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Structural Estimation at the Product Level: The impact of the Kobe Earthquake*

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Abstract

This paper studies the link between product-level dynamics and macroeconomic fluctuations using rich census data from Kobe covering the period 1992-2013. The dataset includes two major disruptions─the 1995 Kobe earthquake and the 2008 global financial crisis─and provides annual information for more than 1,000 six-digit product categories. To isolate the effects of the earthquake, we construct counterfactual cities, such as Nagoya. We estimate a multi-product firm DSGE model using maximum likelihood with a computationally robust estimation strategy. The results reveal substantial heterogeneity in product-level responses to shocks, with important implications for aggregate dynamics, the propagation of large disasters, and the role of product-specific characteristics in shaping macroeconomic resilience.

Keywords: Product dynamics; Firm heterogeneity; DSGE; DID
JEL classification: D24, E23, E32, L11, L60

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1 Introduction

Large local shocks such as natural disasters disrupt economic activity abruptly, yet their economic consequences unfold unevenly within affected locations. Some products experience sharp and persistent declines, while others recover quickly or even expand. These divergent trajectories are often obscured in aggregate or sectoral statistics, making it difficult to identify which margins of adjustment—aggregate, location-specific, or product–location–specific— ultimately shape local economic dynamics in the aftermath of large disasters.

This paper studies the 1995 Kobe earthquake through the lens of product-level dynamics. Using rich census data on manufacturing establishments in Kobe over the period 1992–2013, we document substantial heterogeneity in the response of individual products to the disaster, along both the intensive margin (real sales) and the extensive margin (the number of producing establishments). We show that regional averages, and even sectoral averages within the region, mask large within-sector dispersion, and that product–location–specific forces play a dominant role in driving post-disaster adjustment.

The paper addresses four related questions. First, how important are product–location–specific shocks relative to aggregate and location-level disturbances in explaining fluctuations in product-level sales and establishment dynamics following a large local disaster? Second, to what extent do extensive-margin adjustments at the product level contribute to the persistence of local economic losses? Third, can a structurally estimated product-level DSGE model reconcile reduced-form event-study evidence with observed macroeconomic and microeconomic dynamics? Finally, how would local outcomes have evolved in the absence of the disaster once product-specific shocks are explicitly taken into account?

To answer these questions, we construct a panel of manufacturing establishments covering more than 1,000 six-digit product categories and exploit the Kobe earthquake as an exogenous local shock. To isolate the earthquake's impact, we focus on the subset of products jointly produced in Kobe and Nagoya prior to the event, thereby controlling for fine-grained product composition. Nagoya serves as a natural counterfactual location, as it shares similar economic characteristics with Kobe but was not affected by the earthquake.

Our empirical strategy combines reduced-form and structural approaches. We first estimate product-level dynamic difference-in-differences specifications to identify the causal impact of the earthquake on real sales and establishment counts. These estimates reveal large and persistent average losses, alongside pronounced heterogeneity across products. We then develop and structurally estimate a multi-product firm DSGE model with endogenous entry and exit and an explicit location dimension. The model is estimated separately for each product using maximum likelihood, jointly matching aggregate GDP dynamics and heterogeneous product-level outcomes. This framework allows us to map reduced-form treatment effects into structural shocks and to quantify the relative importance of aggregate, location-specific, and product–

location–specific disturbances.

The structural analysis delivers three main findings. First, variance decompositions show that product-level outcomes are overwhelmingly driven by product–location–specific demand and operating cost shocks, whereas aggregate shocks primarily govern aggregate GDP and local extensive margins. Second, relative historical decompositions reveal that the earthquake-induced dynamics of product-level sales and establishment counts are largely accounted for by product–location–specific shocks rather than by aggregate or purely local disturbances. Third, counterfactual simulations replacing Kobe shocks with Nagoya shocks indicate that the impact of the earthquake is highly heterogeneous across products, even within narrowly defined sectors, with both positive and negative effects observed across the distribution.

The paper relates to the empirical literature on the economic effects of natural disasters and large local shocks. A central finding of this literature is that disasters generate sizable and often persistent effects on output, employment, and firm dynamics, with outcomes shaped by exposure, propagation mechanisms, and local adjustment margins (Cavallo and Noy, 2011; Noy, 2009). In the broader disaster-economics literature, damaged firms may permanently close down (e.g., Craioveanu and Terrell, 2016 for Hurricane Katrina; Cole et al., 2019 for the Kobe earthquake), and surviving firms often experience persistent losses in growth and productivity (e.g., Boarnet, 1998; Tanaka, 2015; Okazaki et al., 2024). In contrast, other studies find heterogeneous post-disaster adjustment among survivors, including recovery, expansion, and productivity gains in DiD-type frameworks (e.g., Leiter et al., 2009; Okubo and Strobl, 2021; Okazaki et al., 2019). For example, Okazaki et al. (2019) show that some surviving firms upgraded machinery after the Great Kanto Earthquake of 1923. Focusing on the 1995 Kobe earthquake, Cole et al. (2019) combine detailed building-level damage measures with plant-level data and show that disaster impacts are highly heterogeneous within locations, affecting plant survival, entry, and productivity in a persistent manner. A related literature studies how shocks propagate through financial intermediation and credit supply; our focus instead is on product-level reallocation and churning following a disaster shock (e.g., Khwaja and Mian, 2008; Hosono et al., 2016).

While this literature convincingly establishes the causal effects of disasters at the firm or plant level, it typically abstracts from heterogeneity below the sector and firm. As a result, it provides limited guidance on how shocks propagate through fine-grained product-level margins within locations. Our paper fills this gap by focusing on product–location dynamics and by structurally quantifying how product-specific shocks interact with aggregate and local disturbances following a large natural disaster. As far as we know, there are no previous studies on the impact of large negative shocks on product-level outcomes such as product churning. In particular, existing work typically does not quantify which products stop being produced locally, which products survive, and which products expand (either through recovery or reallocation) after a disaster. Furthermore, there are no dynamic theoretical models that discipline these mechanisms at the product level and allow for counterfactual comparisons to a path in which the negative shock did not occur. For these reasons, our paper investigates how production patterns change at the product level following a large negative shock by combining a DSGE model with a DiD-style empirical design, which enables disciplined counterfactual analysis.

Second, the paper connects to the literature on firm and product heterogeneity in macroeconomics. The canonical framework for endogenous firm entry and exit is developed by Hopenhayn (1992), who shows how firm-level heterogeneity shapes industry dynamics in equilibrium. Quantitative macroeconomic models further demonstrate that micro-level dispersion and non-convex adjustment frictions play a central role in aggregate fluctuations (Khan and Thomas, 2008). In international macroeconomics and trade, heterogeneous-firm general equilibrium models emphasize how selection, fixed costs, and extensive-margin adjustments feed back into macroeconomic dynamics (Bilbiie et al., 2012; Ghironi and Melitz, 2005). Empirical and theoretical work on granular shocks and production networks further highlights the role of micro-level heterogeneity in shaping aggregate volatility (Gabaix, 2011; Acemoglu et al., 2012; Carvalho and Gabaix, 2013; Di Giovanni et al., 2014; Carvalho, 2014; Baqaee and Farhi, 2019).

Our earlier work develops this line of research by explicitly modeling and estimating product-level dynamics. Hamano and Oikawa (2022) develop a general equilibrium model with multi-product establishments, heterogeneous product-level tastes, and endogenous product creation and destruction, and estimate the model using Japanese manufacturing data. That paper shows that product-specific demand and operating-cost shocks dominate aggregate shocks in explaining product-level business cycles. More recently, Hamano (2025) studies how heterogeneity in tastes and productivities shapes aggregate volatility, highlighting the importance of product-level fixed costs and taste dispersion for macroeconomic fluctuations.

The present paper builds on these insights but shifts the focus from aggregate business cycles to a large, localized disaster. By exploiting the 1995 Kobe earthquake as a natural experiment, we study how product-level heterogeneity conditions local adjustment and resilience in the presence of a sharp spatial shock, a dimension that is absent from aggregate-shock-based analyses.

Third, this study contributes to the literature that combines reduced-form identification with structural macroeconomic interpretation. Nakamura and Steinsson (2014) exploit regional variation within a monetary union to identify dynamic responses to government spending and provide a framework for mapping relative regional estimates into aggregate implications. Chodorow-Reich (2019) clarify the conditions under which regional identification strategies can be used to answer macroeconomic questions. We follow this approach by using the Kobe earthquake as an exogenous source of variation to discipline and interpret a product-level DSGE model. Relative to purely reduced-form studies of disasters, the structural framework allows us to quantify the contribution of different shocks and adjustment margins and to conduct economically meaningful counterfactual experiments.

Finally, the paper relates to the literature on product variety, multi-product firms, and product switching. Broda and Weinstein (2010) document substantial product turnover and changes in variety, while Bernard et al. (2010) and Forslid and Okubo (2023) show that manufacturing firms are predominantly multi-product and that product switching and concentration constitute important margins of adjustment. Related theoretical work studies optimal product scope and flexible manufacturing in general equilibrium (Feenstra and Ma, 2008; Eckel and Neary, 2010; Nocke and Yeaple, 2014; Mayer et al., 2014). Minniti and Turino (2013) develops a DSGE model that examines the dynamics of multi-product firms under oligopolistic competition.

While much of this literature focuses on firm scope, trade, or globalization, our contribution is to emphasize product-level outcomes within locations. We show that within-sector, product-level heterogeneity dominates sectoral averages in shaping local economic resilience following a large disaster.

The remainder of the paper is organized as follows. Section 2 provides empirical motivation and documents reduced-form evidence on the impact of the Kobe earthquake using product-level dynamic difference-in-differences estimates. Section 3 introduces the product-level DSGE framework with endogenous entry and exit and describes the estimation strategy. Section 4 presents the structural estimation results and reports variance decompositions that quantify the relative importance of aggregate, location-specific, and product–location–specific shocks. Section 5 analyzes relative historical decompositions between Kobe and Nagoya and conducts counterfactual experiments to assess the role of product-level heterogeneity in shaping local economic dynamics. Section 6 discusses the consistency between the reduced-form and structural results and highlights their implications. The final section concludes.

2 Empirical motivation

2.1 Data

We use the Census of Manufacture (Kogyo Tokei in Japanese) conducted by the Ministry of Economy, Trade and Industry. The Census covers all manufacturing plants with more than four regular employees and is conducted annually. It includes the number of regular employees and output at the six-digit product level. We focus on the period from 1992 to 2013 in order to use time-consistent product categories, following Pierce and Schott (2012). Plant-level microdata with time-consistent plant identifiers are available from 1992 onward, which allows us to construct panel data. Using time-consistent municipality codes, we construct a balanced panel dataset at the municipality level. We aggregate plant–product-level output data to the municipality–product level. The dataset provides key plant characteristics, including location, industry sector, age, wages, employment, and value added.

To conduct empirical analysis, structural estimation, and a counterfactual analysis, we select a control group. There are several reasons for selecting Nagoya City as a counterpart to Kobe City. First, Nagoya City was neither directly nor indirectly affected by the 1995 Kobe earthquake. Nagoya is located approximately 140 kilometres east of Kobe. Second, the two cities are similar

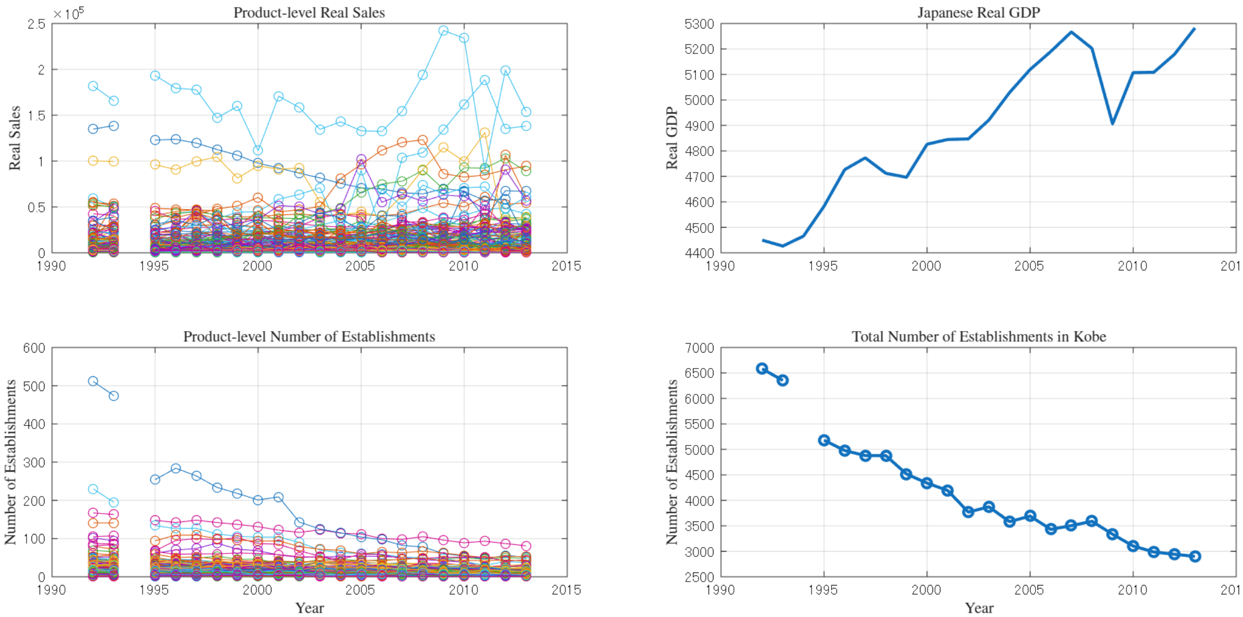


Figure 1: Data for Kobe

Note: The figure presents product-level real sales, the number of product-producing establishments, and the total number of establishments in Kobe. Observations for 1994 are excluded due to measurement errors caused by the January 1995 earthquake.

in population size and geographic characteristics. Nagoya has a population of about 2 million, while Kobe has about 1.5 million. Both cities have long histories as centres of manufacturing, whereas Tokyo and Osaka are megacities as centres of commerce. Third, both cities host large manufacturing clusters driven by international trade and are home to major international ports, making them highly export-oriented. We note, however, that their manufacturing industrial structures differ somewhat. Prior to the 1995 earthquake, Kobe had large clusters in footwear, metals and steel, rubber, food, and machinery. In contrast, Nagoya specialises in machinery, food, textiles, and pottery. In particular, Toyota is outside Nagoya City, but in its suburbs, and as a result, many automobile parts and components manufacturers are located in Nagoya City.

