colors Pink (fire), Red (severe) and Orange (moderate), Yellow (low).

[Table 1 about here]

Table 1 shows that the rubber industry had the largest number of plants in Kobe, reflecting the fact that this industry includes the non-leather shoe firms that have been previously discussed. The rubber industry also experienced a high level of moderate to severe damage (46.1%) with only the non-ferrous metals industry experiencing greater damage. We are reassured that these summary statistics match the anecdotal evidence and Kobe City statistics.

Table 2 presents the average damage percentages for the seven Wards in the City of Kobe that experienced earthquake damage, again making the distinction between Pink (fire), Red (severe), Orange (moderate) and Yellow (low) damage levels. As previously discussed, the largest number of plants are located in the Nagata Ward which was home to the non-leather shoe industry. The Nagata Ward also experienced a high level of damage with over 42% of plants experiencing moderate to severe damage.[22]

[Table 2 about here]

The average age of a plant is just over 18 years old, while 14% of plants are part of a multi-plant firm and 17% of plants moved within Kobe during this period. It is interesting to note that 40% of plants were designated as being located in one of the special reconstruction zones defined earlier. Other interesting observations are that most firms were built between 1966 and 1975 and are fairly equally distributed between brick, wood, steel and reinforced concrete.

4. Plant Survival

4.1 Kaplan Meier Function

To investigate the effect of earthquake damage on plant survival we first consider a simple nonparametric estimate of the survivor function *S(t)*, i.e., the probability of surviving beyond time *t*. The Kaplan-Meier function estimates the survivor function as follows:

$$\hat{S}(t) = \prod_{t_j<t} \frac{n_j - d_j}{n_j} \quad (1)$$

where n_j is the number of plants that have survived to t_j years of age and d_j is the number of plants that die at age t_j.

Figure 4 illustrates our estimates of the survivor functions for plants that were damaged by the earthquake and for those that were undamaged, where a damaged plant is here defined as a plant

[22] In addition to the seven wards in Table 2, there are four wards on the mountainous periphery of the city (Kita, Nishi, Tarumi and Suma) that did not experience earthquake damage. These wards are omitted from our analysis.

that has experienced yellow, orange, red, or pink damage. Time refers to the number of years that the plant has been in the sample. Not surprisingly, the probability of plant survival is higher for undamaged plants at all points in time.

[Figure 4 about here]

4.2 Cox Proportional Hazard Model

Of course some, or even possibly all, of the difference in survival between damaged and non-damaged plants could feasibly be due to differences in other characteristics. To disentangle the quantitative effect of earthquake damage more precisely we thus estimate a Cox proportional hazards model (Cox 1972). We denote the hazard rate of plant *i* by λ_{it} which represents the probability that the plant exits in interval *t* to *t+1*, conditional upon having survived until period *t*. This can be expressed as:

$$\lambda_{it} = \lambda_0(t)exp(\boldsymbol{Z}\beta) \tag{2}$$

where $\lambda_0(t)$ is the baseline hazard, *t* is the analysis time, $\boldsymbol{Z}$ is a vector of explanatory variables, and β are our parameters to be estimated. A key feature of the Cox model is that the baseline hazard is given no particular parameterization and can be left un-estimated. However, the proportional hazards assumption requires that each plant's hazard is a constant multiplicative replica of another plants hazard.[23] As equation (2) demonstrates, the effect of the function $exp\ (Z\beta)$ is to scale the baseline hazard function that is common to all units up or down. The implication is that the effect of covariates in proportional hazards models is assumed to be fixed over time. We test this assumption by analysing the residuals in the manner proposed by Grambsch and Therneau (1994).[24]

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[23] Equation (2) can be modified to incorporate unobservable heterogeneity across plants or 'frailty' as it is often known. If not controlled for, frailty can reduce the magnitude of estimated coefficients (or hazard ratios) and can change the interpretation of hazard ratios which, in the presence of frailty, would decline over time as a result of the frailty effect. We therefore test a specification in which plant-specific frailty is included and which provides an estimate of θ, the frailty variance component. In all estimations θ was not statistically significant and was very close to zero (typically in the region of 1e-07). These results suggest that frailty is neither economically nor statistically significant in our models. As a result, the estimated hazard ratios are identical (to at least 4 decimal places) in models which include and exclude frailty. Our main results therefore do not incorporate frailty although our sensitivity analysis does include a parametric model which incorporates plant-specific frailty.

[24] More specifically we undertake a test of nonzero slope in a generalized linear regression of the scaled Schoenfeld (1982) residuals on functions of time.

Apart from damage proxies, vector $\boldsymbol{Z}$ contains other variables likely to influence plant survival described in the previous section. A number of previous papers have examined the factors that influence the survival of plants. For example, key papers by Dunne *et al.* (1988, 1989) establish the important role played by plant age and size and most subsequent papers confirm these findings (for example Bernard *et al.* 2006). A variety of other factors have also been shown to be important. Bernard and Jensen (2007) find that multi-plant and multinational firms in the US have lower survival rates, while Gorg and Strobl (2003) find that Irish plants that are majority foreign owned also have lower survival rates. Disney *et al.* (2003) examine UK manufacturing plants and find that those that belong to a larger group are less likely to fail. Bridges and Guariglia (2008) examine the role played by financial variables and find that lower collateral and higher leverage result in lower survival probabilities for purely domestic firms than globally engaged firms, suggesting that global engagement may shield firms from financial constraints. Bernard *et al.* (2006) find that plant survival is negatively associated with industry exposure to low-wage country imports. This study, along with several others (e.g. Bernard and Jensen 2007) also emphasises the positive role played by productivity which is shown to increase survival rates. Neffke *et al.* (2012) examine the effect of agglomeration economies on plant survival and find that results differ depending on the type and age of the plant. Finally, in a related study, Falck (2007) finds that a new establishment has greater survival probabilities the greater the number of new businesses in the same region and same industry, a finding supported by Boschma and Wenting (2007). Here we assemble the relevant factors suggested by the literature, as much as was possible with our data.

While older plants are more likely to survive than younger plants we cannot directly include plant age in a Cox proportional hazards model as it would be collinear with the baseline hazard function. Hence, we include each plant's age in 1995 (*AGE*) as a time invariant measure of plant age. Since larger plants have been shown to be more likely to survive than smaller plants we include dummy variables for three of the four quartiles of total employment (the first quartile dummy is omitted). We also include a measure of the average wage within a plant (*WAGE*) as a proxy for the skill level of the workforce and also a measure of TFP on the basis that productive plants are more likely to survive than less productive plants. We also examine whether being part of a multi-plant firm helps survival (*MULTI*), the impact on survival of a plant relocating within Kobe (*MOVE*) and whether a plant being originally located in a reconstruction zone (*RECON*) influences the probability of survival. Given that the close proximity to other plants in the same industry may also impact on survival either positively or negatively, we also include our agglomeration measure (*CLUSTER*).

Our survival estimations also include dummies for 162 industries, year dummies, and dummies to capture the possible influence of being located in different wards within Kobe city. Finally, we include the five different dummies for the average age of the buildings within each plant's chome and the share of building construction types within each chome (wooden, reinforced concrete, steel or brick).

Following our main survival analysis we examine a possible 'cleansing effect' by re-estimating equation (2) for the lowest quartile of plants in terms of productivity, size, age and skill-level (wage). Tables 1 and 2 of the appendix provides definitions of all our variables and summary statistics respectively and also details of how we measure TFP.

4.3 Econometric Results

Our main survival analysis results are presented in Table 3. To interpret a hazard ratio if, for example, the hazard ratio on a continuous variable (e.g. WAGE) is 1.1 then a 1 unit change in that variable will increase the hazard of plant death by 10%. Similarly, if the hazard ratio is 0.9 then a 1 unit increase in the variable will reduce the hazard by 10%.[25]

[Table 3 about here]

Model (1) of Table 3 includes only our control variables. Both *AGE* and *WAGE* have significant hazard ratios that are less than, but very close to, one. This implies that older plants and higher wage paying plants are less likely to die but the effect is small. We also find that *SIZE2*, *SIZE3* and *SIZE4* have hazard ratios below one indicating that larger plants are less likely to die than the smallest plants which form the omitted category. Other results show that plants that move within Kobe following the earthquake are less likely to close than those that stay in their original location. Interestingly, plants that are part of a multi-plant firm are more likely to close, a finding consistent

[25] As discussed in Section 4.2, for each model we test whether the effect of covariates is constant over time, an assumption of the proportional hazards model. For the models in Table 3 we find that this assumption is inappropriate for the variables *WAGE* and *RECON*. We therefore interact these variables with a linear time trend, thereby allowing the hazard ratio to vary over time. It is worth noting that the inclusion of these interactions does not affect the sign and significance of these or any other variables.

with Bernard and Jensen's (2007) and Craioveanu and Terrell (2010)'s finding for US plants. *TFP* consistently displays a hazard ratio of less than 1 suggesting that more productive firms are more likely to survive. Finally, our measure of the degree of plant agglomeration (*ClusterFirms*) which measures the number of plants from the same 2-digit industry in a given chome has a hazard ratio greater than 1. This suggests that plants that belong to a cluster are more likely to die and, although seemingly counter-intuitive, may reflect the increased competition associated with a heavy spatial concentration of plants from the same industry and more importantly a breakdown of agglomeration economies that had previously allowed the cluster to thrive despite for example increased competition from China.[26] Our variable to capture whether a plant was located in one of the eight special reconstruction zones is not significant.

In terms of examining the impact of earthquake damage on plant survival we begin, for the purposes of comparison, with two damage proxies that have been previously used in the literature, namely distance to epicenter and local peak ground acceleration, as shown in models (2) and (3) of Table 3. In terms of distance to the epicenter we find, surprisingly, a hazard ratio that is significantly greater than one, suggesting that the further away from the epicenter the greater the chance of plant closure. This result may reflect the actual pattern of the earthquake damage which was concentrated in a narrow strip of land stretching away from the epicenter, as shown in Figure 1. Figure 3 similarly indicates the existence of highly damaged areas at the end of this strip that was furthest from the epicenter. Thus our result implies that distance to the epicenter may be a poor proxy of damage incurred. In model (3) we find that our measure of local peak ground acceleration, *SHAKE*, is not statistically significant. This again brings into question how accurate this measure is as a proxy for plant or firm damage.