Figure 1 contrasts aggregate economic trends with micro-level heterogeneity. We exclude observations for 1994 due to data limitations. The aggregate Japanese economy grew throughout the post-disaster period (top right panel). Horwich (2000) attributes this stability to the macroeconomic environment. Because the earthquake occurred during a recession, there was significant excess capacity in the broader economy. This slack absorbed the shock, preventing supply shortages and keeping inflation and interest rates stable. Conversely, the total number of establishments in Kobe experienced a persistent structural decline (bottom right panel). Importantly, the left panels reveal that the trajectories of sales and the number of establishments varied considerably. This variation suggests that the earthquake's impact was highly heterogeneous across products. These patterns motivate our empirical and structural estimation.

2.2 Aggregate Impact

We begin by estimating the causal dynamic impact of the 1995 Kobe earthquake on local economic activity. We employ a dynamic difference-in-differences framework. This approach allows us not only to quantify the immediate magnitude of the damage but also to trace the persistence of the shock and test for the presence of pre-existing differential trends. We estimate the following dynamic linear model at the product-location level, exploiting variation across 6-digit product categories:

$$\ln(Y_{ijt}) = \sum_{\tau=-2}^{5} \beta_\tau \left[\mathbb{1}(t - 1995 = \tau) \times \text{Damage}_j\right] + \alpha_{ij} + \lambda_t + \varepsilon_{ijt}$$

where Y_{ijt} denotes the outcome of interest (either total sales or the number of establishments) for product i in location j at year t.

The core of our identification strategy relies on the interaction term, $\mathbb{1}(t - 1995 = \tau) \times \text{Damage}_j$. Damage_i is equal to one in the treatment area affected by the Kobe earthquake. Damage_j is a time-invariant binary variable equal to one if location j falls within the treatment area affected by the Kobe earthquake, and zero otherwise. The term $\mathbb{1}(t - 1995 = \tau)$ is an indicator function that takes the value of one only when the observation year t corresponds to the specific event-time τ. Consequently, the interaction term effectively "turns on" only for the treated location during the specific lag or lead year τ. This structure allows the coefficients $\{\beta_\tau\}_\tau$ to capture the differential evolution of the outcome in the damaged area relative to the control area for each period, normalised against the base year of 1993 ($\tau = -1$).

Our model includes high-dimensional fixed effects to isolate the exogenous shock from confounding factors. First, we include product-location fixed effects, α_{ij}. These absorb all time-invariant heterogeneity specific to a product in a given location. For example, if the food processing industry (i) in Kobe (j) historically operates at a larger scale than the same industry in Nagoya due to proximity to ports, α_{ij} captures this permanent level difference. This ensures that our estimates are derived solely from within-unit variation over time, rather than cross-sectional differences. Second, we control for year fixed effects, λ_t. These absorb aggregate shocks that affect all locations simultaneously, such as the Japanese asset price collapse, changes in national tax policy, or fluctuations in global demand.

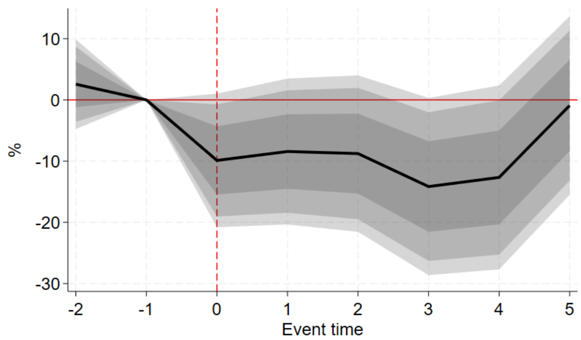
Rather than comparing aggregate sectors, we construct a balanced sample based on product availability. As detailed in Table 1, we identify approximately 300 distinct 6-digit products that were produced in both Kobe and Nagoya prior to the shock. By restricting our analysis to this intersection, we ensure comparisons between firms producing similar goods and facing identical sectoral shocks, thereby minimising bias from unobserved sector-specific heterogeneity.

The validity of our design rests on the parallel trends assumption. While this assumption is untestable for the post-treatment period, we assess its plausibility by examining the pre-treatment coefficients (β_τ for $\tau < 0$). If our identification is valid, we expect these coefficients to be statistically indistinguishable from zero, indicating that damage intensity is uncorrelated with prior sales growth. Furthermore, unlike policy changes which may be anticipated, the 1995 earthquake was an unanticipated exogenous shock. This rules out anticipation effects in which firms might adjust investment before the event. Finally, to account for serial correlation in outcomes within industries over time, we cluster standard errors at the product-location (ij) level. This allows for arbitrary correlation of the error terms ε_{ijt} across specific industries and locations, addressing potential sector-specific shocks not captured by the fixed effects.

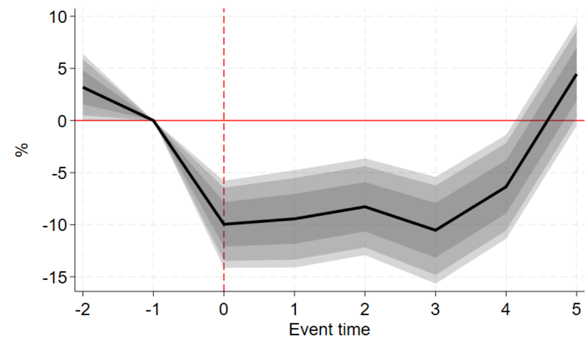
Sector	Nb. Products	Sales Values		% Share		Nb. Establishment		% Share	
		Kobe	Nagoya	Kobe	Nagoya	Kobe	Nagoya	Kobe	Nagoya
9 Food	42	45,945,137	38,822,369	25.7	15.1	542	892	13.8	8.2
10 Beverage, Tobacco, and Feed	6	20,237,914	2,443,765	11.3	1.0	75	42	1.9	0.4
11 Textile	14	1,946,154	5,446,966	1.1	2.1	166	523	4.2	4.8
12 Lumber and Wood Products	4	239,381	2,633,811	0.1	1.0	27	134	0.7	1.2
13 Furniture and Fixtures	9	1,086,445	5,640,935	0.6	2.2	168	549	4.3	5.0
14 Pulp and Paper Products	14	1,667,845	5,123,817	0.9	2.0	104	402	2.7	3.7
15 Printing	9	6,626,349	28,079,033	3.7	11.0	391	1,275	10.0	11.7
16 Chemical	12	3,950,732	7,788,619	2.2	3.0	47	70	1.2	0.6
17 Petroleum and Coal Products	1	390,207	203,481	0.2	0.1	8	4	0.2	0.0
18 Plastic Products	13	1,538,566	12,245,591	0.9	4.8	99	548	2.5	5.0
19 Rubber products	8	3,824,515	3,929,643	2.1	1.5	164	175	4.2	1.6
20 Leather Tanning, Leather Products and Fur Skins	1	6,087,459	224,109	3.4	0.1	141	12	3.6	0.1
21 Ceramic, Stone and Clay Products	4	2,555,550	2,054,400	1.4	0.8	43	37	1.1	0.3
22 Iron and Steel	12	12,779,550	17,938,619	7.1	7.0	91	506	2.3	4.7
23 Non-ferrous Metals and Products	7	943,202	1,696,392	0.5	0.7	44	152	1.1	1.4
24 Fabricated Metal Products	32	14,121,726	23,004,174	7.9	9.0	520	1,691	13.3	15.5
25 General Machinery	28	6,401,592	15,920,243	3.6	6.2	301	812	7.7	7.5
26 Production Machinery	29	3,861,114	13,707,616	2.2	5.4	328	1,410	8.4	13.0
27 Business Oriented Machinery	8	1,121,842	945,637	0.6	0.4	34	42	0.9	0.4
28 Electronic Parts, Devices and Electronic Circuits	3	2,058,557	4,483,359	1.2	1.8	49	115	1.3	1.1
29 Electrical Machinery	16	20,738,570	26,354,494	11.6	10.3	186	521	4.7	4.8
30 Information and Communication Electronics	2	2,430,547	676,601	1.4	0.3	14	20	0.4	0.2
31 Transportation Equipment	15	12,875,226	33,429,822	7.2	13.0	245	639	6.3	5.9
32 Other Manufacturing	11	5,595,368	3,639,254	3.1	1.4	133	315	3.4	2.9
Total	300	179,023,548	256,432,750	100.0	100.0	3,920	10,886	100.0	100.0

Notes: This table shows the summary statistics of the common products produced in Kobe, Hyogo, as the treatment group and in Nagoya, Aichi, as the control group. The row enlists 2-digit sector classifications.

Table 1: Characteristics of Common Products between Treatment and Control Group



(a) Log sales



(b) Log number of establishments

Notes: This figure plots the event-study coefficients estimating the impact of the 1995 Kobe earthquake on sales (Panel a) and number of establishment (Panel b). Event time $t = 0$ corresponds to the year 1995. The reference period is $t = -1$, which corresponds to 1993; data for 1994 are omitted due to collection limitations. The solid line plots the difference in log sales between firms in the treatment city (Kobe, Hyogo) and the control city (Nagoya, Aichi). The shaded areas represent the 66%, 90%, and 95% confidence intervals (from darkest to lightest).

Figure 2: The relative response of log sales and the number of establishments to the 1995 Kobe Earthquake

Panel A of Figure 2 plots the dynamic difference-in-differences estimates for log sales.[1] The estimation identifies a statistically significant and persistent negative impact of the event on the outcome variable. After rigorously controlling for all confounding factors, the results show that the event causes an immediate drop in log sales of approximately 9.9% (coefficient -0.099) at time t. This negative shock deepens over time, reaching a magnitude of -0.142 by $t + 3$. Importantly, the validity of this causal interpretation is supported by the pre-event coefficients ($t - 2$), which are statistically indistinguishable from zero (0.026). This confirms that the parallel trends assumption holds, implying that, conditional on the fixed effects, the treated and control units followed similar trajectories before the shock, ensuring that the post-event divergence is indeed a treatment effect.

Panel B of Figure 2 plots the dynamic difference-in-differences estimates for the log number of establishments.[2] The figure reveals a sharp, statistically significant decline in the number of establishments following the event. Specifically, the event causes an immediate 10% drop in the number of firms (coefficient -0.100) at time t. This effect is highly persistent for the next three years, with coefficients hovering around -0.100 from $t + 1$ to $t + 3$. Interestingly, there is a signal of recovery by $t + 5$, where the coefficient flips to positive (0.045). While the pre-trend coefficient (0.032) is marginally significant at the 10% level, it is positive. This implies that treated areas actually had slightly more firms relative to the trend before the event, making the subsequent sharp drop to -0.100 convincing.

[1] Detailed estimation results are reported in Appendix Table B.1.

[2] Detailed estimation results are reported in Appendix Table B.2.

2.3 Heterogeneity across products

In this subsection, we document the variation in the dynamics of the difference-in-differences results of sales and establishment of manufacturing firms in Kobe, Nagoya prefecture, compared to those in Nagoya, Aichi prefecture, at the 6-digit product level. Figure 3 shows the results. To interpret the graph, each grey line represents the point estimate of the relative response for a specific sector. The coefficient is normalised to zero in the pre-event reference year ($t = -1$). The trajectories diverge sharply following the earthquake ($t \geq 0$). This significant dispersion in the coefficients indicates that the Kobe earthquake did not impose a uniform shock across industries. The impact is highly heterogeneous, with some sectors experiencing severe downturns while others show resilience or rapid recovery. In the following section, we will explore the sources of heterogeneity in the dynamics of economic variables and the mechanisms behind the outcomes observed in the empirical analysis.

3 The Model

The theoretical environment is isomorphic to Hamano and Okubo (2023) and Hamano (2025). We extend their framework by incorporating an explicit location index that specifies where entry and production of differentiated products take place.

Specifically, consider an economy with a continuum of locations $j \in [0, 1]$, normalized to unit measure. In each location j, a particular differentiated product i is produced. Product i is supplied by establishments that operate under monopolistic competition.

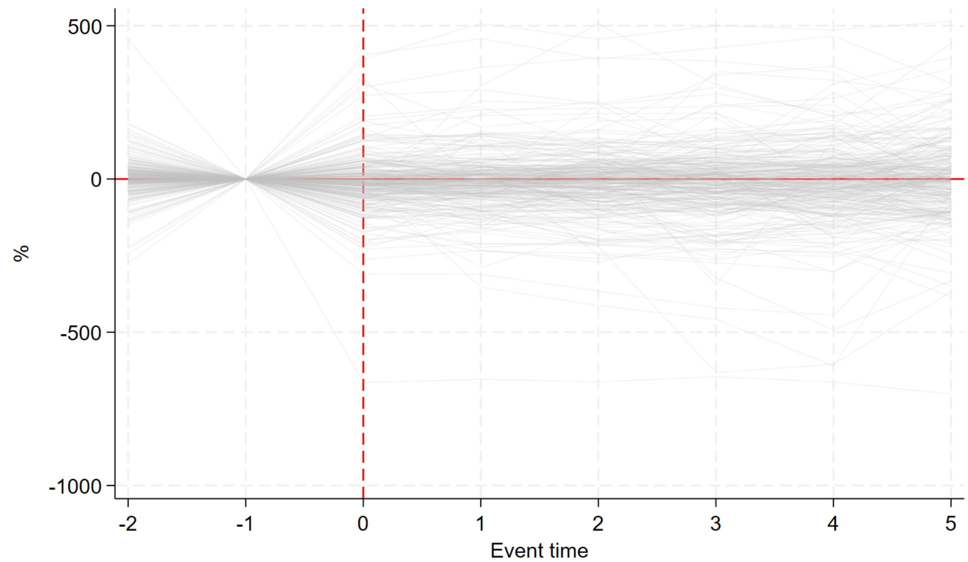
In each period, a mass $H_t(j)$ of potential entrants arrives in location j. Upon entry, establishments draw an idiosyncratic productivity level φ and a product-specific taste parameter λ_i for product i. Among the total stock of establishments $N_t(j)$ in location j, only a subset $M_{i,t}(j)$ chooses to operate in product i, because producing this product entails paying an operational fixed cost $f_{i,t}(j)$ that is common to all local establishments. Consequently, in location j there are $M_{i,t}(j)$ distinct varieties of product i, each corresponding to a firm–product pair, and this measure of active varieties is determined endogenously.

All remaining goods in the economy are summarized by a perfectly competitive sector, indexed by o.

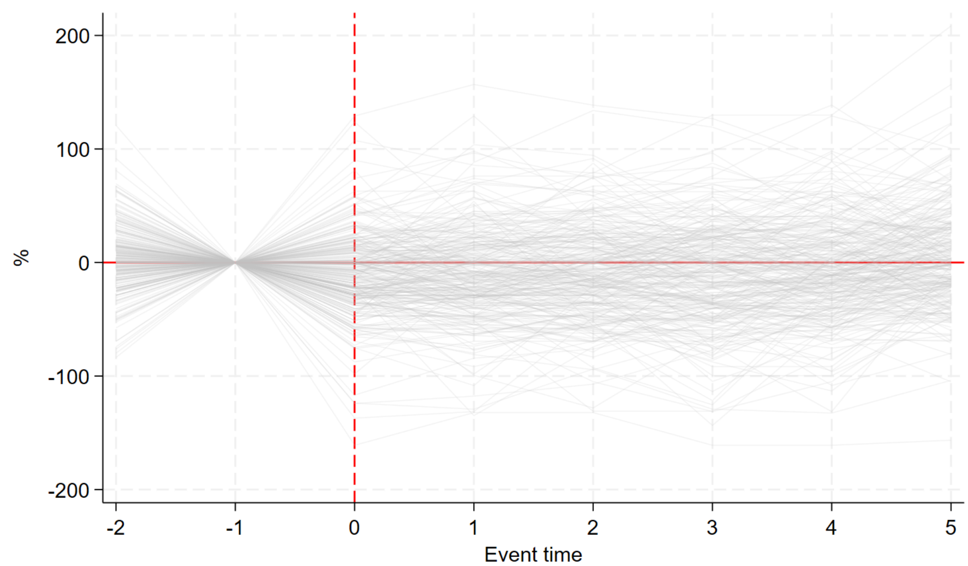
3.1 Households

The representative household maximizes expected utility

$$E_t \sum_{s=t}^{\infty} \beta^{s-t} U_s,$$



(a) Sales



(b) Nb. of establishment

Figure 3: The relative response of log sales and the number of establishments to the 1995 Kobe Earthquake (By 6-digit Products)

where $0 < \beta < 1$ is the discount factor. Period utility is

$$U_t = A_t \ln C_t - \chi \frac{L_t^{1+\varsigma}}{1+\varsigma},$$

where A_t is an exogenous demand shifter, $\chi > 0$ governs the disutility of labor, and $\varsigma > 0$ is the inverse Frisch elasticity of labor supply.

Consumption is assembled from baskets produced across a continuum of locations $j \in [0,1]$. At each location j, the household allocates expenditure between the differentiated product $C_{i,t}(j)$ and the composite of other goods $C_{o,t}(j)$. Aggregate consumption is

$$C_t = \int_0^1 \left(\frac{C_{i,t}(j)}{\alpha_{i,t}(j)} \right)^{\alpha_{i,t}(j)} \left(\frac{C_{o,t}(j)}{1-\alpha_{i,t}(j)} \right)^{1-\alpha_{i,t}(j)} dj, \tag{1}$$

where $\alpha_{i,t}(j)$ is the (possibly location-specific) preference weight on product i.

Product i consists of a continuum of varieties indexed by $\omega \in \Omega_{i,t}(j) \subset \Omega_i(j)$. Within each location j, the CES aggregator over varieties is

$$C_{i,t}(j) = \left(\int_{\omega \in \Omega_{i,t}(j)} \left[\lambda_i(\omega)\, c_{i,t}(j,\omega) \right]^{1-\frac{1}{\sigma}} d\omega \right)^{\frac{1}{1-\frac{1}{\sigma}}},$$

where $c_{i,t}(j,\omega)$ is consumption of variety ω produced in location j, $\lambda_i(\omega)$ is a taste/quality shifter, and $\sigma > 1$ is the elasticity of substitution across varieties.

Cost minimization given the CES aggregator yields the optimal demand for each variety produced in location j:

$$\lambda_i(\omega) c_{i,t}(j,\omega) = \left(\frac{p_{i,t}(j,\omega)/\lambda_i(\omega)}{P_{i,t}(j)} \right)^{-\sigma} C_{i,t}(j), \tag{2}$$

where $p_{i,t}(j,\omega)$ denotes the price of variety ω produced in location j, and the corresponding CES price index is

$$P_{i,t}(j) = \left(\int_{\omega \in \Omega_{i,t}} \left(\frac{p_{i,t}(j,\omega)}{\lambda_i(\omega)} \right)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}. \tag{3}$$

Given the local Cobb–Douglas structure (1), demand for the two baskets in each location is

$$C_{i,t}(j) = \left(\frac{P_{i,t}(j)}{P_t} \right)^{-1} \alpha_{i,t}(j)\, C_t, \qquad C_{o,t}(j) = \left(\frac{P_{o,t}(j)}{P_t} \right)^{-1} [1-\alpha_{i,t}(j)]\, C_t, \tag{4}$$

where $P_{o,t}(j)$ is the local price index for the composite of other goods.

The aggregate consumption price index implied by (1) is

$$P_t = \int_0^1 P_{i,t}(j)^{\alpha_{i,t}(j)} P_{o,t}(j)^{1-\alpha_{i,t}(j)} dj. \tag{5}$$

In what follows, we choose P_t as the numeraire.

3.2 Production, Pricing and Producing Decision in the Differentiated Product Sector

In each period, for product i in location j, a number of new establishments, $H_t(j)$, enter the market. Prior to entry, these plants are identical, but upon entry each establishment draws a specific productivity level φ from a cumulative distribution $G(\varphi)$ with support on $[\varphi_{\min}, \infty)$, and a consumer taste level for product i, λ_i, from a cumulative distribution $R_i(\lambda_i)$ with support on $[\lambda_{i\,\min}, \infty)$.

The production of product i requires a location-specific fixed operational cost of $f_{i,t}(j)/Z_t$ in effective labor units each period. To produce $y_{i,t}(j, \varphi, \lambda_i)$ units, the plant with productivity φ and taste λ_i in location j demands the following amount of labor:

$$l_t(j, \varphi) = I_i \left[\frac{y_{i,t}(j, \varphi, \lambda_i)}{Z_t \varphi} + \frac{f_{i,t}(j)}{Z_t} \right], \tag{6}$$

where I_i is an indicator that takes the value 1 if the plant produces product i and 0 otherwise.

Note that there are no operational fixed costs at the establishment level (i.e., no headquarters or overhead costs). This contrasts with Hamano (2025), who incorporates such establishment-level fixed costs in addition to product-specific operational costs.

3.2.1 Product Entry and Exit

We assume that establishments entering at time t only begin producing at time $t+1$. Entrants face local sunk entry costs of $f_{E,t}(j)/Z_t$ in effective labor units. Establishment entry occurs until the expected plant value $v_t(j)$ (defined below) is equal to entry costs, leading to the free entry condition in location j:

$$v_t(j) = w_t \frac{f_{E,t}(j)}{Z_t}. \tag{7}$$

The timing of entry and production implies that the number of establishments in location j evolves according to the law of motion

$$N_t(j) = (1 - \delta_t(j)) \left(N_{t-1}(j) + H_{t-1}(j) \right), \tag{8}$$

where $\delta_t(j)$ denotes the establishment destruction rate at time t in location j.

3.2.2 Average Productivity and Profits

Following Bernard et al. (2010), the taste-weighted average productivity of producers of product i in location j is defined as

$$\widetilde{\varphi}_{i,t}(j) \equiv \left[\int_{\varphi_{\min}}^{\infty} \widetilde{\lambda}_{i,t}(j,\varphi)\, dG(\varphi)\right]^{\frac{1}{\sigma-1}}, \quad \text{where} \quad \widetilde{\lambda}_{i,t}(j,\varphi) \equiv \int_{\lambda^*_{i,t}(j,\varphi)}^{\infty} (\lambda_i \varphi)^{\sigma-1} \frac{dR_i(\lambda_i)}{1-R_i(\lambda^*_{i,t}(j,\varphi))}. \tag{9}$$

In the above expression, $\lambda^*_{i,t}(j,\varphi)$ denotes the cutoff taste level required to profitably produce product i for an establishment with productivity φ in location j. Thus, $\widetilde{\lambda}_{i,t}(j,\varphi)$ represents the average productivity-weighted taste for product i among establishments with productivity φ in location j. It summarizes the range of consumer tastes compatible with producing product i at that productivity level.

Since there are no establishment-specific fixed operational costs, the minimum productivity level required for producing product i is simply $\varphi_{\min}$ in our setup. The term $\widetilde{\varphi}_{i,t}(j)$ therefore contains information about the full joint distribution of productivities and consumer tastes in location j, and can be interpreted as the taste-weighted average productivity of product i in that location.

Using this average, the taste-adjusted real price of product i produced in location j is defined as

$$\widetilde{\rho}_{i,t}(j) = \frac{\sigma}{\sigma-1}\frac{w_t}{Z_t \widetilde{\varphi}_{i,t}(j)}.$$

Based on this real price, we define average profits for product i in location j as

$$\widetilde{d}_{i,t}(j) = \frac{1}{\sigma}\frac{\widetilde{\rho}_{i,t}(j) C_{i,t}(j)}{M_{i,t}(j)} - \frac{w_t f_{i,t}(j)}{Z_t}, \tag{10}$$

and average real profits among all producers in the location as

$$\widetilde{d}_t(j) = \frac{M_{i,t}(j)}{N_t(j)} \widetilde{d}_{i,t}(j). \tag{11}$$

3.2.3 Parametrization of Productivity and Taste Distribution

We assume the following Pareto distributions for $G(\varphi)$ and $R_i(\lambda_i)$, respectively:

$$G(\varphi) = 1 - \left(\frac{\varphi_{\min}}{\varphi}\right)^{\kappa}, \qquad R_i(\lambda_i) = 1 - \left(\frac{\lambda_{i\min}}{\lambda_i}\right)^{\upsilon},$$

where $\varphi_{\min}$ and $\lambda_{i\min}$ are the minimum productivity and minimum taste levels, and where κ and υ determine the shape of the distributions. The parameters κ and υ index the dispersion of productivity and tastes across products: dispersion decreases as these parameters increase, meaning that productivity and tastes become more concentrated near their lower bounds, $\varphi_{\min}$

and $\lambda_{i\,\min}$. In the calibration, we set $\varphi_{\min} = \lambda_{i\,\min} = 1$ without loss of generality. To ensure that the variance of the productivity distribution is finite and that the measure of producers is positive, we assume $\kappa > v > \sigma - 1$.
[3]

$$\widetilde{\varphi}_{i,t}(j) = \left[\frac{v}{v-(\sigma-1)}\right]^{\frac{1}{\sigma-1}} \varphi_{\min} \left(\frac{M_{i,t}(j)}{N_t(j)}\frac{\kappa - v}{\kappa}\right)^{-\frac{1}{v}}. \tag{14}$$

As mentioned earlier, for a firm with the cutoff productivity $\varphi_{\min}$, the zero-profit consumer taste cutoff is defined by $d_{i,t}(\varphi_{\min}, \lambda^*_{i,t}(j, \varphi_{\min})) = 0$. This condition implies

$$\widetilde{d}_{i,t}(j) = \frac{\sigma - 1}{v - (\sigma - 1)} w_t \frac{f_{i,t}(j)}{Z_t}. \tag{15}$$

3.3 Household Budget Constraints and Intertemporal Problems

The household receives labor income by supplying labor L_t at the wage rate w_t. She also receives a share $x_t(j)$ of dividends $\widetilde{d}_t(j)$ and the value $v_t(j)$ associated with the $N_t(j)$ existing establishments held through a mutual fund in each location j. The household spends its income on consumption C_t and on acquiring $x_{t+1}(j)$ shares of the firm composed of existing products $N_t(j)$ and new products $H_t(j)$ at the share price $v_t(j)$. The household budget constraint is therefore

$$L_t w_t + \int_0^1 x_t(j) N_t(j) \big(v_t(j) + \widetilde{d}_t(j)\big)\, dj = C_t + \int_0^1 x_{t+1}(j) v_t(j) \big(N_t(j) + H_t(j)\big)\, dj. \tag{16}$$

During each period t, the household chooses consumption C_t, shareholdings $x_{t+1}(j)$, and labor supply L_t to maximize expected utility subject to the budget constraint (16). The first-order conditions for consumption and labor supply imply the standard labor supply condition:

$$\chi L_t^{\varsigma} = w_t \Lambda_t,$$

where $\Lambda_t = A_t / C_t$ denotes the shadow value of the budget constraint, which is also the marginal utility of consumption.