In model (4) we include the average building damage at the Chome-level (*ChomeDAM*) but find this variable to be statistically insignificant. We include our building-level damage variable (*PlantDAM*) in model (5). As can be seen, this variable is statistically significant with a hazard ratio of 1.61 suggesting that a one unit increase in damage (representing a 100% damaged building) leads to a 61% increase in the probability of permanent plant closure. In model (6) we also control for the average level of *ChomeDAM* but this has little effect on the *PlantDAM* variable and remains

[26] We also alternatively used our other clustering proxies described in the data section. The results were qualitatively similar, however, and hence are not reported here.

insignificant itself. One should note, however, that including these damage variables in this manner allows only for a permanent impact of earthquake damage on plant survival.

More realistically, one might expect the impact to fall over time. In model (7) we thus interact the chome-level damage and plant-level damage variables with *Time*, a variable capturing the number of years that have passed since the earthquake.[27] This produces a number of interesting results. Firstly, we now find that *ChomeDAM* is now statistically significant, with a hazard ratio indicating that greater chome level damage increases the probability of death of a plant. Perhaps surprisingly, we find that the magnitude of the hazard ratio on *ChomeDAM* is greater than that on *PlantDAM* suggesting that damage to surrounding infrastructure potentially has a larger impact on plant survival than damage to the plant itself. However, the significance and value of our *Time* interaction terms reveals that the negative effect of these factors on survival diminishes over time and more rapidly for *ChomeDAM*.

As part of our robustness checks, in Table 4 our primary finding that plant damage significantly impacts plant survival. For reasons of space, only the various damage variables are reported, although each model includes all of the plant characteristics reported in Table 3 together with controls for industries, years, wards, and the age and type of buildings in each chome. In model (1) we replace our Cox proportional hazard model with a Probit model to estimate the probability of plant death. *PlantDAM* is again shown to be a positive and statistically significant determinant of plant death, but its interaction term with years since the earthquake is not significant. In contrast, *ChomeDAM* and its interaction term with *Time* are significant. Model 2 is a parametric survival model provided for comparison.[28] It is also a model which incorporate plant-specific frailty, as discussed in Section 4.2. Again, *PlantDAM* and its interaction with time are statistically significant, as are *ChomeDAM* and its interaction with time. Table 4 also reports θ, the frailty variance component. As can be seen, θ is very close to zero indicating that frailty has almost no effect within this model. Furthermore, it is not statistically significant. Model 3 replaces our *PlantDAM* variable with individual dummy variables for pink, red, orange, and yellow levels of damage, where green (no damage) is omitted again, under a Cox Proportional Hazard specification. All four dummy variables,

[27] We also experimented with the inclusion *Time* squared together with variables capturing its interaction with chome and plant damage. However, both *Time* squared and its interaction terms were always insignificant.

[28] The parametric model was estimating using the exponential distribution. Of all the available distributions, the exponential distribution provided the lowest Akaike Information Criterion. Frailty itself is modelled using a gamma distribution although an inverse Gaussian distribution was also tested. The estimation of θ is not sensitive to these choices of distribution.

together with their time interactions, are statistically significant. As one might have expected, the hazard ratios for pink and red plant damage are larger than those for orange and yellow damage. Model 4 also includes individual variables capturing the chome-level share of each building damage type together with their interactions with time. The proportion of red, orange and yellow damaged buildings in a chome is found to influence plant death in a statistically significant manner. The magnitude of the hazard ratios on the chome damage variables is broadly similar to those on the plant damage variables and, again, the hazard ratios decline over time. Models 3 and 4 confirm that our plant-level damage variables are not sensitive to the specification of the chome damage variables.

[Table 4 about here]

We now explore the overall quantitive implications of our results. In almost all cases we find not only the plant and chome level damages variables themselves to be significant, but also their time interaction terms, where the hazard ratios suggest a negative impact that declines over time. In Figure 5 we plot the implied plant specific damage hazard ratios over time for the final model in our main results table (model 7 in Table 3), and, separately, for the individual levels of damage (model 4 in Table 4). As can be seen, the net hazard ratio remains above one until at least 2002 for all but the most minor level of damage (yellow). This indicates that plants that were damaged by the earthquake were more likely to die than undamaged plants up to seven years after the earthquake. For plants that experienced fire (pink) damage, the effect lasted for up to nine years. Plants that experienced the least severe yellow level of damage were more likely to die than undamaged plants for five years following the earthquake.[29]

[Figure 5 about here]

For reasons of space we do not plot the hazard ratios associated with chome level damages over time. However, the results from model 7 in Table 3 and models 2 and 3 in Table 4 indicate that the effects of *ChomeDAM* are of a similar, or even greater, magnitude than the effects of *PlantDAM* but are shorter lasting. More specifically, within four years plants that were located in a chome that

[29] Hazard ratios from models 2 and 3 in Table 4 are not included in Figure 9 for reasons of clarity, however the duration of the earthquake impact from these models is very similar to those presented in Figure 9. In model 2 the risk of plant death for damaged plants becomes equal to that of undamaged plants by 2003. In model 3, the effect of pink, red, orange and yellow damage lasts until 2005, 2002, 2002 and 2001, respectively.

suffered complete building damage were no more likely to die than plants that did not experience any damage.

Finally, to assess the sensitivity of our results to the construction of our single index *PlantDAM* variable, which uses the median value of damage within each damage category, we randomised this factor for each damage category. Firstly, we assigned the same randomly chosen damage value to all plants within a damage category. Secondly, we randomly assigned a different value of damage to each plant within a category. For both procedures the randomly chosen value was bounded by the upper and lower damage values within each category.[30] This exercise was conducted 500 times for each case and then our specification of model (7) in Table 3 re-estimated. Figures 6 and 7 depict the distribution of the estimated hazard ratio derived from the coefficients on the plant specific damage variable and its interaction with time. More specifically, Figure 6 provides the mean, 5% level and 95% level of implied hazard ratios over time from the 500 different estimations in which the same randomly chosen damage value is assigned to each plant within a damage category, whereas Figure 7 provides the counterpart for when a different randomly chosen damage value is assigned to each plant within a damage category.[31] As can be seen, the two figures show that the mean hazard ratio is similar in magnitude to those from the 'main Cox' model in Figure 9, although there is more confidence in the estimated effect from the sample where plants can differ in their damage value from other plants in the same damage category. These results therefore provide some confidence that our results are not sensitive to the manner in which we have constructed the *PlantDAM* index.

[Figures 6 and 7 about here]

To investigate the possible cleansing effect of the Kobe earthquake we estimate our survival model using the specification in model 7, Table 3 separately for the lowest quartile of plants in terms of TFP, labor productivity, size, age and wage-level. Table 5 provides the results for the damage variables and their interactions with time. Compared to the full sample the hazard ratio on *PlantDAM* is greater in magnitude for plants that are in the lowest quartile in terms of TFP, labor productivity, size, age and skill-level (wage). This indicates that unproductive, small, young, low-skill plants were more likely to immediately fail as a result of earthquake damage than the average plant in

[30] For the chome level damage variable we similarly randomly assigned a value within each category's upper and lower threshold.

[31] In both exercises, the *PlantDAM* and *PlantDAM*Time* variables were significant in all 500 estimations.

the sample.[32] The interaction of *PlantDAM* with time suggests that the effect of earthquake damage on these plants lasts for a similar length of time to the plants in the full sample.

5. Firm Performance Post Earthquake

5.1. Fixed Effects Model

Having examined the effect of earthquake damage on plant survival more generally, we now investigate how such damage may have affected the performance of surviving plants concentrating on levels of plant employment, value added and productivity. Note that we limit our sample to those plants that still exist at the end of our sample period although the results do not change substantially when including those that exited throughout the period. The result is a balanced panel of 835 surviving plants for the period 1992-2007. Starting in 1992 means we have plant data before and after the earthquake.

To determine the impact on plant performance we estimate a fixed effects panel model of the following form:

$$Y_{it} = \alpha_i + \gamma_t + X\delta + \varepsilon_{it} \tag{3}$$

where Y_{it} denotes the log of employment, the log of value added, the log of labor productivity or TFP, in plant *i*, year *t*, X is a vector of explanatory variables, including our earthquake damage proxies, and α and γ are plant and year fixed effects, respectively. Equation (3) is estimated using Driscoll and Kraay (1998) standard errors which are robust to very general forms of cross-sectional and temporal dependence.

5.2. Results

Table 6 presents the results for equation (3) in terms of the impact of the Kobe earthquake on employment, value added, TFP, and labor productivity. For each of our left hand side variables we

[32] As would be expected, plants in the upper quartile of productivity, size, age and skill have lower hazard ratios on *PlantDAM* than the average plant in the sample. This same finding is made if we focus on the upper and lower deciles or the upper and lower halves of the sample.

run the regression with and without time interaction terms. The employment results show that plant damage reduces employment, where the coefficient on *PlantDAM* in model (1) indicates that a one unit increase in *PlantDAM* reduces employment by 7.9% in plants that survived the earthquake.[33] Across all 835 surviving plants in our sample, this represents a reduction in employment of 2,589 workers. Chome-level damage also reduces employment, reflecting the effect of local infrastructure damage on the performance of individual plants. More precisely, a one unit increase in *ChomeDAM* reduces employment by an additional 3.6%, representing a further loss of 998 workers across all surviving plants. We note that *PlantDAM* interacted with time is not statistically significant suggesting that, within the sample period at least, the effect of the earthquake was a permanent fall in employment. Interacting *ChomeDAM* with time results in neither *ChomeDAM* itself or its interaction with time being statistically significant. In terms of the other controls, we find *AGE* and *MULTI* increase employment levels, while *WAGE* reduces employment. Hence, older plants and plants that are part of large corporations grew employment levels perhaps reflecting greater resilience from experience and parental firm support.

[Table 6 about here]

In terms of value added models (3) and (4), value added is negatively affected by plant damage although such damage is not statistically significant when *PlantDAM*time* is included. Similarly chome damage is statistically significant in model (4) but not in model (3). Quantitatively, model (3) indicates that a one unit increase in *PlantDAM* reduces a plant's value added by 5.7%. In terms of the other controls, being in a reconstruction zone, having higher wages and being an older plant all increase value added, it is reduced if a plant belongs to a multi-plant firm.