[3]With this parametrization, the taste-weighted average productivity $\widetilde{\varphi}_{i,t}(j)$ in equation (9) can be written as

$$\widetilde{\varphi}_{i,t}(j) = \left[\frac{v}{v-(\sigma-1)}\right]^{\frac{1}{\sigma-1}} \varphi_{\min}\, \lambda^*_{i,t}(j, \varphi_{\min}), \tag{12}$$

noting that

$$M_{i,t}(j) = \int_{\varphi_{\min}}^{\infty} \left[1 - R_i(\lambda^*_{i,t}(j,\varphi))\right] dG(\varphi)\, N_t(j),$$

so that the fraction of producing plants is

$$\frac{M_{i,t}(j)}{N_t(j)} = \frac{\kappa}{\kappa - v}\, \lambda^*_{i,t}(j, \varphi_{\min})^{-v}. \tag{13}$$

Combining (12) and (13) yields equation (14).

The first-order condition with respect to shareholdings of establishments in location j yields

$$v_t(j) = \beta\big(1 - \delta_t(j)\big)E_t\left[\frac{\Lambda_{t+1}}{\Lambda_t}\big(v_{t+1}(j) + \widetilde{d}_{t+1}(j)\big)\right]. \tag{17}$$

By iterating this condition forward, $v_t(j)$ is the present discounted value of the stream of current and expected profits $\{\widetilde{d}_k(j)\}_{k=t+1}^{\infty}$:

$$v_t(j) = E_t \sum_{k=t+1}^{\infty} \big[\beta\big(1 - \delta_t(j)\big)\big]^{k-t}\left(\frac{\Lambda_t}{\Lambda_k}\right)\widetilde{d}_k(j). \tag{18}$$

3.4 Model Equilibrium and Solution

In the other sectors in location j, where plants are perfectly competitive, the real price $\rho_{o,t}(j)$ equals marginal cost:

$$\rho_{o,t}(j) = \frac{w_t}{Z_t}.$$

Goods market clearing requires

$$Q_t(j) = C_{o,t}(j),$$

where $Q_t(j)$ denotes production in the perfectly competitive sector.

In equilibrium, aggregating household budget constraints yields

$$L_t w_t + \int_0^1 N_t(j)\widetilde{d}_t(j)\,dj = C_t + \int_0^1 v_t(j)H_t(j)\,dj.$$

We express average real sales and define the total real sales of product i in location j as

$$\widetilde{y}_{i,t}(j) = \sigma\left(\widetilde{d}_{i,t}(j) + w_t\frac{f_{i,t}(j)}{Z_t}\right), \qquad \mathcal{Y}_{i,t}(j) \equiv M_{i,t}(j)\widetilde{\rho}_{i,t}(j)\widetilde{y}_{i,t}(j).$$

Real GDP is defined as[4]

$$Y_t \equiv L_t w_t + \int_0^1 N_t(j)\widetilde{d}_t(j)\,dj.$$

We assume symmetry across locations such that $\int_0^1 C_t(j)\,dj = C_t(j)$, $\int_0^1 v_t(j)\,dj = v_t(j)$, $\int_0^1 \rho_{i,t}(j)\,dj = \rho_{i,t}(j)$, $\int_0^1 \rho_{o,t}(j)\,dj = \rho_{o,t}(j)$, $\int_0^1 \widetilde{d}_t(j)\,dj = \widetilde{d}_t(j)$, $\int_0^1 N_t(j)\,dj = N_t(j)$, and $\int_0^1 H_t(j)\,dj = H_t(j)$.

[4] Any empirically relevant variable X_t^e is defined as

$$X_t^e \equiv \frac{P_t}{P_t^e}X_t, \qquad \frac{P_t}{P_t^e} = \frac{\int_0^1 P_{i,t}(j)^{\alpha_{i,t}(j)}P_{o,t}(j)^{1-\alpha_{i,t}(j)}dj}{\int_0^1 P_{i,t}^e(j)^{\alpha_{i,t}(j)}P_{o,t}^e(j)^{1-\alpha_{i,t}(j)}dj} = \int_0^1\left(\frac{P_{i,t}(j)}{P_{i,t}^e(j)}\right)^{\alpha_{i,t}(j)}dj,$$

since $\int_0^1 P_{o,t}(j)\,dj = \int_0^1 P_{o,t}^e(j)\,dj$ without measurement error in the other sector. Because $\alpha_{i,t}(j)$ is very small, the discrepancy between the welfare-consistent price index and the empirically constructed one is negligible, so we use the approximation $P_t/P_t^e \simeq 1$. This allows direct comparison of theoretical and empirical real time series.

Table 2: Summary of the benchmark model for product i in location j

1. Average pricing	$\widetilde{\rho}_{i,t}(j) = \frac{\sigma}{\sigma-1}\frac{w_t}{Z_t\widetilde{\varphi}_{i,t}(j)}$
2. Real taste-adjusted price	$\rho_{i,t}(j)^{1-\sigma} = M_{i,t}(j)\widetilde{\rho}_{i,t}(j)^{1-\sigma}$
3. Demand for product i in location j	$C_{i,t}(j) = \rho_{i,t}(j)^{-1}\alpha_{i,t}(j)C_t$
4. Demand for other products	$C_{o,t}(j) = \rho_{o,t}(j)^{-1}(1-\alpha_i(j))C_t$
5. Price index	$1 = \rho_{i,t}(j)^{\alpha_{i,t}(j)}\rho_{o,t}^{1-\alpha_{i,t}(j)}$
6. Average product profits	$\widetilde{d}_{i,t}(j) = \frac{1}{\sigma}\frac{\rho_{i,t}(j)C_{i,t}(j)}{M_{i,t}(j)} - \frac{w_t f_{i,t}(j)}{Z_t}$
7. Average profits	$\widetilde{d}_t(j) = \frac{M_{i,t}(j)}{N_t(j)}\widetilde{d}_{i,t}(j)$
8. Consumer taste cutoff	$\widetilde{d}_{i,t}(j) = \frac{\sigma-1}{\upsilon-(\sigma-1)}w_t\frac{f_{i,t}(j)}{Z_t}$
9. Taste weighted productivity	$\widetilde{\varphi}_{i,t}(j) = \left[\frac{\upsilon}{\upsilon-(\sigma-1)}\right]^{\frac{1}{\sigma-1}}\varphi_{\min}\left(\frac{M_{i,t}(j)}{N_t(j)}\frac{\kappa-\upsilon}{\kappa}\right)^{-\frac{1}{\upsilon}}$
10. Free entry condition	$v_t(j) = w_t\frac{f_E(j)}{Z_t}$
11. Motion of establishments	$N_{t+1}(j) = (1-\delta_t(j))\left(N_t(j)+H_t(j)\right)$
12. Euler equation	$v_t(j) = \beta\left(1-\delta_t(j)\right)E_t\left[\frac{\Lambda_{t+1}}{\Lambda_t}\left(v_{t+1}(j)+\widetilde{d}_{t+1}(j)\right)\right]$
13. Optimal labor supply	$\chi_t L_t^{\varsigma} = w_t\Lambda_t$
14. Definition of discount factor	$\Lambda_t = A_t/C_t$
15. Aggregation	$L_t w_t + N_t(j)\widetilde{d}_t(j) = C_t + v_t(j)H_t(j)$
16. Good market clearing	$Q_t(j) = C_{o,t}(j)$
17. Pricing in other sectors	$\rho_{o,t}(j) = \frac{w_t}{Z_t}$
18. Definition of total sales of product i	$\mathcal{Y}_{i,t}(j) \equiv M_{i,t}(j)\widetilde{\rho}_{i,t}(j)\widetilde{y}_{i,t}(j)$
19. Definition of GDP	$Y_t = L_t w_t + N_t(j)\widetilde{d}_t(j)$

Finally, the aggregate and product-specific shocks evolve according to

$$\begin{pmatrix} \ln(A_t) \\ \ln(Z_t) \\ \ln(\delta_t(j)/\delta(j)) \\ \ln(\alpha_{i,t}(j)/\alpha_i(j)) \\ \ln(f_{i,t}(j)/f_i(j)) \end{pmatrix} = \begin{pmatrix} \rho_A & 0 & 0 & 0 & 0 \\ 0 & \rho_Z & 0 & 0 & 0 \\ 0 & 0 & \rho_{\delta(j)} & 0 & 0 \\ 0 & 0 & 0 & \rho_{\alpha_i(j)} & 0 \\ 0 & 0 & 0 & 0 & \rho_{f_i(j)} \end{pmatrix} \begin{pmatrix} \ln(A_{t-1}) \\ \ln(Z_{t-1}) \\ \ln(\delta_{t-1}(j)/\delta(j)) \\ \ln(\alpha_{i,t-1}(j)/\alpha_i(j)) \\ \ln(f_{i,t-1}(j)/f_i(j)) \end{pmatrix} + \begin{pmatrix} \sigma_A\varepsilon_{A,t} \\ \sigma_Z\varepsilon_{Z,t} \\ \sigma_{\delta(j)}\varepsilon_{\delta,t(j)} \\ \sigma_{\alpha_i(j)}\varepsilon_{\alpha_{i,t}(j)} \\ \sigma_{f_i(j)}\varepsilon_{f_{i,t}(j)} \end{pmatrix}.$$

Here ρ_A, ρ_Z, $\rho_{\delta(j)}$, $\rho_{\alpha_i(j)}$, and $\rho_{f_i(j)}$ denote the persistence parameters, and the innovations $\varepsilon_{A,t}$, $\varepsilon_{Z,t}$, $\varepsilon_{\delta,t(j)}$, $\varepsilon_{\alpha_{i,t}(j)}$, and $\varepsilon_{f_{i,t}(j)}$ are normally distributed with zero means and variances σ_A^2, σ_Z^2, $\sigma_{\delta(j)}^2$, $\sigma_{\alpha_i(j)}^2$, and $\sigma_{f_i(j)}^2$, respectively. The shocks $\varepsilon_{A,t}$ and $\varepsilon_{Z,t}$ are "aggregate shocks," affecting all products and both sectors. The shock $\varepsilon_{\delta,t(j)}$ is location-specific, while $\varepsilon_{\alpha_{i,t}(j)}$ and $\varepsilon_{f_{i,t}(j)}$ are *location–product-specific shocks* that impact only the corresponding sector. Table 1 summarizes the benchmark model for product i in location j.

4 Calibration and Estimation

We calibrate and estimate the parameters of the theoretical model separately for each product in Kobe. A subset of parameters is assumed to be common across locations and products and is calibrated using standard values from the literature. Product-specific expenditure weights are calibrated using data on final-use expenditures.

The remaining parameters, in particular the persistence and variance of the structural shocks, are estimated at the product level. The estimation exploits both aggregate macroeconomic dynamics and product-specific dynamics as observables, allowing the model to jointly match aggregate fluctuations and heterogeneous product-level responses.

4.1 Calibration

Parameters that are common across products and locations are calibrated using values standard in the literature. The discount factor β is calibrated to imply a 4% annual real interest rate. The inverse Frisch elasticity of labor supply, ς, is taken from Sugo and Ueda (2008), who estimates labor supply elasticity for the Japanese economy. The elasticity of substitution across product varieties, σ and the exogenous establishment destruction rate, δ, are set following Ghironi and Melitz (2005). The parameters υ and κ, which govern the dispersion of tastes and productivity, respectively, are calibrated as in Hamano and Oikawa (2022). These values satisfy the parametric restriction $\kappa > \upsilon > \sigma - 1$ required for aggregation and equilibrium existence.

The fixed operating cost of production for each product i in location j, denoted by $f_i(j)$, is calibrated to replicate the steady-state share of producing establishments in that location, $M_i(j)/N(j)$. Entry fixed costs are normalized to $f_e = 1$ at the steady state without loss of generality. Finally, the parameter governing the disutility of labor, χ, is chosen so that steady-state labor supply is normalized to unity.

Because all goods are assumed to be final goods in the theoretical model, we explicitly calibrate the expenditure weight of each product. Since these weights are preference parameters, we assume that they are not location-specific, so that $\alpha_i(j) = \alpha_i$ for all j. The calibration of α_i is based on household expenditure data from the use table of the JIP 2005, combined with information on Japanese product classifications.[5]

The manufacturing census data define 2,061 product categories at the six-digit product level. These products are mapped into two-digit JIP sectors according to the concordance reported in Table C.1 in the Appendix. For each product i belonging to sector k, the expenditure weight is computed as

$$\alpha_i = \frac{1}{n_k} \alpha_k^{\mathrm{IO}}, \qquad i \in k,$$

where n_k denotes the number of six-digit product categories in two-digit sector k, and α_k^{IO} is

[5] https://www.rieti.go.jp/jp/database/jip.html

Table 3: Calibration

Common for all products		
β	Discount factor	0.9615
ς	Inverse of Frisch elasticity of labor	2.149
σ	Elasticity of substitution of product varieties	3.80
κ	Productivity dispersion	11.5
υ	Taste dispersion	4.18
δ	Exogenous death shock	0.1
f_e	Entry fixed costs	1
Product Specific		
$\alpha_i(j)$	Preference weight	computed
$f_i(j)$	Operational Fixed costs	computed
χ	Labor supply dis-utility	computed

the sectoral expenditure share from the JIP 2005 use table. The resulting calibrated expenditure weights at the two-digit level are summarized in Table C.2 in the Appendix.

4.2 Estimation

The remaining parameters—namely the autoregressive coefficients and the variances of the structural innovations $\varepsilon_{A,t}$, $\varepsilon_{Z,t}$, $\varepsilon_{\delta,t}(j)$, $\varepsilon_{\alpha_{i,t}}(j)$, and $\varepsilon_{f_{i,t}}(j)$—are estimated by maximum likelihood. The estimation is conducted separately for each product. Our sample consists of 406 products defined at the six-digit level in Kobe over the estimation period.

For each product, we use four observables: the growth rate of aggregate Japanese GDP, Y_t, the growth rate of the total number of establishments in a location, $N_t(j)$, the real product-level sales growth, $\widetilde{y}_{i,t}(j)$, and the growth rate of the number of producing establishments, $M_{i,t}(j)$. Measurement errors are explicitly incorporated into the state-space representation to account for noise in the product-level data.[6]

Figure 4 displays the distribution of the estimated parameters across products, together with the estimated standard deviations of the measurement errors.