The final four columns of Table 6 examine TFP and labour productivity and we find that our damage variable is positive and significant when we include time interaction terms, with the interaction terms being negative. This suggests that the earthquake had a positive effect on productivity although this effect disappears over time. Hence, model (8) shows that a one unit increase in *PlantDAM* initially increases labor productivity by 1.10%, with this effect falling to zero after eight years. The effects for TFP are similar. One explanation is that this is capturing Schumpeterian creative destruction for those plants that survived driven by, for example, the introduction of new (more efficient) physical capital investment replacing old, earthquake damaged

[33] The effect of plant damage on employment is calculated as exp (0.076)-1 = 0.079.

physical capital. In terms of labour it may be the case that the least skilled workers left Kobe following the earthquake as they may have had less incentive to see if their jobs at damaged plants would resume following reconstruction or they may simply have been laid off by the plant as a short term cost saving exercise until the plant was repaired at which time new workers would be hired. Interestingly, *ChomeDAM* also has a negative effect on labor productivity with this effect also declining over time. Both of our productivity variables were positively influenced by the level of wages and whether or not the plant was within a reconstruction zone.

6. Natural Disaster and Plant Births

6. 1. Entry Rate Model

So far we have examined how the Kobe earthquake affected those plants that existed at the time of the earthquake. In the final stage of the analysis we consider the effect of earthquake damage on plant births. We undertake this analysis at the chome level estimating the following regression:

$$Births_{jt} = Z\vartheta + \alpha_j + \gamma_t + \epsilon_{jt} \quad (4)$$

where α and γ are chome and year fixed effects, respectively, and vector Z contains chome-level earthquake damage as well as road damage, whether or not the chome was part of a reconstruction zone, and the number of plants within the chome in the previous year. Subscripts j and t denote chomes and years, respectively. Equation (4) is estimated using a fixed effects negative binomial approach in order to account for both the count data nature of the dependent variable and for the over-dispersion of the data.[34]

6.2. Results

Table 7 provides the results of our chome-level estimates of the determinants of plant births. In models (1) and (2) we use the *ChomeDAM* variable with and without time interactions, respectively, while models (3) and (4) separate damages into the different damage categories, again with and

[34] In unreported sensitivity analyses we replace the number of births with the birth rate of plants within a linear fixed effects model. We also estimate the probability of plant birth using a fixed effects logit model. In each case the results were very similar to those estimated using the fixed effects negative binomial regression.

without time interactions. As can be seen, *ChomeDAM* deters plant births and this effect does not statistically change over time. In model (1), for example, *ChomeDAM* has a coefficient of -0.96 which corresponds to an incidence rate ratio of 0.38, implying that a 100% damaged chome would have only 38% of the births of an undamaged chome. Interestingly, the reconstruction dummy, *RECON*, is significantly negative indicating that being classified as a reconstruction zone reduces plant births. From model (1), reconstruction zones only experienced 26% of the births in non-reconstruction zones. This may relate to the nature of the reconstruction which was often residential and retail. Also, Kobe planners were keen to ensure that the city did not make the mistakes of the past, for example relying too heavily on wooden buildings. For that reason, reconstruction zones can actually be considered to have been subject to more, rather than less, stringent planning regulations.

The results of models (3) and (4) show that the number of buildings that were fire damaged in a chome (pink) do not influence plant births in a statistically significant manner, but the level of severely damaged buildings (red) increases plant births. The incidence rate ratio for *ChomeDAMRed* in model (3) tells us that a chome in which all buildings experienced 'red' damage would experience 84% more plant births than an undamaged chome. This suggests that the fact that buildings were razed to the ground in the most severely damaged chomes meant new investment and plant births was more likely. In contrast, being moderately damaged reduces plant births, with 'orange' and 'yellow' chomes experiencing only 25% and 47%, respectively, of the births of an undamaged chome. Again, reconstruction is found to deter plant births for reasons discussed above.

[Table 7 about here]

6 Conclusions

In this paper we investigate the impact of the Kobe 1995 earthquake on the death, performance, and birth of plants using a detailed and comprehensive micro-econometric approach. More specifically, we assemble an exhaustive 16 year panel of manufacturing plants and construct building-specific and area-specific measures of damage. Our results show that plant survival is negatively impacted by plant-level damage and that this effect persists for a number of years. More precisely, damaged plants are more likely to fail than undamaged plants up until 2002 – that is seven years after the earthquake. This result stands in stark contrast to the findings of more aggregated studies where the implied duration was much more short-term. Our results also indicate that damage to local infrastructure affects plant failure, although such effects do not last as long as the effects of plant damage. What is evident is that studies that employ far more aggregated measures of damage using shake maps, broad regional measures of damage or distance to the epicentre may be misleading due to the heterogeneous nature of damage caused by earthquakes.

The firms that are most likely to cease trading compared to the average plant appear to be the relatively unproductive, small, young and low-skill plants. In terms of productivity at least, this suggests that natural disasters may play a cleansing role similar to that performed by recessions, according to some (Caballero and Hammour 1994 and Ouyang 2009). While an assessment of the overall impact on welfare of the Kobe earthquake is beyond the remit of this paper, such a cleansing role would partially mitigate some of the other economic losses generated by the earthquake.

Examining the performance of plants that survived the earthquake we discover evidence of a similar negative impact resulting in the permanent downsizing of affected establishment in terms of employment and value added. However, at the same time there was also some evidence of creative destruction type behaviour among those plants that survived. More precisely, we find that the productivity of damaged plants increased in the years following the earthquake although this disappeared 8 years after the earthquake. Finally, in terms of plant births, we find that earthquake damage deterred such start-ups, although a closer inspection suggests that this effect is driven by moderately damaged areas. In contrast, our results indicate that severe infrastructure damage acted as a stimulus for plant births.

More generally, our paper provides a number of lessons for the literature on the economic impact of natural disasters. Natural disasters tend to be localised events and moving beyond the micro-level impact is likely to mask the size and duration of any local impacts. Related to this, it is important to be able to precisely capture the heterogeneous nature of these large negative shocks across space in order to have reasonable confidence in their estimated consequences.

With increasingly public attention being given to natural disasters it is important that policymakers and academics understand the economic and social costs associated with natural disasters, and how best to allocate scarce resources to ensure a rapid and sustainable recovery. In the case of the Kobe earthquake the national economy fared fairly well in the immediate aftermath. However, this recovery hid considerable longer term problems as evidenced by continued plant failures long after the earthquake.

References

Agarwal, R. and Gort, M. (1996), The Evolution of Markets and Entry, Exit and Survival of Firms, *Review of Economics and Statistics*, Vol. 78, 1, pp. 21-43.

Agarwal, R. and Gort, M. (2002), Firm and Product Life Cycles and Firm Survival, *American Economic Review*, Vol. 92, 3, pp. 184-190.

Ahlerup, P. (2013), Are Natural Disasters Good for Economic Growth, *University of Gothenburg Working paper* no. 553.

Albala-Bertrand, J.M. (1993), *Political Economy of Large Natural Disasters With Special Reference to Developing Countries*, Oxford: Clarendon Press. Princeton University Press.

Ashitani, T. (1995), Jobless in Kobe: New Fears for Post-Quake Residents, *Mainichi Daily News*, May 19, pp. 12.

Audretsch, D.B. and Mahmood, T. (1995), New Firm Survival: New Results Using a Hazard Function, *Review of Economics and Statistics*, Vol. 77, 1, pp. 97-103.

Barlevy, G. (2002), The Sullying Effect of Recessions, *Review of Economic Studies*, Vol. 69, 1, pp. 65-96.

Baskar, E. and Miranda, J. (2012), Taken by Storm: Business Survival in the Aftermath of Hurricane Katrina, *mimeo*.

Beaumann, C. (1998), *The Challenge of Land Use Planning After Urban Earthquakes: Observations from the Great Hanshin Earthquake of 1995*, Oakland: Earthquake Engineering Research Institute.

Bernard, A.B. and Jensen, J.B. (2007), Firm Structure, Multinationals and Manufacturing Plant Deaths, *Review of Economics and Statistics*, Vol. 89, 2, pp. 193-204.

Bernard, A.B., Jensen, J.B. and Schott, P.K. (2006), Survival of the Best Fit: Exposure to Low-Wage Countries and the (Uneven) Growth of US Manufacturing Plants, *Journal of International Economics*, Vol. 68, pp. 219-237.

Beron, K., Murdoch, J.C., Thayer, M.A. and Vijverberg, W.P.M. (1997), An Analysis of the Housing Market Before and After the 1989 Loma Prieta Earthquake, *Land Economics*, Vol. 73, 1, pp. 55-73.

Boarnet, M. (1996), Business Losses, Transportation Damage and the Northridge Earthquake, unpublished paper available at: http://econpapers.repec.org/paper/cdluctcwp/qt80w9g0rd.htm.

Boschma, R.A., and Wenting, R. (2007), The Spatial Evolution of the British Automobile Industry: Does Location Matter? *Industrial and Corporate Change*, Vol. 16, pp. 213-238.

Brakman, S., Garretsen, H. and Schramm, M. (2004). The Strategic Bombing of German Cities During World War II and its Impact on City Growth. *Journal of Economic Growth*, 4, pp. 201-18.

Bridges, S. and Guariglia, A. (2008), Financial Constraints, Global Engagement and Firm Survival in the UK: Evidence from Microdata, *Scottish Journal of Political Economy*, Vol. 55, 4, pp. 444-464.

Caballero, R.J. and Hammour, M.L. (1994)., The Cleansing Effect of Recessions, *American Economic Review*, Vol. 84, 5, pp. 1350-1368.

Carter, M., Little, P., Mogues, T and Negatu, N. (2007), Poverty Traps and Natural Disasters in Ethiopia and Honduras, *World Development*, Vol. 35, 5, pp. 835-56.

Cavallo, E. and Noy, I. (2010), The Economics of Natural Disasters – A Survey, IDB Working Paper 124.

Chang, S.E. (2001), Structural Change in Urban Economies: Recovery and Long-Term Impacts in the 1995 Kobe Earthquake, *Kokumin Keizai Zasshi: Journal of Economics and Business Administration*, Vol. 183, pp. 47-66.

City of Kobe (1995), Kobe City Restoration Plan (abridged).

City of Kobe (2012), The Great Hanshin-Awaji Earthquake Statistics and Restoration Progress, http://www.city.kobe.lg.jp/safety/hanshinawaji/revival/promote/january.2012.pdf.

Cole. M.A., Elliott, R.J.R., Okubo, T. and Strobl, E. (2013), Natural Disasters and Plant Survival: The impact of the Kobe earthquake, Discussion papers 13063, Research Institute of Economy, Trade and Industry (RIETI).

Collins, S. (2008), Knowledge Clusters and the Revitalization of Regional Economies in Japan: A Case Study of the Biomedical Industry in Kobe, *Prometheus*, Vol. 26, pp. 111-122.

Cuaresma, J.C., Hlouskova, J. and Obersteiner, M. (2008), Natural Disasters as Creative Destruction? Evidence from Developing Countries, *Economic Inquiry*, Vol. 46, 2, 214-226.

Cui, J., Lapan, H. and Moschini, G. (2012), Are Exporters More Environmentally Friendly than Non-Exporters? Theory and Evidence. Iowa State University Staff General Research Paper No. 35549.

Craioveanu, M. and Terrell, D. (2010), The Impact of Storms on Firm Survival: A Bayesian Spatial Econometric Model for Firm Survival, *Paper presented at the Ninth Annual Missouri Economics Conference, University of Missouri, Columbia, 27-28 March 2009*.

Davis, D.R. and Weinstein, D. E. (2002). Bones, Bombs and Break Points: The Geography of Economic Activity. *American Economic Review,* 92, 5, pp. 1269-1289.

De Mel, S. McKenzie, D. and Woodruff, C. (2011), Enterprise Recovery Following Natural Disasters, *Economic Journal*, Vol. 122, pp. 64-91.

Deng, G., Gan, L. and Hernandez, M.A. (2013), Do People Overreact? Evidence from the Housing Market After the Wenchuan Earthquake, *NBER working paper* 19515.

Deryugina, T. Kawano, L. and Levitt, S. (2013), The Economics Impact of Hurricane Katrina on its Victims, *mimeo.*

Disney, R., Haskel, J. and Heden, Y. (2003), Entry, Exit and Establishment Survival in UK Manufacturing, *Journal of Industrial Economics*, Vol. 51, 1, pp. 91-112.

Dorfman, M., Fortier Wasser, S. and Bergman, B. (2007), The Effects of Hurricane Katrina on the New Orleans Economy, *Monthly Labor Review*, June.

Driscoll, J. C., and Kraay, A.C. (1998). Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data. *Review of Economics and Statistics*, Vol. 80, pp. 549–560.

Dunne, T., Roberts, M.J. and Samuelson, L. (1988), Patterns of Firm Entry and Exit in US Manufacturing Industries, *Rand Journal of Economics*, Vol. 19, 4, pp. 495-515.

Dunne, T., Roberts, M.J. and Samuelson, L. (1989). The Growth and Failure of US Manufacturing Plants, *Quarterly Journal of Economics*, Vol. 104, 4, pp. 671-698.

Edgington, D.W. (2010), *Reconstructing Kobe: A Geography of Crisis and Opportunity*, UBC Press, Vancouver Toronto.

Elliott, R.J.R., Strobl, E. and Sun, P. (2015), The local impact of typhoons on economic activity in China: A view from outer space, *Journal of Urban Economics*, Vol. 88.

Falck, O. (2007), Survival Chances of New Businesses: Do Regional Conditions Matter? *Applied Economics*, Vol. 39, pp. 2039-2048.

Felbemayr, G. and Gröshel, J. (2013), Naturally Negative: The Growth Effects of Natural Disasters, CESifo working paper no. 4439.

Ferreira, F. and Schady, N. (2009), Aggregate Economic Shocks, Child Schooling and Child Health, *World Bank Research Observer*, Vol. 24, 2, pp. 147-81.

Fisker, P.S. (2012), Earthquakes and Economic Growth, Institute for Advanced Development Studies Working paper -1/2012.

Fomby, T. Ikeda, Y. and Loayza, N. (2009), The Growth Aftermath of Natural Disasters, World Bank Policy Research Working Paper 5002.

Fukushima, T. (1995), The Great Hanshin Earthquake, JPRI Occasional Paper no. 2, San Francisco: Japan Policy Research Institute, http://www.jpri.org.

Fujimoto, K. and Midorikawa, S. (2002), Ground-shaking Mapping for a Scenario Earthquake Considering Effects of Geological Conditions: A Case Study of the 1995 Hyogo-ken Nambu, Japan Earthquake, *Earthquake Engineering and Structural Dynamics*, Vol. 31, pp. 2103-2120.

Garmaise, M. and Moskowitz, T. (April 2009), Catastrophic Risk and Credit Markets, *Journal of Finance*, Vol. 64, 2, pp.657-707.

Gorg, H. and Strobl, E. (2003), Footloose Multinationals? *Manchester School*, Vol. 71, pp. 1-19.

Griliches, Z. and Regev, H. (1995), Firm Productivity in Israeli Industry: 1979-1988, *Journal of Econometrics*, Vol. 65, pp. 175-203.

Groen, J., Kutzbach, M. and Polivka, A. (2013), Storms and Jobs: The Effects of Hurricanes on Individual's Employment and Earnings Over the Long Term, *mimeo*.

Hallegatte, S. and Dumas, P. (2009), Can Natural Disasters Have Positive Consequences? Investigating the Role of Embodies Technical Change, *Ecological Economics*, Vol. 68, pp. 777-786.

HERO (Hanshin-Awaji Economic Revitalization Organization), (1998), New Perspective of Revitalization of Urban Retail Markets, *Economic Revitalization*, Vol. 7, pp. 2-8.

Hochrainer, S. (2009), Assessing the Macroeconomic Impacts of Natural Disasters – Are There Any? World Bank Policy Research Working Paper 4968.

Hosono, K., Miyakawa, D., Uchino, T., Hazama, M., Ono, A., Uchida, H. and Uesugi, I. (2012), Natural Disasters, Bank Lending, and Firm Investment, *RIETI Discussion Paper Series* 12-E-062.

Horwich, G. (2000), Economic Lessons of the Kobe Earthquake, *Economic Development and Cultural Change*, Vo. 48, pp. 521-42.

Johnston, E. (1999), Kobe Recovery Four Years After Quake: Direction of City's Future Under Debate, *Japan Times*, January 17, pp. 3.

Johnston, E. (2005), City's New Face Conceals Unhealed Wounds, a Sense of Communities Lost, *Japan Times*, January 18, 1.

Leiter, A.M., Oberhofer, H. and Raschky, P.A. (2009), Creative Disasters? Flooding Effects on Capital, Labor and Productivity within European Firms, *Environmental and Resource Economics*, Vol. 43, pp. 333-350.

Loayza, N. Olaberria, E. Rigolini, J. and Christiaensen, L. (2009), Natural Disasters and Growth – Going Beyond the Averages, *Policy Research Working Paper Series, The World Bank*.

Maejima, S. (1995), Kobe Manufactures Race to Recover, *Asahi Evening News*, May 31, pp. 6.

Maki, F. (1996), A Solid Base to Promote Private Enterprise, *Economic Revitalization*, Vol. 1, pp. 1-3.

Mata, J. and Portugal, P. (1994), Life Duration of New Firms, *Journal of Industrial Economics*, Vol. 27, pp. 227-246.

Neffke, F.M.H., Henning, M. and Boschma, R. (2012), The Impact of Aging and Technological Relatedness on Agglomeration Externalities: A Survival Analysis, *Journal of Economic Geography*, Vol. 12, pp. 485-517.

Nikkei Weekly (2005), *Kobe: Ten Years After the Nightmare*, January 1, 3.

Noy, I. (2009), The Macroeconomic Consequences of Disasters, *Journal of Development Economics*, Vol. 88, pp. 221-231.

Okazaki, T., Ito, K. and Imaizumi, A. (2009), Impact of Natural Disasters on Industrial Agglomeration: The Case of the 1923 Great Kanto Earthquake, CIRJE-F-602 discussion paper.

Orr, B. (2007), Kobe: Disaster Response and Adaptation, Case study prepared for the Enhancing Urban Safety and Security: Global Report on Human Settlements. Available at: www.unhabitat.org/grhs/2007.

Ouyang, M. (2009), The Scarring Effect of Recessions, *Journal of Monetary Economics*, Vol. 56, 2, pp. 184-99.

Rasmussen, T.N. (2004), Macroeconomic Implications of Natural Disasters in the Caribbean, *IMF Working paper WP/04/224*.

Saito, J. (2005), Firms Claw Back to Pre-Quake Levels, *Asahi Shimbun*, January 31, 3.

Schoenfeld, D. (1982). Partial Residuals for the Proportional Hazards Regression Model. *Biometrika*, Vol. 69, pp. 239-41.

Shaw, R. and Goda, K. (2004), From Disaster to Sustainable Society: The Kobe Experience, *Disasters*, Vol. 28, 1.

Shimizu, H. (1997), For Area's Sake Makers, A Sour Taste Lingers, *Nikkei Weekly*, Jan. 20, pp. 8.

Skidmore, M. and Toya, H. (2002), Do Natural Disasters Promote Long-Run Growth? *Economic Inquiry*, Vol. 40, pp. 664-687.

Skoufias, E. (2008), Economic Crises and Natural Disasters: Coping Strategies and Policy Implications, *World Development*, Vol. 31, 7, pp. 1087-1102.

Smith, S.K. and McCarty, C. (1996), Demographic Effect of Natural Disaster: A Case Study of Hurricane Andrew, *Demography*, Vol. 33, 2, pp. 265-75.

Strobl, E. (2011), The Growth Impact of Hurricane Activity: Evidence from US Coastal Counties (2011), *Review of Economics and Statistics*, Vol. 93, pp. 575-589.

Strobl, E. (2012), The Economic Growth Impact of Natural Disasters in Developing Countries: Evidence from Hurricane Strikes in Central American and Caribbean Regions, *Journal of Development Economics*, Vol. X, pp. 130-141.

Sumiya, F. (1995), Earthquake Aftermath: Survival of Biggest Roles Among Ruined Firms, *Nikkei Weekly*, February 2, 1, 8.

Tanaka, A. (2015). The Impacts of Natural Disasters on Plants' Growth: Evidence from the Great Hanshin-Awaji (Kobe) Earthquake. *Regional Science and Urban Economics*, 50, pp. 31-41.