We observe substantial heterogeneity in the product–location–specific shocks, in particular those associated with $\alpha_i(j)$ and $f_i(j)$. The estimated variances of these shocks exhibit fat-tailed distributions with pronounced right tails. In contrast, the aggregate shocks and location-specific aggregate shocks are more tightly concentrated, displaying considerably less dispersion. An interesting feature is that the innovation variance of the location-specific exit shock, $\varepsilon_{\delta,t}(j)$, exhibits a bimodal distribution, with peaks near zero and around 0.01.

Measurement errors for real sales growth are relatively large, with most estimates concentrated around 0.3, whereas measurement errors for the other observables are generally small, except for GDP growth in a limited number of products. A similar pattern is observed for other

[6]The estimation is carried out using the RISE toolbox (Maih, 2015).

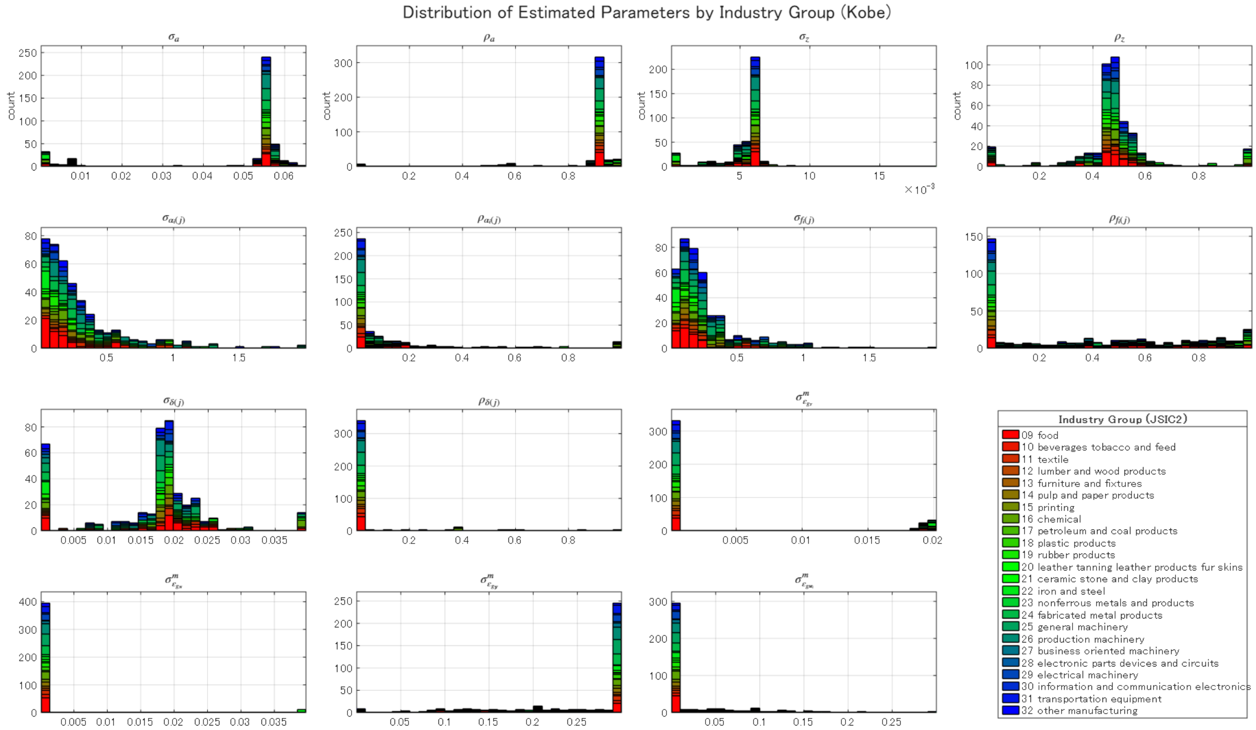


Figure 4: Parameter Distribution for Kobe

cities, such as Nagoya (see Figure E.1 in the Appendix).

To investigate whether there are systematic differences across sectors, we construct median products based on the subset of products common to both Kobe and Nagoya. This yields a sample of 300 products. Nagoya features a larger product coverage than Kobe, with 685 products compared to 406 in Kobe. For the common sample, we define the median product as the product whose estimated parameter vector is closest, in terms of distance, to the median parameter vector computed across products. This definition is used for subsequent analysis.

Table D.1 reports the median product for the full set of 300 common products, as well as for each two-digit sector. The median product for Kobe is identified as a six-digit product belonging to the fabricated metal products sector.

Table 4 reports the median parameter estimates for the 300 common products in Kobe and Nagoya, as well as sector-specific medians at the two-digit level. Consistent with the full-sample results, we find that heterogeneity is most pronounced for the product–location–specific shocks, $\varepsilon_{\alpha_{i,t}}(j)$ and $\varepsilon_{f_{i,t}}(j)$, while aggregate and location-level shocks display substantially less dispersion across sectors.

Table 4: Median Parameter Vectors — Kobe

Region	2 digit	σ_a	ρ_a	σ_z	ρ_z	σ_{α_i}	ρ_{α_i}	σ_{f_i}	ρ_{f_i}	σ_δ	ρ_δ	$\sigma_{\varepsilon^m_{g_Y}}$	$\sigma_{\varepsilon^m_{g_N}}$	$\sigma_{\varepsilon^m_{g_{MYI}}}$	$\sigma_{\varepsilon^m_{g_{MI}}}$
Panel A: Overall Median (All Products)															
Kobe	–	0.055666	0.90757	0.0059469	0.46933	0.20482	0.016718	0.18245	0.27638	0.018501	0.001	0.0001	0.0001	0.3	0.0001
Panel B: Median by 2 digit															
Kobe	9	0.055502	0.90802	0.0059312	0.46797	0.10246	0.066723	0.13610	0.51568	0.019256	0.001	0.0001	0.0001	0.22913	0.0001
Kobe	10	0.039114	0.92095	0.0047167	0.52080	0.16114	0.085677	0.10458	0.45187	0.025371	0.001	0.0092094	0.0001	0.20491	0.0001
Kobe	11	0.055747	0.90727	0.0059530	0.48099	0.28631	0.012657	0.16774	0.13354	0.018743	0.001	0.0001	0.0001	0.3	0.0001
Kobe	12	0.056370	0.91016	0.0056436	0.48382	0.34786	0.069900	0.21995	0.45116	0.018655	0.001	0.0001	0.0001	0.3	0.0001
Kobe	13	0.055763	0.90750	0.0059588	0.46617	0.14746	0.030134	0.13427	0.00100	0.018016	0.001	0.0001	0.0001	0.3	0.0001
Kobe	14	0.055684	0.90702	0.0059451	0.46831	0.25034	0.0075119	0.26742	0.046538	0.018552	0.001	0.0001	0.0001	0.29831	0.0001
Kobe	15	0.055661	0.90748	0.0059721	0.46715	0.12562	0.0054149	0.11042	0.00100	0.018542	0.001	0.0001	0.0001	0.3	0.0001
Kobe	16	0.055516	0.90756	0.0059740	0.47904	0.31394	0.0072307	0.24663	0.29963	0.018888	0.001	0.0001	0.0001	0.3	0.0001
Kobe	17	0.0043883	0.00100	0.0057827	0.53786	0.086512	0.092870	0.060144	0.099236	0.000100	0.001	0.018666	0.0001	0.27053	0.0001
Kobe	18	0.055631	0.90753	0.0059893	0.47582	0.24475	0.00100	0.19972	0.25489	0.019033	0.001	0.0001	0.0001	0.3	0.0001
Kobe	19	0.055986	0.90956	0.0058317	0.47060	0.12319	0.040874	0.12059	0.26359	0.018614	0.001	0.0001	0.0001	0.23281	0.0001
Kobe	20	0.055646	0.90758	0.0059692	0.46666	0.034127	0.00100	0.066896	0.80827	0.018685	0.001	0.0001	0.0001	0.059111	0.0001
Kobe	21	0.055677	0.90756	0.0059773	0.46988	0.21624	0.00100	0.17283	0.75550	0.018840	0.001	0.0001	0.0001	0.26394	0.0001
Kobe	22	0.028534	0.94405	0.0014882	0.62666	0.013626	0.14770	0.11947	0.34345	0.017915	0.001	0.0048253	0.0001	0.3	0.0001
Kobe	23	0.055694	0.90753	0.0059557	0.46637	0.080203	0.00100	0.18755	0.096329	0.018379	0.001	0.0001	0.0001	0.18241	0.0001
Kobe	24	0.055640	0.90748	0.0058916	0.46369	0.20837	0.038721	0.15813	0.11208	0.018207	0.001	0.0001	0.0001	0.3	0.0001
Kobe	25	0.055727	0.90726	0.0059606	0.46878	0.38366	0.0079807	0.29136	0.029077	0.018505	0.001	0.0001	0.0001	0.3	0.0001
Kobe	26	0.055684	0.90748	0.0059638	0.46746	0.27645	0.0031723	0.22038	0.32696	0.018414	0.001	0.0001	0.0001	0.3	0.0001
Kobe	27	0.055413	0.90117	0.0052150	0.41935	0.18074	0.028817	0.22394	0.51033	0.020387	0.0051875	0.0001	0.0001	0.3	0.0001
Kobe	28	0.010783	0.58105	0.0053658	0.47319	0.23659	0.00100	0.17604	0.48244	0.012513	0.001	0.018807	0.0001	0.3	0.0001
Kobe	29	0.055749	0.90805	0.0058947	0.47434	0.19682	0.020648	0.29044	0.034066	0.018560	0.001	0.0001	0.0001	0.3	0.0001
Kobe	30	0.055515	0.90780	0.0059927	0.47121	0.065765	0.044033	0.15868	0.22446	0.019700	0.001	0.0001	0.0001	0.26073	0.013394
Kobe	31	0.055582	0.90756	0.0059064	0.46846	0.22090	0.00100	0.19499	0.50662	0.019494	0.001	0.0001	0.0001	0.3	0.0001
Kobe	32	0.055735	0.90755	0.0059532	0.47106	0.17312	0.052504	0.16682	0.29366	0.017813	0.001	0.0001	0.0001	0.26409	0.037426

5 Macroeconomic Dynamics at the Product Level

5.1 Variance Decomposition

The estimation results in Section 4.2 reveal substantial heterogeneity in both the persistence and the variance of structural shocks across products. This heterogeneity is particularly pronounced for product–location–specific demand and operating cost shocks, $\varepsilon_{\alpha_{i,t}}(j)$ and $\varepsilon_{f_{i,t}}(j)$, whose estimated variances display considerable dispersion. In contrast, aggregate shocks and location-level exit shocks are much more tightly concentrated across products. While these results establish heterogeneity at the level of estimated parameters, they do not by themselves indicate how this heterogeneity maps into fluctuations of observable quantities.

To assess the quantitative implications of the estimated structural heterogeneity, we conduct an infinite-horizon variance decomposition based on the estimated model. This exercise links the estimated shocks to fluctuations in aggregate GDP, product-level real sales, and both the location-wide and product-level extensive margins. In doing so, the variance decomposition provides a disciplined interpretation of the estimation results and clarifies the distinct roles played by aggregate, location-specific, and product–location–specific shocks.

The analysis focuses on the subset of products common to Kobe and Nagoya (300 products), which ensures comparability across locations and facilitates the subsequent relative historical decompositions and counterfactual analysis.

As Figures 5 and 6 show, product-level outcomes are governed by product–location–specific shocks. In particular, product-level real sales are almost entirely explained by product-specific demand shocks, while fluctuations in the number of establishments producing a given product

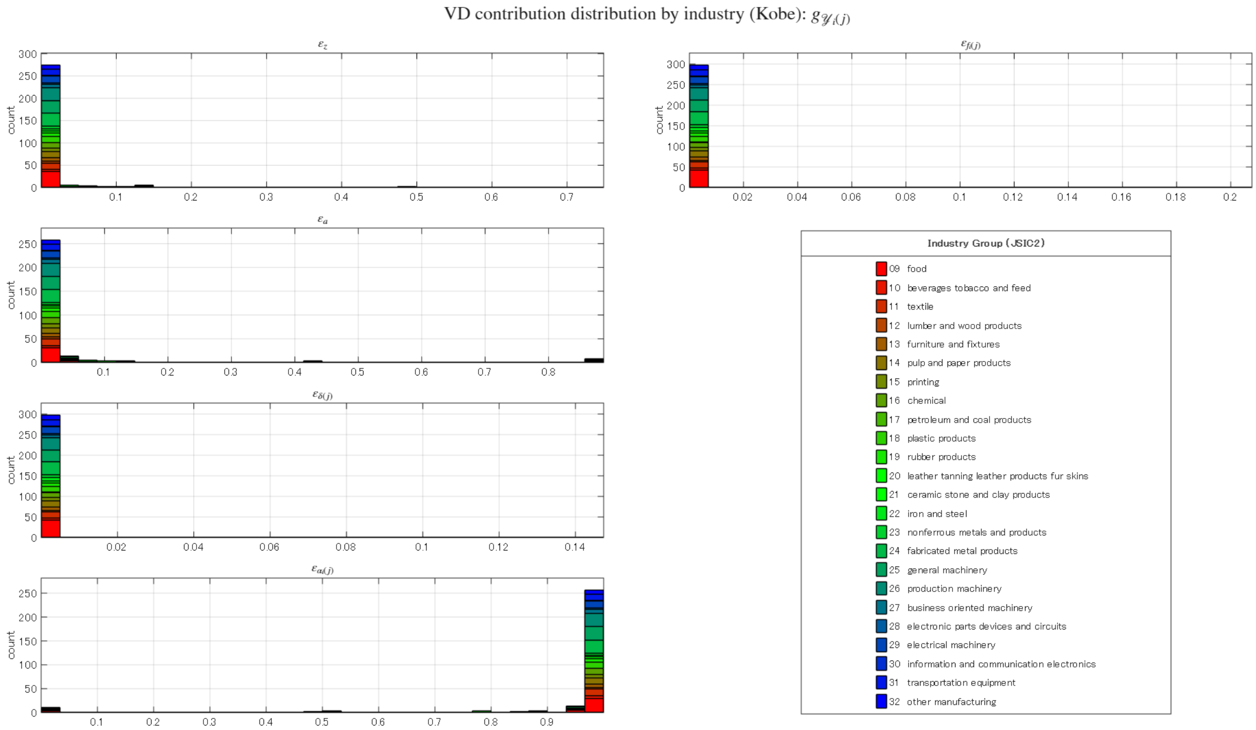


Figure 5: Variance decomposition of the growth rate of product real sales

Note: The figure presents the distribution of the variance decomposition of the growth rate of product real sales. In each panel, the horizontal axis shows the relative contribution of each shock.

are driven by product-specific demand and operating cost shocks.