Takagi, M. (1996), Social, Economic, and Administrative Issues, Kobe, Disaster Prevention Division, *mimeo*.

Toya, H and Skidmore, M (2007), Economic Development and the Impacts of Natural Disasters, *Economic Letters*, Vol. 94, 1, pp. 20-25.

UNRCD eds. (1995), *Comprehensive Study of the Great Hanshin Earthquake*, UNCRD, Nagoya.

Figure1: Observed seismic intensity map of the Kobe earthquake (source: Fujimoto and Midorikawa, 2002)

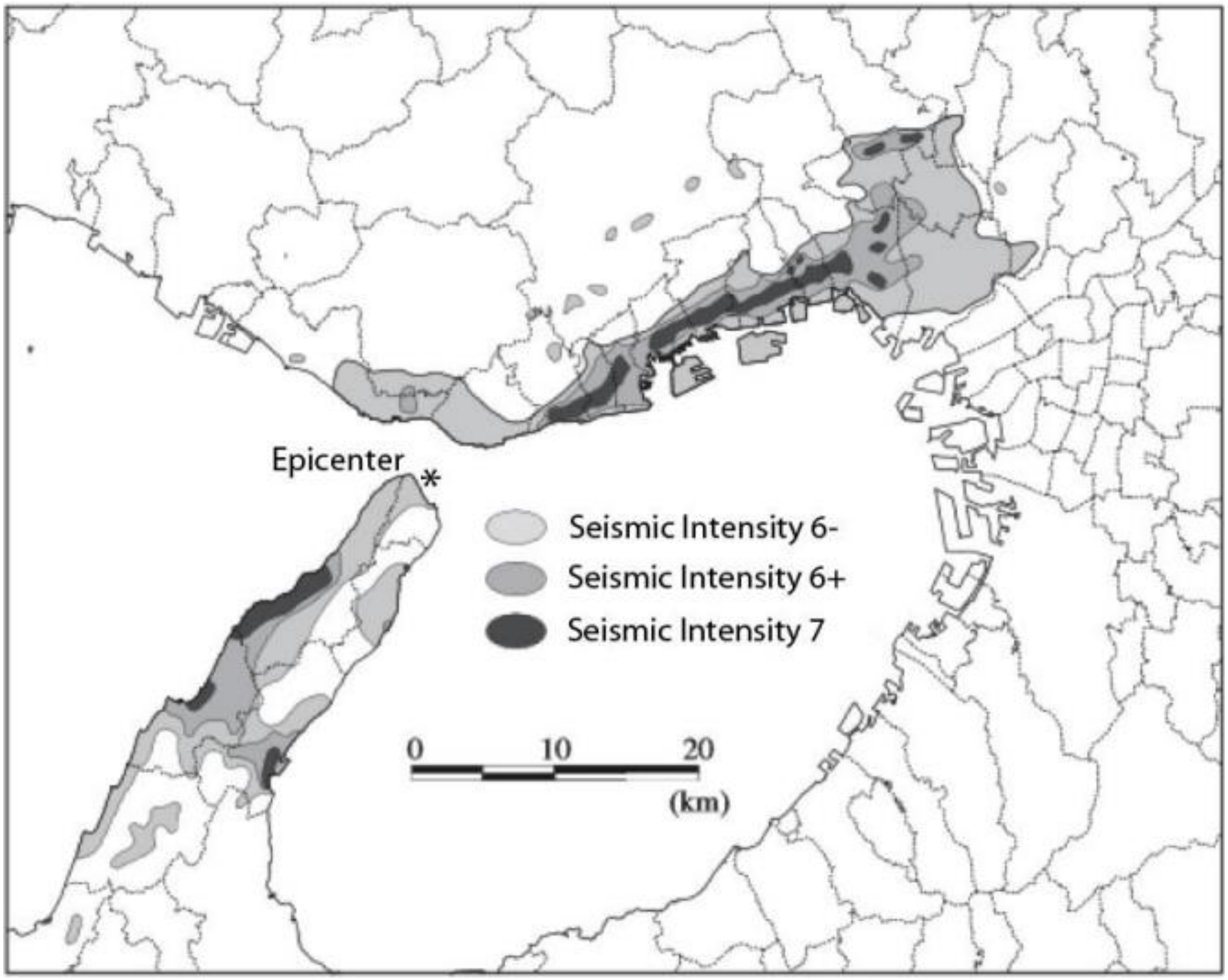


Figure 2: Example of building level damage in Kobe (raw data)

Figure 3: Chome-level damages

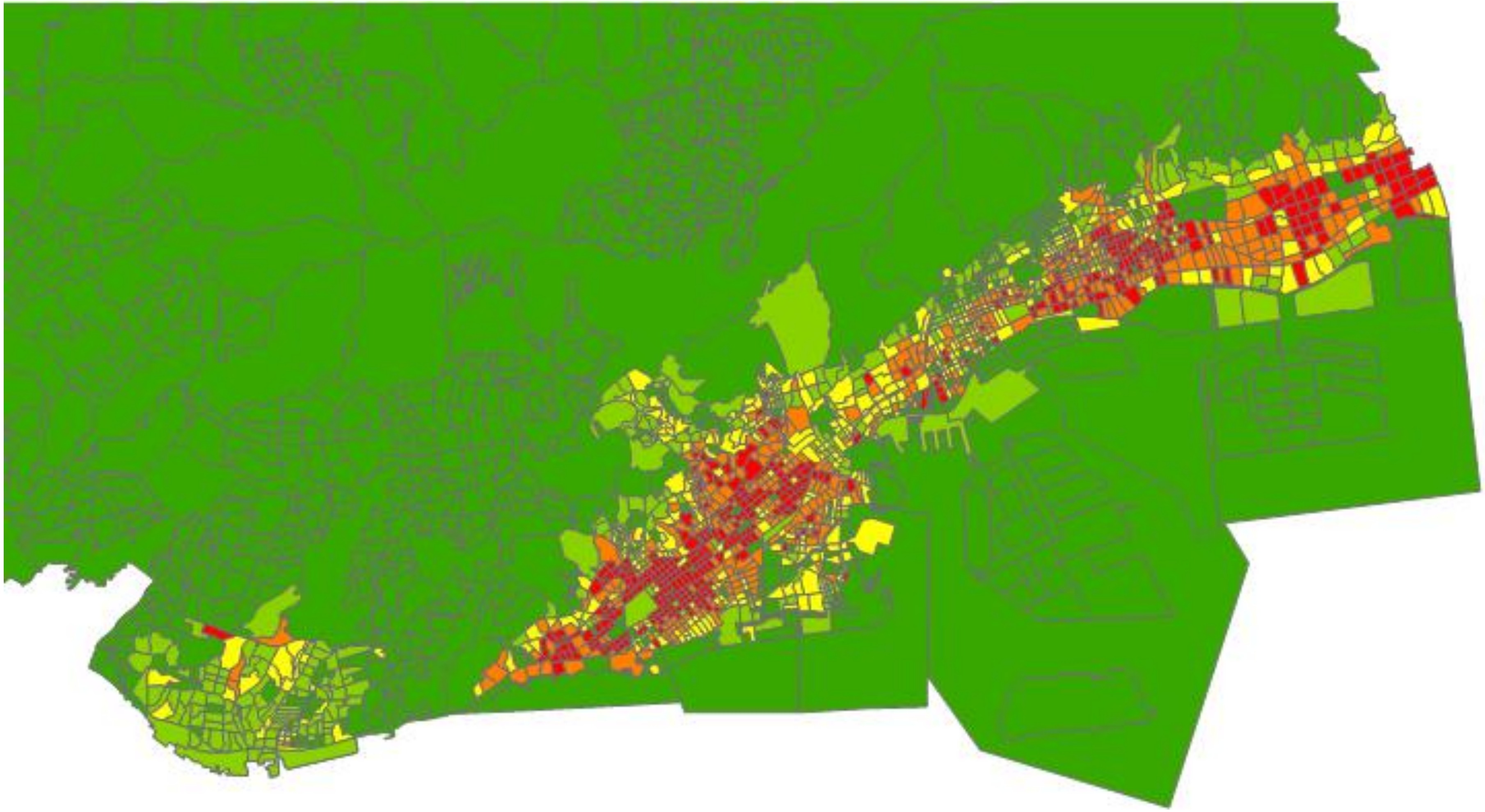
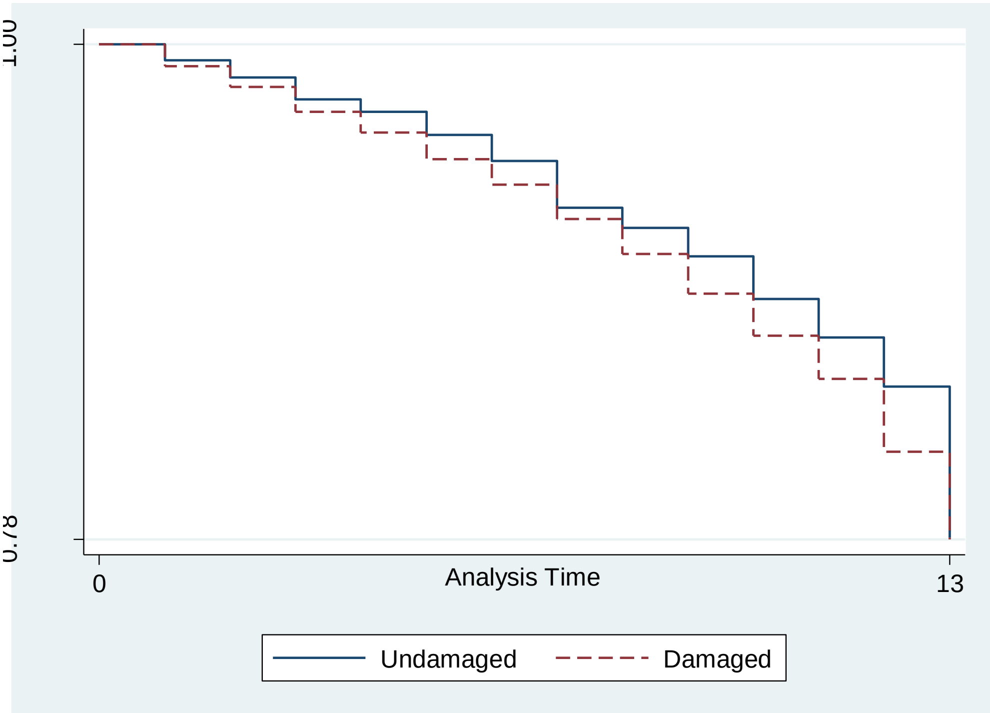


Figure 8. Kaplan-Meier survival curves for damaged and undamaged plants



Note: Damaged consists of plants that were in buildings of green, pink, orange, or yellow color, where as Undamaged plants are those residing in green colored buildings.

Figure 9. *PlantDAM* hazard ratios over time (from Table 3 (model 7) and Table 4 (model 2))

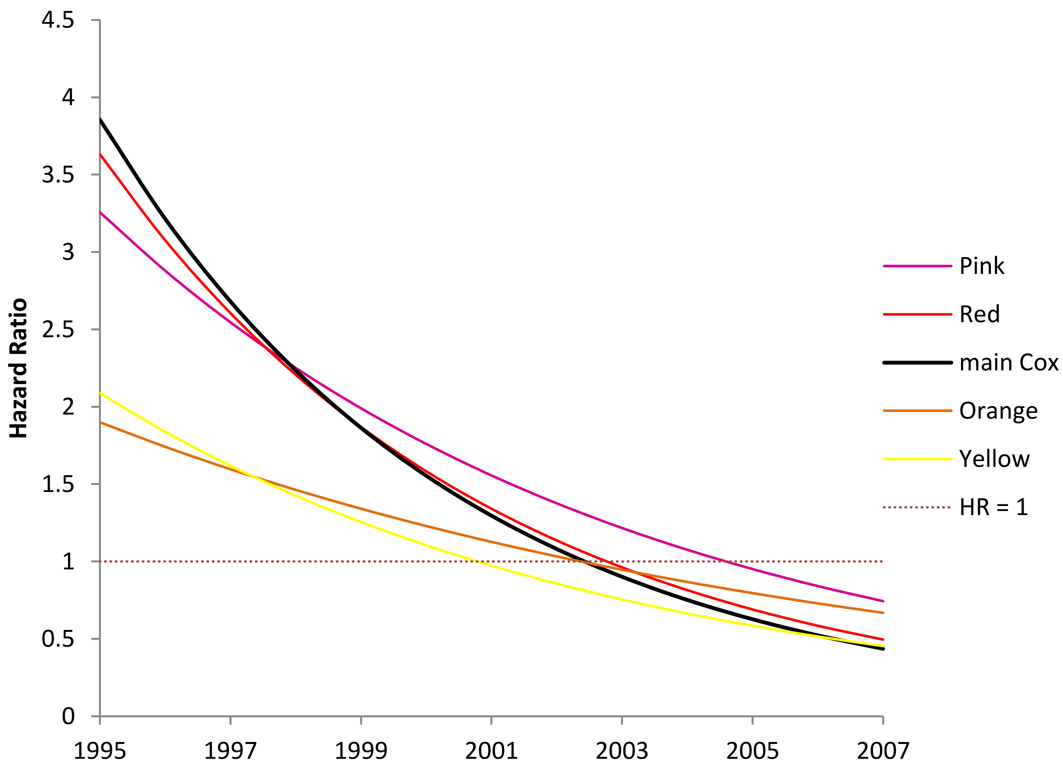


Figure 10: *PlantDAM* hazard ratios over time, based on all plants within a damage category being given the same random variable.

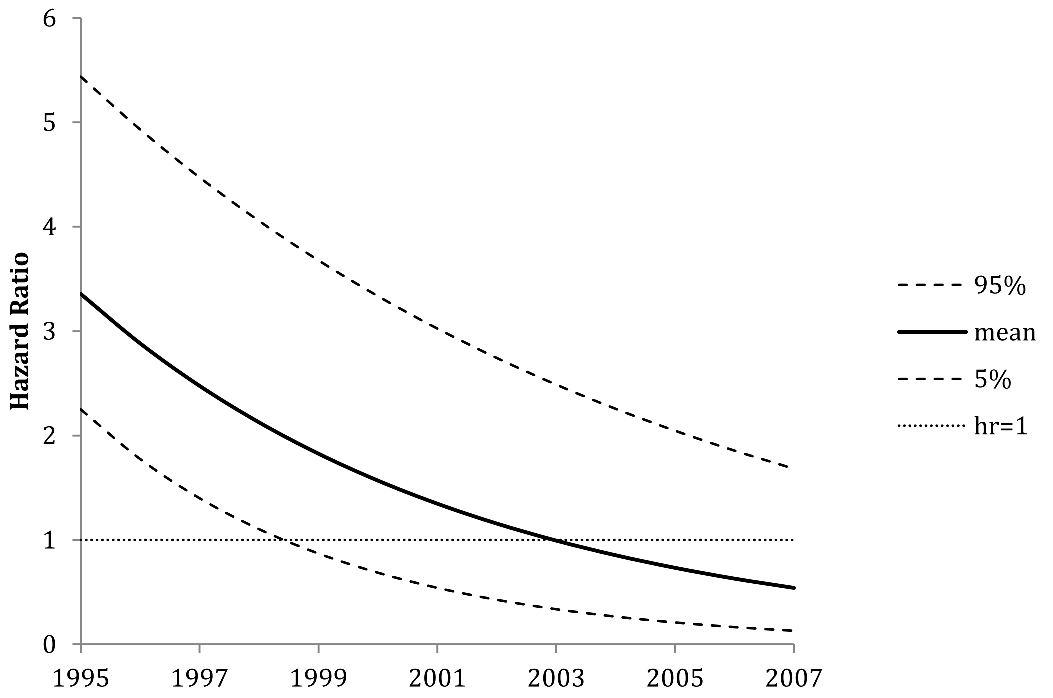


Figure 11. *PlantDAM* hazard ratios over time, based on all plants within a damage category being given a different random variable

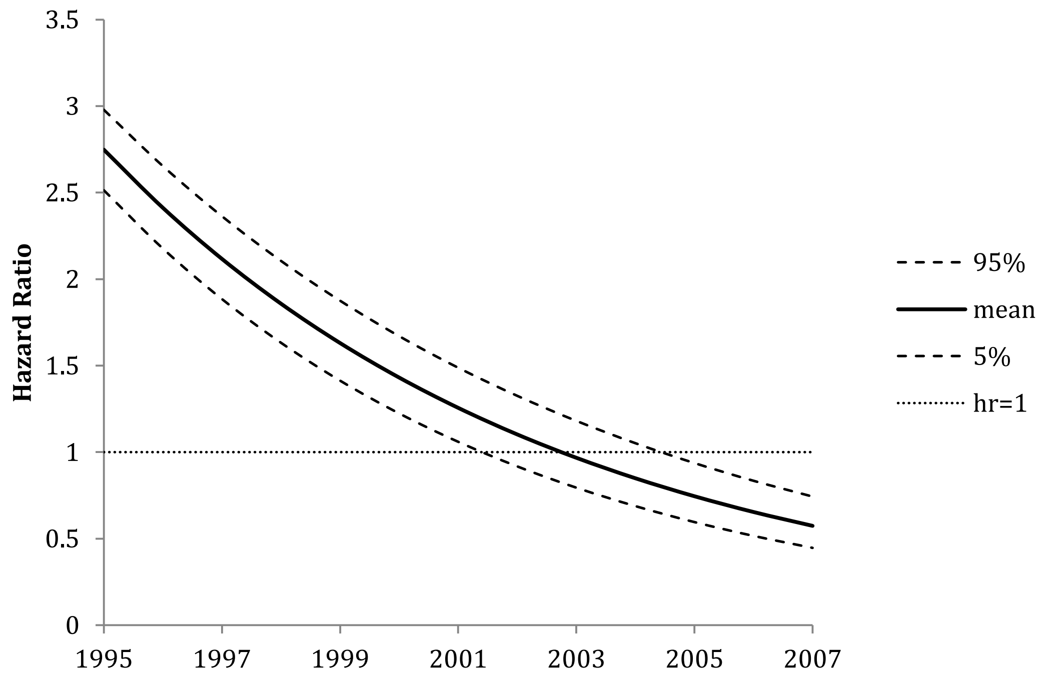


Table 1. Damage by industry (ranked by All Damage)[1]

Industry	% of Sample	All Damage	PINK	RED	ORANGE	YELLOW
Non-Ferrous Metals	0.6	85.4	0	15.6	38.5	31.3
Rubber	17	76.2	5.5	24.8	15.8	30.1
Leather and Fur	6.8	74.8	7.5	19.8	16.8	30.7
Information & Communication Machinery	0.4	71.6	0	33.8	8.1	29.7
Pulp, Paper	2.5	71.5	3.4	16.5	21.7	29.9
Furniture	1.4	70.9	0	16.9	23.5	30.5
Industrial Machinery	6	69.1	0.6	14.1	14.9	39.5
Printing	10.5	68.1	0.9	16.5	19.1	31.6
General Machinery	4.6	63.4	1.2	10.4	11.4	40.4
Textiles	4.8	62.4	0	17.4	19.5	25.5
Plastic Products	1.8	60	0	14.9	17.6	27.5
Metal Products	8.6	59.3	1.9	11.2	18.5	27.7
Wood Lumber	1.8	58.3	0	16	17.3	25
Electronic Machinery	3	56.5	3.6	10.1	12.7	30.1
Transport Machinery	5.1	56.2	1.8	8.1	20.7	25.6
Chemicals	1.2	55.6	13.1	19.2	4.6	18.7
Beverages and Tobacco	2.1	55.5	0	9.1	13	33.4
Food	12.3	54.6	1.6	9.4	13.5	30.1
Electronic Devices & Semi-Conductors	0.6	52.1	0	8.3	24	19.8
Oil and Coal Products	0.5	49.4	16.1	0	1.2	32.1
Other Manufacturing	4.6	47.8	0.7	4.9	9.8	32.4
Porcelain and Pottery	1.3	42.9	6.1	18.1	6.1	12.6
Household Machinery	0.8	39.7	0	8.4	6.1	25.2
Iron and Steel	1.3	35.4	0	16.5	2.8	16.1
Newspapers	0.6	23.5	0	7.8	2	13.7

[1] Where 'All Damage' is the sum of pink, red, orange and yellow.