In contrast, fluctuations in the total number of establishments in a location are driven primarily by aggregate productivity and demand shocks, as well as by the location-specific exit shock, as shown in Figure F.2 in the Appendix. Fluctuations in GDP growth are driven exclusively by aggregate productivity and demand shocks, as illustrated in Figure F.1 in the Appendix.

These findings provide a direct bridge between the structural estimation and the subsequent analysis. They justify our focus on median products as representative objects and motivate the use of product-level historical decomposition and counterfactual experiments.

5.2 Relative Historical Decomposition between Kobe and Nagoya

Figure 7 shows the relative historical decomposition of the observables for the Kobe median product with respect to Nagoya. It reveals the pattern indicated by the variance decomposition in the previous section: aggregate shocks matter only for the growth rate of real GDP and for local extensive margins. Product–location–specific demand shocks account solely for the variation in real sales, while both product–location–specific demand and operating cost shocks drive fluctuations in the growth rate of the number of producing establishments. The growth rate of local extensive margins is driven primarily by the location-specific exit shock as well as by aggregate

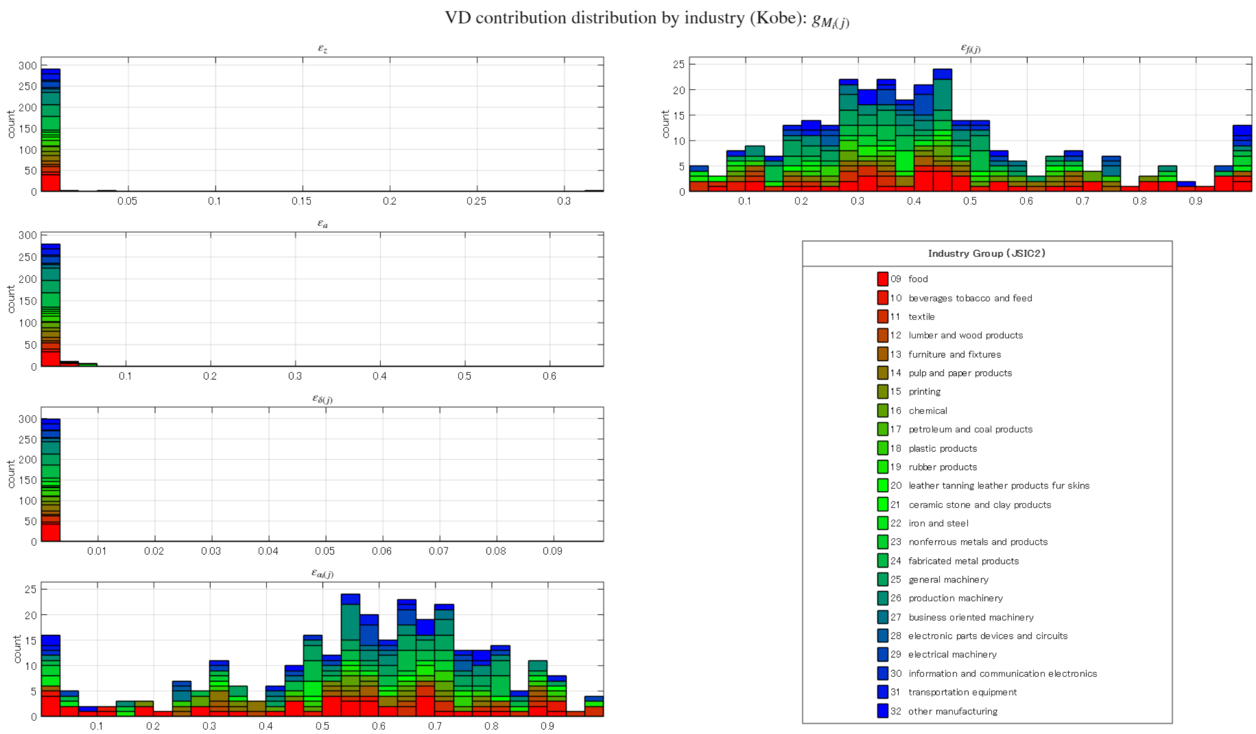


Figure 6: Variance decomposition of the growth rate of the number of product-producing establishments

Note: The figure presents the distribution of the variance decomposition of the growth rate of the number of product-producing establishments. In each panel, the horizontal axis shows the relative contribution of each shock.

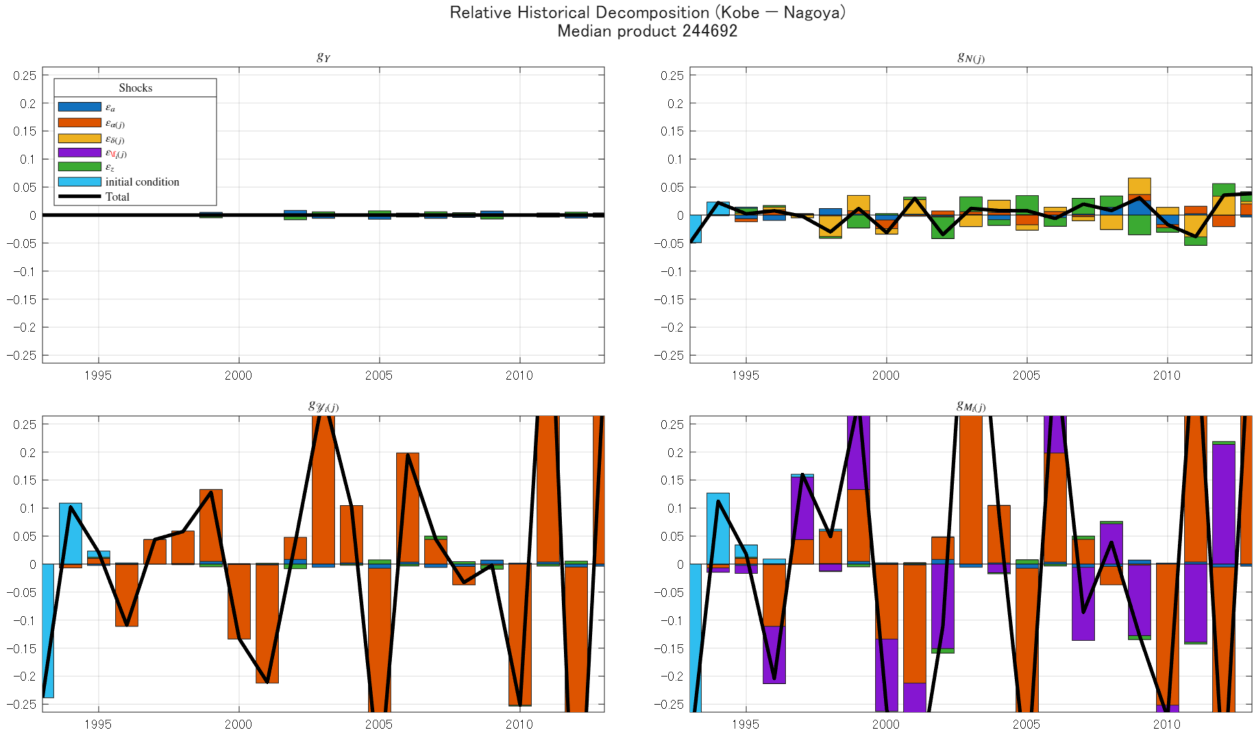


Figure 7: Power conversion equipment / apparatus (e.g., converters, inverters, rectifiers, etc.)

shocks.

We confirm very similar patterns for the median products defined within two-digit sectors (Figures G.1–G.4 in the Appendix). These results therefore point to the presence of heterogeneity across sectors.

5.3 Counterfactual analysis

In this section, we perform a counterfactual analysis. The specificity of the analysis lies in using Nagoya shocks for the period 1994–1997 as the benchmark counterfactual case. This period corresponds to the years in which Kobe is assumed to have been subject to earthquake-related disturbances. As shown in the variance decompositions, the prominence of product–location–specific shocks implies that replacing aggregate shocks alone is insufficient to replicate the local dynamics induced by large disasters such as the Kobe earthquake. Accordingly, our counterfactual consists of a model parameterized using the Kobe estimates and smoothed shocks for each product common to Kobe and Nagoya, except that the series of smoothed shocks from 1994 to 1997 are replaced by those obtained from the Nagoya estimates for the purpose of counterfactual simulation.

Figure 8 presents the actual and counterfactual simulations for the Kobe median product. The figure reports the observables, as well as the average taste-weighted efficiency of producing establishments for the median product and the number of entrants in the region. Counterfactual

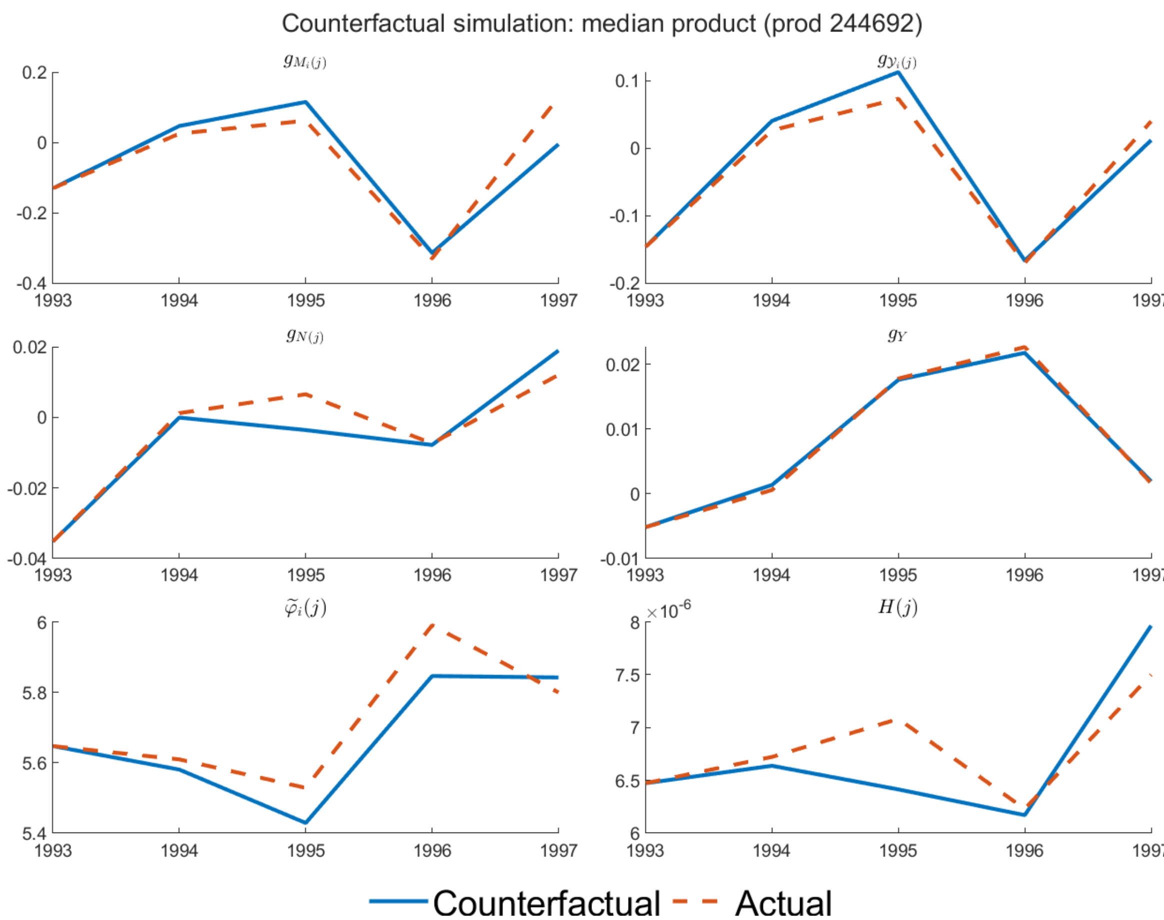


Figure 8: Counterfactual simulation

Note: The figure plots actual and counterfactual series from 1993 to 1997 for the Kobe median product. Solid and dashed lines correspond to the counterfactual (Nagoya smoothed shocks) and actual (Kobe smoothed shocks) simulations, respectively. All series are expressed in level. Measurement errors are ignored in the simulation.

simulations using Nagoya shocks are shown with solid lines, while the benchmark simulations are shown with dashed lines.

For the median product, the counterfactual growth rates of the number of producing establishments and real sales are higher in 1995 than in the benchmark simulations. As expected, the counterfactual path of Japanese GDP is almost identical to that of the benchmark case. The growth rate of the total number of local establishments is slightly lower in the counterfactual simulation; however, the difference is negligible and consistent with the nearly identical changes in the number of entrants between the benchmark and counterfactual simulations.

In both the benchmark and counterfactual simulations, we observe a "Schumpeterian" mechanism at work, whereby taste-weighted efficiency increases. In the counterfactual case with Nagoya shocks, however, this mechanism is moderated.

We also report counterfactual simulations for the median product within each two-digit sector in Figures H.1–H.2 in the Appendix. These correspond to the same median products used in the relative historical decompositions. Because the differences are small, we report only the simulations for the growth rate of the number of producing establishments and real product sales. We observe some heterogeneity across these median products. For example, real sales of the median product in the food sector exhibit almost identical benchmark and counterfactual simulations.