Table 2. Damage by ward (ranked by All Damage)[1]

	% of sample	*All Damage*	*PINK*	*RED*	*ORANGE*	*YELLOW*
Nagata	38.7	75.8	3.5	21.3	18.1	32.9
Suma	6.4	63.4	14.4	11.9	17.8	19.3
Nada	5.5	60.9	1.4	20.4	10.4	28.7
Hyogo	20.4	60.73	0.23	11.1	16.4	33
Higashi Nada	14.5	50.76	0.86	14.5	12.5	22.9
Chuo	12.4	48.43	0.63	3.9	11.8	32.1
Tarumi	2.1	42.4	0	0	18.1	24.3

[1] Where 'All Damage' is the sum of pink, red, orange and yellow.

Table 3. Main results of survival analysis (Cox proportional hazard)

	1	2	3	4	5	6	7
DISTEPI		1.01***					
		(3.9)					
SHAKE			0.99				
			(-0.3)				
PlantDAM					1.61***	1.66***	3.86***
					(4.1)	(4.3)	(7.2)
ChomeDAM				1.10		1.01	7.80***
				(0.5)		(0.1)	(7.0)
*PlantDAM*Time*							0.83***
							(-5.5)
*ChomeDAM*Time*							0.66***
							(-8.7)
AGE	0.99**	0.99**	0.99**	0.99**	0.99**	0.99**	0.99
	(-2.2)	(-2.2)	(-2.2)	(-2.3)	(-2.3)	(-2.4)	(-2.2)
SIZE2	0.50***	0.50***	0.50***	0.50***	0.50***	0.50***	0.52***
	(-9.0)	(-9.0)	(-9.0)	(-9.0)	(-9.1)	(-9.1)	(-8.4)
SIZE3	0.39**	0.39***	0.39***	0.39***	0.40***	0.40***	0.42***
	(-11.7)	(-11.7)	(-11.7)	(-11.7)	(-11.5)	(-11.5)	(-11.0)
SIZE4	0.85***	0.85***	0.85***	0.85***	0.85***	0.85***	0.86***
	(-8.5)	(-8.5)	(-8.5)	(-8.5)	(-8.4)	(-8.3)	(-7.7)
WAGE	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***	0.99***
	(-5.0)	(-5.0)	(-5.0)	(-5.0)	(-5.1)	(-5.1)	(-4.9)
TFP	0.89**	0.89**	0.90**	0.90**	0.90**	0.91**	0.92*
	(-2.3)	(-2.3)	(-2.2)	(-2.1)	(-2.1)	(-2.0)	(-1.7)
MULTI	1.59***	1.59***	1.58***	1.45***	1.58***	1.43***	1.43***
	(4.3)	(4.3)	(4.2)	(3.5)	(4.3)	(3.4)	(3.3)
MOVE	0.76***	0.75***	0.76***	0.76***	0.74***	0.74***	0.76***
	(-3.4)	(-3.5)	(-3.4)	(-3.4)	(-3.6)	(-3.7)	(-3.2)
RECON	1.002	1.002	1.003	1.0004	0.99	0.99	0.99
	(0.2)	(0.2)	(0.3)	(0.04)	(-0.2)	(-0.4)	(-1.2)
ClusterFirms	1.03**	1.03**	1.03**	1.02**	1.02**	1.03***	1.03***
	(2.5)	(2.5)	(2.5)	(2.0)	(2.0)	(2.5)	(2.7)
observations	16,658	16,658	16,658	16,658	16,658	16,658	16,658
Wald	423418***	308594***	318471***	304152***	338214***	323214***	294578***

Each model contains controls for 3-digit industry, year, ward, age of buildings in a chome and type of buildings in a chome

***, **, * denote statistical significance at 99%, 95% and 90% confidence levels, respectively

Table 4. Survival analysis sensitivity results

	1	2	3	4
PlantDAM	0.19**	1.83***		
	(2.0)	(3.5)		
*PlantDAM*Time*	-0.019	0.93**		
	(-1.2)	(-2.5)		
PlantDAMpink			3.05***	3.26***
			(3.2)	(3.4)
PlantDAMred			3.98***	3.63***
			(7.0)	(6.4)
PlantDAMorange			2.41***	1.90***
			(4.3)	(3.2)
PlantDAMyellow			2.33***	2.09***
			(4.7)	(4.1)
*PlantDAMpink*Time*			0.90**	0.88**
			(-2.0)	(-2.3)
*PlantDAMred*Time*			0.84***	0.85***
			(-6.3)	(-5.9)
*PlantDAMorange*Time*			0.89***	0.92***
			(-4.2)	(-3.2)
*PlantDAMyellow*Time*			0.87***	0.88***
			(-5.8)	(-5.6)
ChomeDAMPink				1.95
				(1.7)
ChomeDAMRed				2.36***
				(2.7)
ChomeDAMOrange				3.56***
				(3.5)
ChomeDAMYellow				2.83***
				(3.3)
*ChomeDAMPink*Time*				0.86**
				(-2.7)
*ChomeDAMRed*Time*				0.81***
				(-4.6)
*ChomeDAMOrange*Time*				0.83***
				(-3.6)
*ChomeDAMYellow*Time*				0.80***
				(-5.0)
ChomeDAM	0.27**	2.55***	7.95***	
	(2.4)	(4.3)	(7.0)	
*ChomeDAM*Time*	-0.057***	0.82***	0.66***	
	(-3.8)	(6.5)	(8.7)	
θ		1.01e-7		
(p value)		(0.47)		

In addition to the firm control variables contained in Table 3, each model contains controls for industry, year, wards, age of buildings in chome and type of buildings in chome
***, **, * denote statistical significance at 99%, 95% and 90% confidence levels, respectively

Model 1 uses a Probit estimation; model 2 uses a parametric (exponential distribution) shared frailty model; model 3 uses a Cox proportional hazards model and separates plant-level damages into 4 individual categories; model 4 uses a Cox proportional hazards model and separates both plant-level damage and chome damage into 4 individual categories.

Table 5. *PlantDAM* Hazard ratios for unproductive, small, young and low-skill plants.

	Least Productive (TFP)	Least Productive (Lab Prod)	Smallest	Youngest	Low-Skill
PlantDAM	5.68***	5.25***	7.39***	5.04***	5.09***
	(4.3)	(4.3)	(5.0)	(3.8)	(4.2)
*PlantDAM*Time*	0.74***	0.74***	0.78***	0.76***	0.76***
	(-4.1)	(-4.5)	(-3.5)	(-3.8)	(-3.7)

Each model contains controls for 3-digit industry, year, ward, age of buildings in a chome and type of buildings in a chome and all of the other control variables reported in Table 3, column 7.
***, **, * denote statistical significance at 99%, 95% and 90% confidence levels, respectively
Where unproductive, small, young and low-skill plants refer to the lowest quartile of plants in terms of TFP, labor productivity, size, age and skill-level (wage)

Table 6. Determinants of value added, employment, TFP and labor productivity 1992-2007 (fixed effects panel)

	1	2	3	4	5	6	7	8
	logEMP	logEMP	logVA	logVA	TFP	TFP	logLabProd	logLabProd
PlantDAM	-0.076***	-0.078***	-0.055**	0.019	0.022	0.10***	0.017	0.093**
	(-12.5)	(-5.6)	(-2.2)	(0.5)	(0.9)	(3.9)	(0.7)	(2.6)
*PlantDAM*Time*		0.00023		-0.010**		-0.012***		-0.011***
		(0.1)		(-2.1)		(-4.9)		(-3.0)
ChomeDAM	-0.035***	-0.030	-0.0055	-0.069***	-0.0042	-0.0091	0.039	-0.039**
	(-3.0)	(-1.6)	(-0.2)	(-3.2)	(-0.2)	(-0.4)	(1.3)	(2.0)
*ChomeDAM*Time*		-0.00075		0.011***		0.0018		0.011***
		(-0.5)		(8.9)		(0.6)		(7.3)
Time		-0.18***		-0.53***		0.035***		-0.35***
		(-80.8)		(-108.5)		(6.5)		(-83.5)
AGE	0.083***	0.15***	0.26***	0.47***	-0.019***	-0.033***	0.18***	0.31***
	(143.7)	(122.5)	(140.1)	(126.3)	(-15.4)	(-10.7)	(116.1)	(100.8)
WAGE	-0.00047***	-0.00047***	0.0011***	0.0011***	0.0017***	0.0017***	0.0016***	0.0016***
	(-19.0)	(-19.3)	(7.9)	(8.0)	(14.9)	(14.8)	(12.7)	(12.7)
MULTI	0.051**	0.051**	-0.029**	-0.029**	-0.057***	-0.058***	-0.077***	-0.078***
	(2.2)	(2.2)	(-2.0)	(-2.0)	(-3.8)	(-3.8)	(-3.4)	(-3.5)
MOVE	0.012	0.012	0.019	0.019	-0.0071	-0.0072	-0.0082	-0.0081
	(1.5)	(1.5)	(1.1)	(1.1)	(-0.5)	(-0.5)	(-0.7)	(-0.7)
RECON	0.0063	0.0063	0.050***	0.050**	0.074***	0.074***	0.045***	0.044***
	(0.5)	(0.5)	(2.9)	(2.9)	(7.1)	(7.2)	(3.8)	(3.8)
ClusterFirms	-0.0011	-0.0011	0.00062	0.00067	0.0022	0.0022	0.0018	0.0018
	(1.1)	(1.1)	(0.4)	(0.4)	(1.5)	(1.6)	(1.6)	(1.7)
observations	11,688	11,688	11,688	11,688	11,688	11,688	11,688	11,688
R^2	0.11	0.11	0.15	0.15	0.10	0.10	0.14	0.14

Each model contains plant and year fixed effects.
***, **, * denote statistical significance at 99%, 95% and 90% confidence levels, respectively

Table 7. The determinants of plant births 1992-2007 (negative binomial estimation)

	1	2	3	4
ChomeDAM	-0.96***	-0.93***		
	(-4.9)	(-4.0)		
*ChomeDAM*Time*		-0.0052		
		(-0.3)		
ChomeDAMPink			-0.37	0.50
			(-1.1)	(1.2)
ChomeDAMRed			0.61**	1.43***
			(2.0)	(3.7)
ChomeDAMOrange			-1.37***	-1.66***
			(-3.0)	(-2.9)
ChomeDAMYellow			-0.74**	-0.31***
			(-2.2)	(-0.8)
*ChomeDAMPink*Time*				-0.14***
				(-3.3)
*ChomeDAMRed*Time*				-0.12***
				(-3.6)
*ChomeDAMOrange*Time*				0.045
				(0.8)
*ChomeDAMYellow*Time*				-0.062
				(-1.6)
RECON	-1.34***	-1.34***	-1.25***	-1.38***
	(7.7)	(-7.7)	(-6.8)	(-7.3)
PLANTS	-0.0048	-0.0047	-0.0046	-0.0052
	(-1.0)	(-1.0)	(-1.0)	(-1.1)
Time		-0.44***		-0.42***
		(-3.1)		(-2.9)
observations	10,440	10,440	10,440	10,440
Wald	598.2***	597.3***	593.4***	614.5***

Each model contains chome and year effects
***, **, * denote statistical significance at 99%, 95% and 90% confidence levels, respectively

Appendix

Table A1. Variable definitions[1]

Variable	
DISTEPI	Distance of plant to earthquake epicenter in kilometres
SHAKE	Estimated peak ground velocity in centimetres per second estimated at the 250m grid cell level by Fujimoto and Midorikawa (2002)
PlantDAM	Building-level damage index
ChomeDAM	Chome-level Building damage index
AGE	The age of the plant in years in 1995
SIZE (EMP)	The total level of employment at the plant
SIZE1to SIZE4	Dummy variables =1 if a plant is in the first, second, third or fourth quartiles of total employment, respectively
WAGE	The average annual wage per worker at the plant 10,000 Yen
TFP	Total factor productivity, as defined in the Appendix
MULTI	A dummy variable =1 if a plant is from a multi-plant firm
MOVE	A dummy variable =1 if a plant relocated within Kobe city
RECON	A dummy variable =1 if a plant is located within one of 523 priority reconstruction districts in which reconstruction costs were subsidised and regulations were reduced
Births	The number of new plants born within a chome
ClusterFirms	The number of plants belonging to the same 2 digit industry as the plant in question and within the same chome
ClusterFirmsNb	The number of plants belonging to the same 2 digit industry as the plant in question and within the same chome or neighboring chomes
ClusterEmp	The level of employment within the same 2 digit industry as the plant in question and within the same chome
ClusterEmpNb	The level of employment within the same 2 digit industry as the plant in question and within the same chome or neighboring chomes
VA	The level of value added in 10,000 Yen
LabProd	The level of value added per worker in 10,000 Yen
BUILDpre45	Share of buildings built pre 1945 by chome
BUILD46-55	Share of buildings built 1946-55 by chome
BUILD56-65	Share of buildings built 1956-65 by chome
BUILD66-75	Share of buildings built 1966-75 by chome
BUILD76-85	Share of buildings built 1976-85 by chome
BUILDafter86	Share of buildings built after 1986 by chome
BUILDbrick	Share of brick built buildings by chome
BUILDrconc	Share of reinforced concrete buildings by chome
BUILDsteel	Share of steel buildings by chome
BUILDwood	Share of wooden buildings by chome

[1] All monetary variables are expressed in year 2000 prices

Variables *SIZE, WAGE, MULTI, MOVE, VA* and *LabProd* come from the Manufacturing Census (Japanese Ministry of Economy, Trade and Industry). Variable *AGE* is from the Establishment and Enterprise Census (Japanese Ministry of Internal Affairs and Communications). Our damage, building age and building type variables are from 'Shinsai Hukkou Akaibu' (archive on the damage of the 1995 Hyogo-Awaji earthquake) by Kobe City Office and Toru Fukushima (University of Hyogo), together with 'Zenrin's Residential Map, Hyogo-ken Kobe city 1995' from Toru Fukushima (University of Hyogo).

Table A2. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
DISTEPI	18.6	13.5	5.7	435.3
SHAKE	79.3	6.4	32.3	93.0
PlantDAM	0.22	0.27	0	0.75
ChomeDAM	0.59	0.25	0.12	1
AGE	18.1	15.0	1	42
SIZE (EMP)	33.2	206.0	3	5673
WAGE	355.9	174.4	67.8	1762.2
TFP	4.40e-12	0.68	-6.9	3.5
MULTI	0.14	0.33	0	1
MOVE	0.17	0.38	0	1
RECON	0.40	0.49	0	1
Births	0.13	0.67	0	35
ClusterFirms	1.5	3.0	0	20
ClusterFirmsNb	5.1	8.5	0	88
ClusterEmp	53.8	276.3	0	5687
ClusterEmpNb	127.0	410.4	0	5712
VA	69164.6	787135.5	1151.7	3.24e+07
LabProd	954.4	1270.6	3.56	19085.6
BUILDpre45	0.13	0.18	0	0.89
BUILD46-55	0.058	0.071	0	0.46
BUILD56-65	0.17	0.15	0	1
BUILD66-75	0.29	0.19	0	1
BUILD76-85	0.16	0.15	0	1
BUILDafter86	0.18	0.19	0	1
BUILDbrick	0.25	0.16	0	0.65
BUILDrconc	0.22	0.15	0	0.64
BUILDsteel	0.28	0.27	0	1
BUILDwood	0.23	0.20	0	0.99

Estimating TFP

A feature of our data is that information on capital stocks is collected only for plants with 30 employees or more. Such plants form a minority of our sample implying that conventional measures of TFP are therefore not available to us. To overcome this problem we follow Cui *et al.* (2012) and estimate a measure of plant level TFP that does not require information on capital stocks. We assume that all plants in the same industry use the same technology and that this technology can be represented by a homogenous production function, written as:

$$V_{ijt} = \theta_{ijt} p_j(l_{ijt}, z_{ijt}) \qquad \text{(A1)}$$

where V_{ijt} is value added in plant i, industry j and year t, l_{ijt} is the labor force, z_{ijt} is a vector of all other inputs and θ_{ijt} represents plant level productivity, measured as the deviation from the industry average productivity. If we assume that the production function is homogenous of degree α_j then equation (1) can be rewritten as:

$$V_{ijt} = \theta_{ijt}(l_{ijt})^{\alpha_j} p_j\left(1, \frac{z_{ijt}}{l_{ijt}}\right) \qquad \text{(A2)}$$

where the degree of homogeneity of the production function captures the industry-specific degrees of returns to scale.

Expressing the production function in this way allows us to separate the plant level labor input l_{ijt} from the input ratios z_{ijt}/l_{ijt} which are not observable in our data. If we continue to assume that plants within the same industry possess the same production function (aside from the plant specific productivity parameter) and also assume that all plants in the same industry are subject to the same input prices, then all plants within the same industry should select the same input ratios z_{ijt}/l_{ijt} due to cost minimisation. This implies that p_j $(1, z_{ijt}/l_{ijt})$ from equation (2) can be captured by industry-by-year-specific variables. We therefore estimate the following:

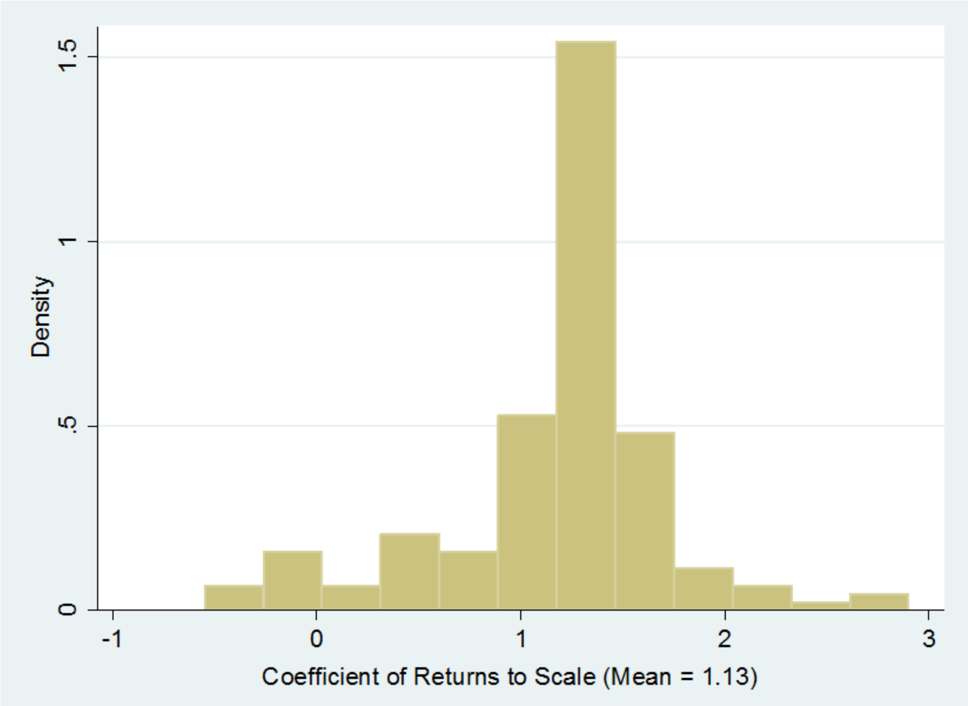
$$log(V_{ijt}) = \sum_j \delta_j IND_j + \sum_j \alpha_j IND_j * log(l_{ijt}) + \lambda_{jt} + \epsilon_{ijt} \qquad \text{(A3)}$$

where IND_j represents dummies for our 162 three-digit industries. The error term ε_{ijt} includes the plant specific productivity parameter θ_{ijt} which captures the deviation of each plant's productivity from the industry average. This can be expressed as:

$$\log(\theta_{ijt}) \equiv log(V_{ijt}) - \sum_j \delta_j IND_j - \sum_j \alpha_j IND_j * log(l_{ijt}) - \lambda_{jt} \qquad \text{(A4)}$$

Figure A1 plots the industry returns to scale coefficients α_j from equation A4 and shows an average of 1.13 which is close to one and confirms a finding of constant returns to scale.

Figure A1. Histogram of Industry Returns to Scale Coefficients (α_j from equation A4)


Density
0
.5
1
1.5
-1
0
1
2
3
Coefficient of Returns to Scale (Mean = 1.13)