Such heterogeneity is most clearly illustrated in Figure 9, which reports histograms of cumulative differences between actual and counterfactual values of each variable from 1995 to 1997. The impact of the earthquake is heterogeneous across products, even within sectors, and we observe both positive and negative impacts on real product sales growth and on the growth rate of the number of producing establishments. Consistent with the results for the Kobe median product, average differences (actual minus counterfactual) are -0.0039 and -0.0045 for real product sales growth and the number of producing establishments.[7]

Relative to product–location–specific variables, the differences between actual and counterfactual values are small for local extensive margins and aggregate GDP. In particular, consistent with the distribution of the total number of local establishments, entry exhibits very limited dispersion. The distribution of taste-weighted efficiency indicates that the Schumpeterian mechanism is also at work, albeit in a highly heterogeneous manner.

6 Discussion

To what extent are the results from the structural estimation using the DSGE model consistent with the event-study analysis developed in the earlier section? The empirical dynamic DID and the structural model yield broadly consistent assessments of the impact of the Kobe

[7] Table H.1 in the Appendix summarizes the list of the most affected products in terms of real product sales growth.

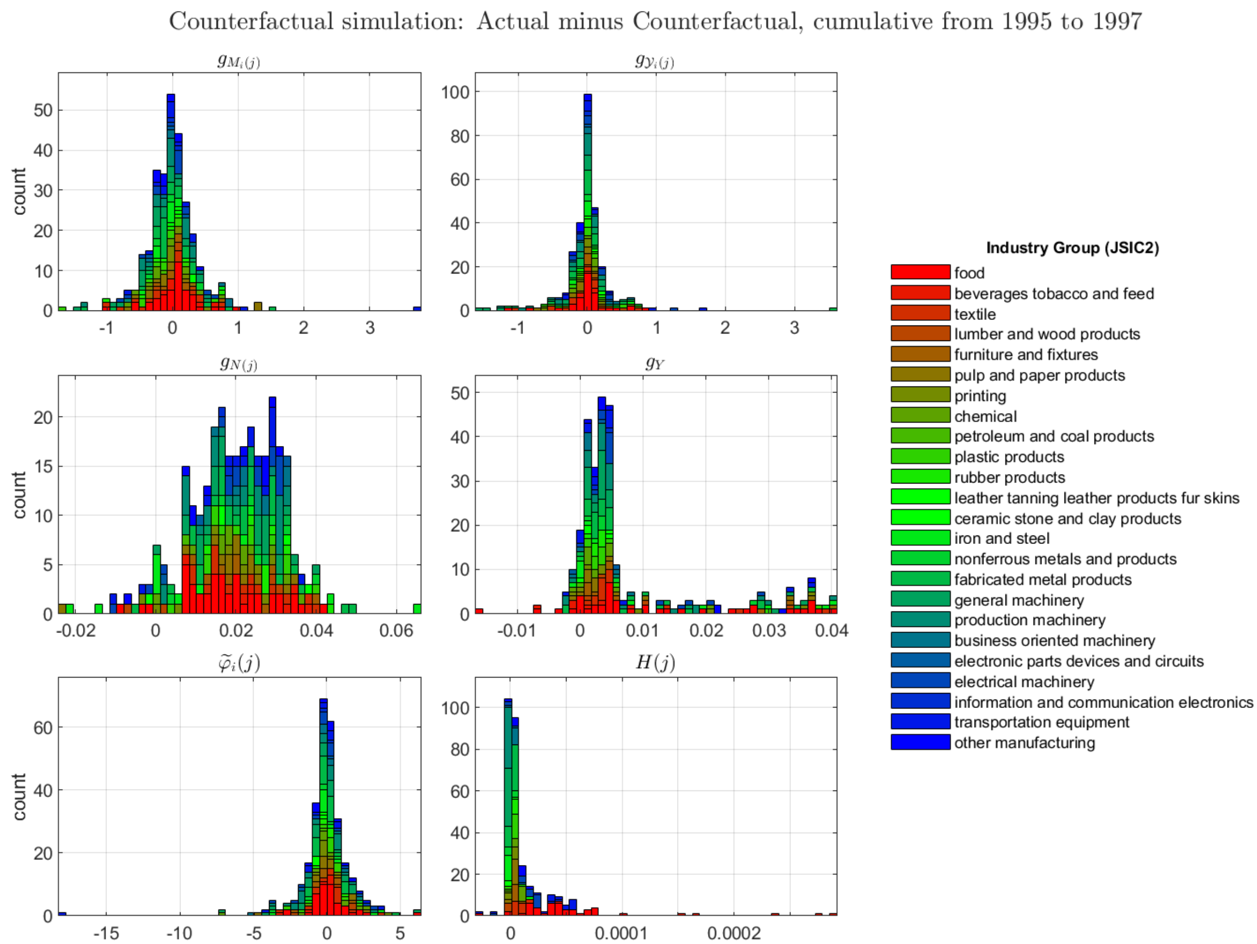


Figure 9: Counterfactual simulation

Note: The figure plots histograms of cumulative differences, defined as actual (Kobe smoothed shocks) minus counterfactual (Nagoya smoothed shocks), for each variable over the period 1995–1997.

	Sales	Nb. of establishment
1995	0.2184***	0.3779***
1996	0.2425***	0.4468***
1997	0.2571***	0.4607***

Table 5: Spearman rank correlation coefficient of the 1995 Kobe earthquake impact between empirical and structural models

Notes: *** indicates significance at 1% level.

earthquake. This consistency is supported by positive Spearman rank correlations between the estimated event-study coefficients and the corresponding coefficients from the relative smoothed value in 1995, as reported in Table 5. The correlation for sales ranges from 0.22 to 0.26, while the corresponding values for the number of establishments range from 0.38 to 0.46, with all coefficients statistically significant at the 1% level. Figures 10 and 11 further illustrate this result: the scatter plots comparing empirical and structural coefficients display upward-sloping fitted lines, indicating that both approaches broadly agree on which products were most affected.

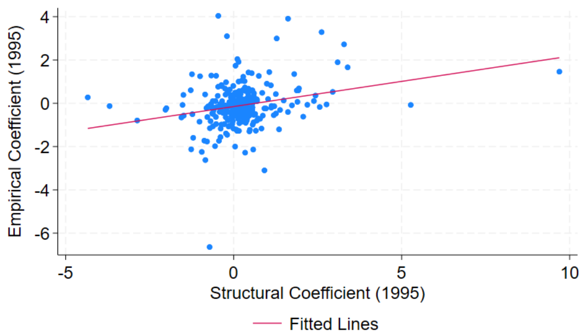
The moderate magnitude of these correlations, however, also reflects discrepancies between the two approaches. We identify two plausible explanations. First, measurement errors in real sales growth are substantial, generating high-frequency noise that is explicitly accounted for in the state-space representation of the structural model. By contrast, the empirical dynamic DID remains more sensitive to such fluctuations.[8]

7 Conclusion

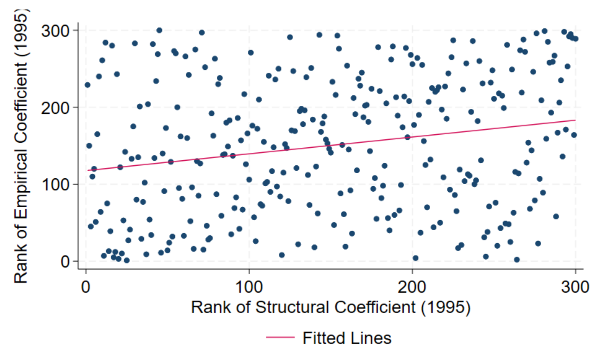
This paper studies how a large, localized disaster propagates through an economy by focusing on product-level dynamics within a structurally estimated macroeconomic framework. Using rich census data on manufacturing establishments in Kobe surrounding the 1995 earthquake, we combine reduced-form identification with a product-level DSGE model to quantify the relative importance of aggregate, location-specific, and product–location–specific shocks.

Our empirical analysis documents large and persistent declines in real sales and the number of producing establishments following the earthquake, alongside substantial heterogeneity across products. Even within narrowly defined sectors, product-level responses vary widely, highlighting the limitations of analyses based solely on sectoral or regional aggregates. Dynamic difference-in-differences estimates confirm the causal impact of the disaster while revealing pronounced dispersion in treatment effects across products.

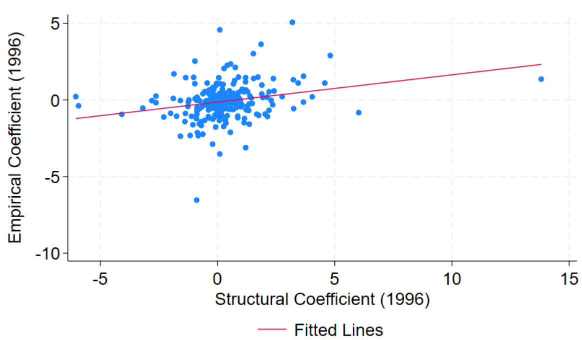
[8] Another explanation is that the possibility that empirical dynamic DID estimates may fail to fully control for unobserved, time-invariant characteristics—such as differences in product scale between Kobe and Nagoya—which can lead to an overestimation of damage. While the DID framework includes fixed effects to mitigate this concern, the structural model disciplines the data using counterfactual Nagoya shocks. This methodological difference can generate divergent product-level rankings across the two approaches.



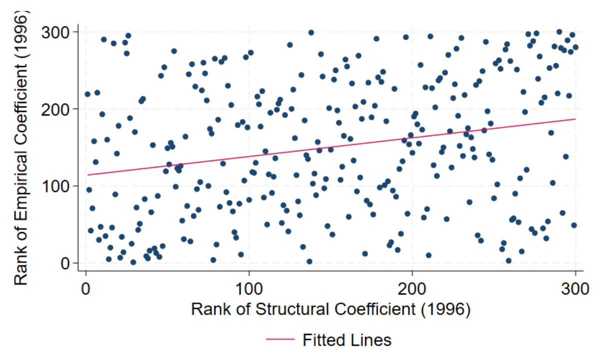
(a) Coefficients for sales in 1995



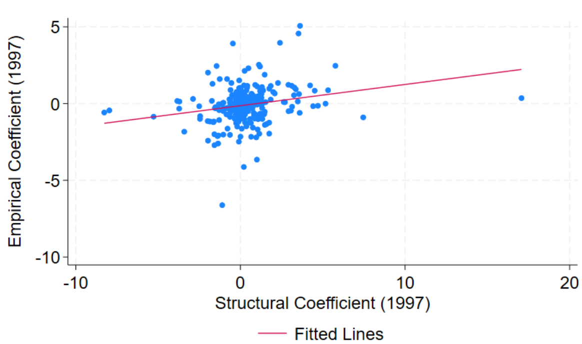
(b) Rank of coefs. for sales in 1995



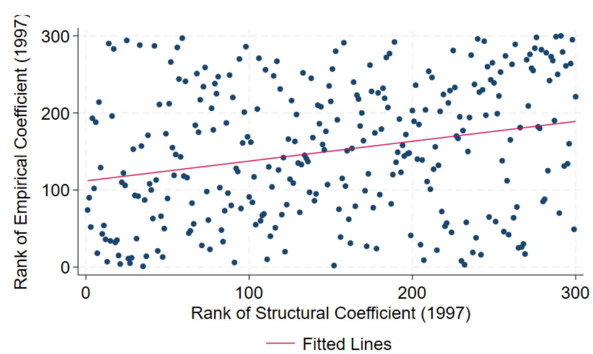
(c) Coefficients for sales in 1996



(d) Rank of coefs. for sales in 1996

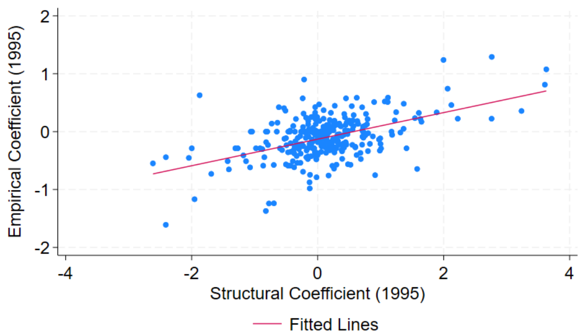


(e) Coefficients for sales in 1997

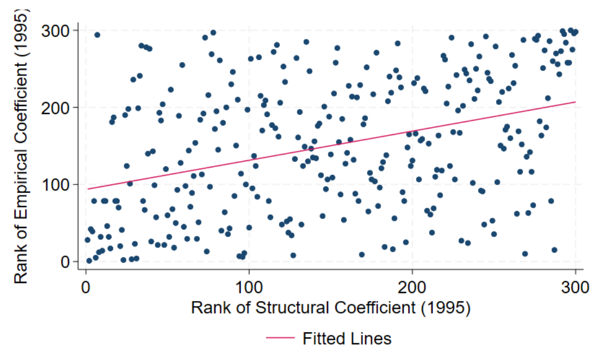


(f) Rank of coefs. for sales in 1997

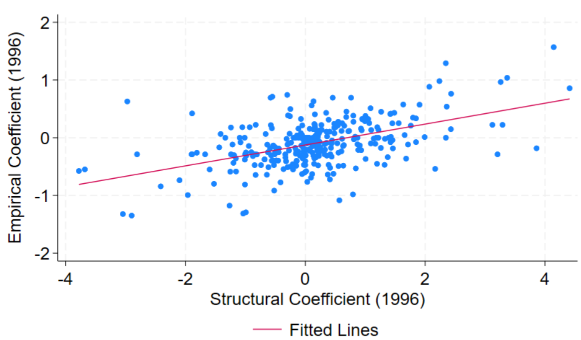
Figure 10: Consistency of the empirical and structural results: Sales



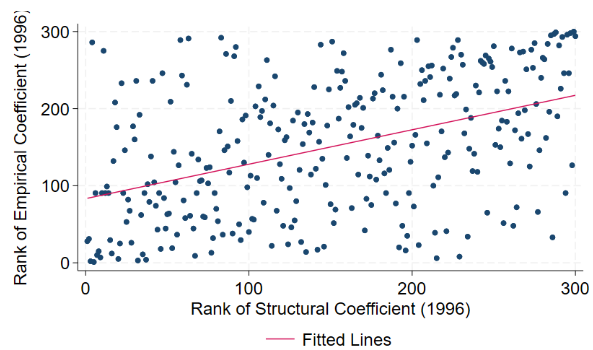
(a) Coefficients for nb. establishment in 1995



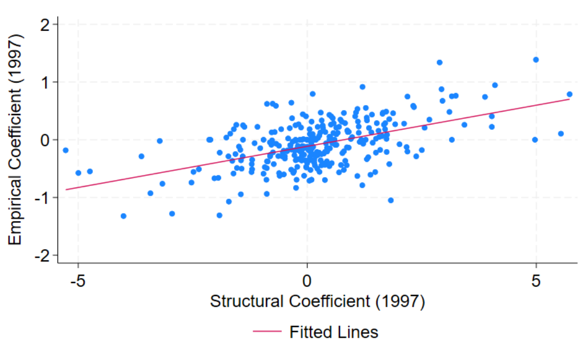
(b) Rank of coefs for nb. establishment in 1995



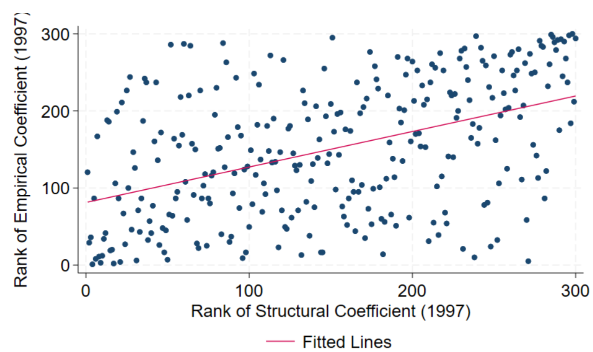
(c) Coefficients for nb. establishment in 1996



(d) Rank of coefs for nb. of establishment in 1996



(e) Coefficients for nb. establishment in 1997



(f) Rank of coefs for nb. establishment in 1997

Figure 11: Consistency of the empirical and structural results: Nb. of establishments

The structural estimation provides a quantitative interpretation of these patterns. Variance decompositions show that fluctuations in product-level outcomes are overwhelmingly driven by product–location–specific demand and operating cost shocks, whereas aggregate shocks mainly govern aggregate GDP and local extensive margins. Relative historical decompositions between Kobe and Nagoya further indicate that the post-earthquake dynamics of product-level sales and establishment counts are largely accounted for by product-specific disturbances. Counterfactual simulations reinforce this conclusion by showing that the impact of the earthquake is highly heterogeneous across products, with both positive and negative effects observed even within the same sector.

Taken together, these findings underscore the central role of product-level heterogeneity in shaping local economic resilience to large shocks. They suggest that disaster propagation and recovery cannot be adequately understood through aggregate or sectoral lenses alone. From a methodological perspective, the paper demonstrates how reduced-form evidence from natural experiments can be disciplined and interpreted within a structural framework, allowing for economically meaningful counterfactual analysis.

More broadly, our results point to the importance of granular data and models for the study of local macroeconomic dynamics. Understanding how shocks transmit through product-level margins is essential for assessing the persistence of local economic losses and for designing policies aimed at fostering resilience in the face of large, spatially concentrated disruptions.

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A Data

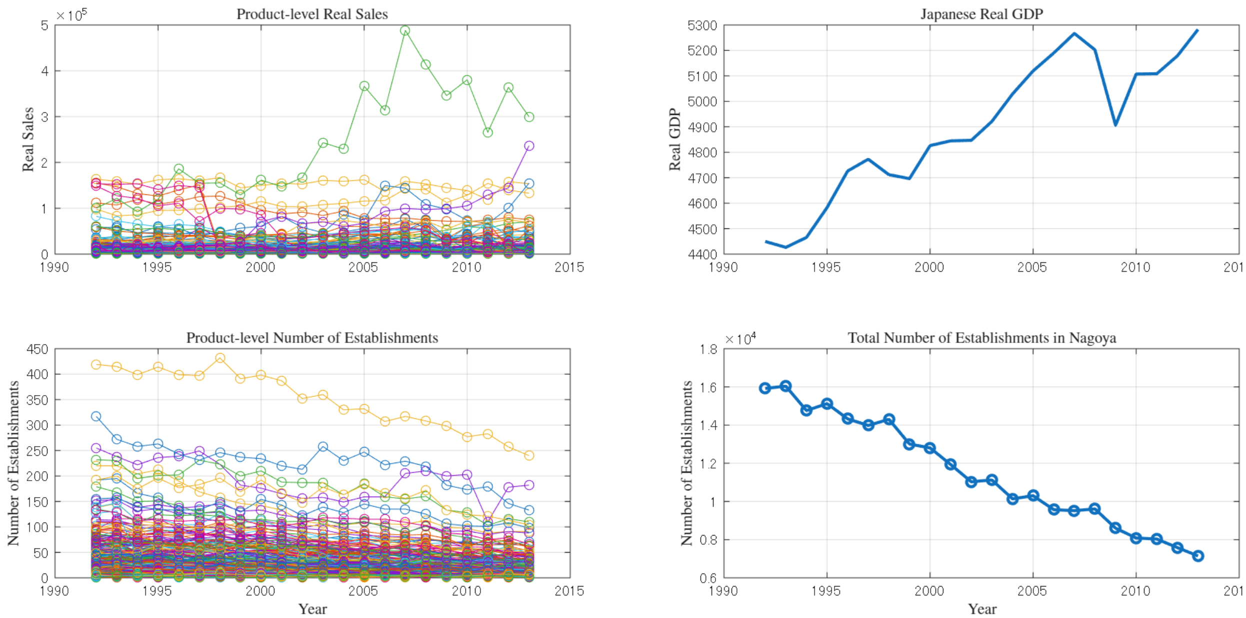


Figure A.1: Data for Nagoya

Note: The figure presents product-level real sales, the number of product-producing establishments, and the total number of establishments in Nagoya.

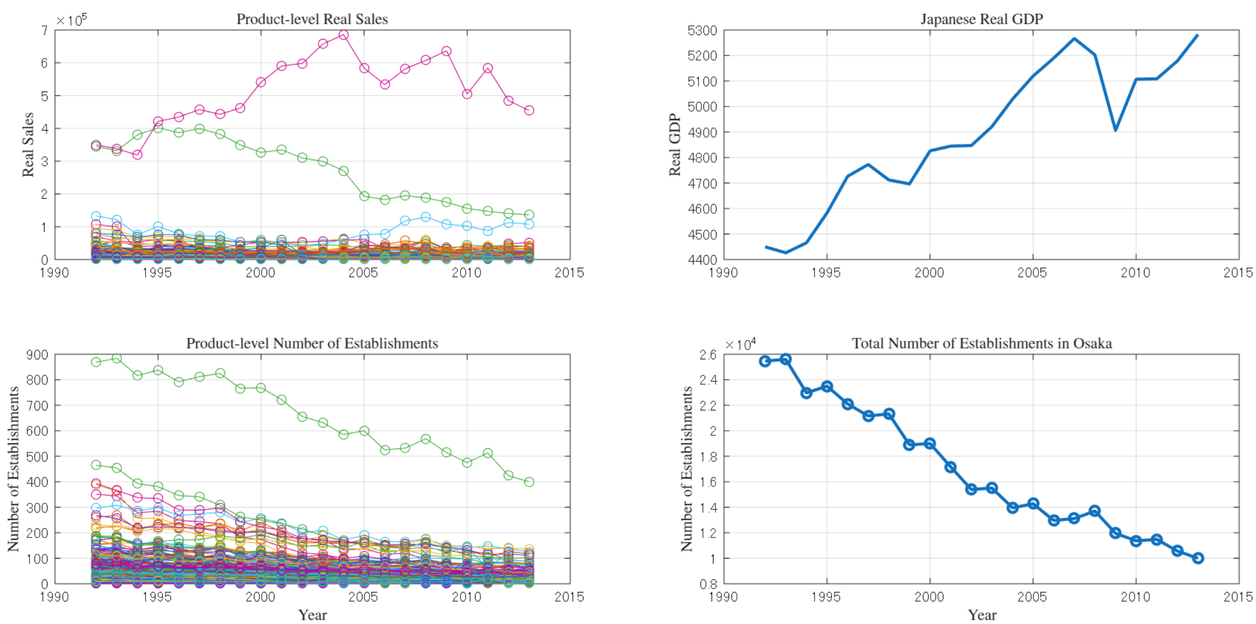


Figure A.2: Data for Osaka

Note: The figure presents product-level real sales, the number of product-producing establishments, and the total number of establishments in Osaka.

B Additional empirical results

B.1 Empirical analysis using Nagoya, Aichi as control group

Table B.1 presents the dynamic difference-in-differences estimates for log sales, using the sample from Nagoya, Aichi Prefecture. Equation 5 is the main result presented in Figure 2. Comparing the main result to earlier specifications, the naive estimator (Equation 1) suggested a massive immediate drop of -0.513, but the inclusion of granular location*times*product fixed effects in Equation 3 reduced this coefficient to -0.174 while raising the R^2 from 0.040 to 0.849. This dramatic shift reveals that the vast majority of the treatment effect observed in the naive model was spurious—driven by the fact that treated units had inherently lower sales regardless of the event. The jump in explanatory power suggests that unobserved, time-invariant characteristics specific to each location-product pair are the primary drivers of performance, and failing to control for them leads us to overestimate the damage of the Kobe earthquake. The inclusion of year-fixed effects and clustering further strengthens the robustness of the final estimate. The transition from Equation 3 to Equation 4 shows that omitting time controls biases the coefficient of t upwards from -0.174 to -0.099, indicating that the event coincided with a general economic downturn that affected all units. By absorbing these common shocks, the model isolates the excess decline specific to the treated group. Finally, Equation 5 refines the statistical inference by clustering standard errors. This adjustment accounts for serial correlation within units, tightening the standard errors (e.g., from 0.084 to 0.056 at time t) and confirming that the estimated 9.9% drop is statistically significant at the 10% level.

Table B.2 details the dynamic difference-in-differences estimates for the log number of establishments. We plot the preferred specification, which is Equation 5. The naive estimator (Equation 1) suggests a catastrophic drop of nearly 58% (-0.577) but explains only 13.6% of the variation. However, introducing the location $\times$ product fixed effects in Equation 3 drastically corrects the coefficient to -0.144. It boosts the explanatory power to 91.5%, implying that the number of establishments is almost entirely determined at the specific location-product pairs. Importantly, the estimated impact shrinks by roughly 75% but remains economically substantial. In addition, including year-fixed effects filters out aggregate economic trends. Treatment effects in Equation 4 become moderate compared to those in Equation 3. This indicates that the event coincided with a broader period of firm exits across the entire economy. Lastly, clustering at product $\times$ location level, equation 5 demonstrates the robustness of our findings. The standard errors in Equation 5 are tight (0.021), confirming that the 10% drop is significant at the 1% level and providing statistical evidence that the Kobe earthquake caused a firm exit.

B.2 Empirical analysis using Osaka, Osaka as control group

To test for robustness, we estimated dynamic difference-in-differences for log sales and log number of establishments using the Osaka sample. As shown in Figure B.1, the results are

	(1)	(2)	(3)	(4)	(5)
	Dep. Var.: log Sales				
$t-2$	-0.219**	0.120+	0.120**	0.026	0.026
	(0.108)	(0.093)	(0.061)	(0.084)	(0.038)
t	-0.513***	-0.174*	-0.174***	-0.099+	-0.099*
	(0.108)	(0.093)	(0.061)	(0.084)	(0.056)
$t+1$	-0.522***	-0.183**	-0.183***	-0.084+	-0.084+
	(0.108)	(0.093)	(0.061)	(0.084)	(0.059)
$t+2$	-0.534***	-0.195**	-0.195***	-0.088+	-0.088+
	(0.108)	(0.093)	(0.061)	(0.084)	(0.066)
$t+3$	-0.651***	-0.312***	-0.312***	-0.142*	-0.142*
	(0.108)	(0.093)	(0.061)	(0.084)	(0.073)
$t+4$	-0.747***	-0.408***	-0.408***	-0.127+	-0.127*
	(0.108)	(0.093)	(0.061)	(0.084)	(0.077)
$t+5$	-0.803***	-0.464***	-0.464***	-0.009	-0.009
	(0.036)	(0.068)	(0.044)	(0.062)	(0.084)
Constant	7.615***	7.454***	7.454***	7.287***	7.287***
	(0.023)	(0.034)	(0.022)	(0.030)	(0.033)
Location FE	No	Yes	No	No	No
Product FE	No	Yes	No	No	No
Location×Product FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Cluster	No	No	No	No	Yes
Observations	12,600	12,600	12,600	12,600	12,600
R-squared	0.040	0.639	0.849	0.856	0.856

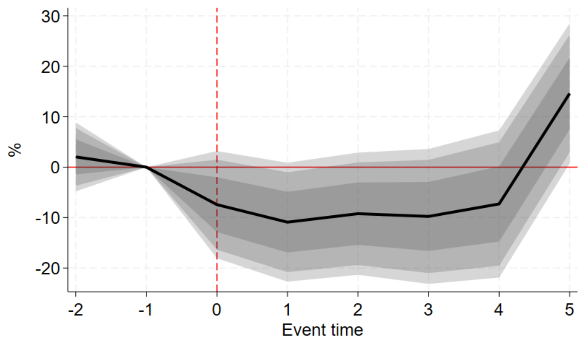
Notes: Standard errors in parentheses. Clustered standard errors in Equation (5) is at location *times* product level. + p<0.33, * p<0.1, ** p<0.05, *** p<0.01

Table B.1: Event Study Regression on Log Sales

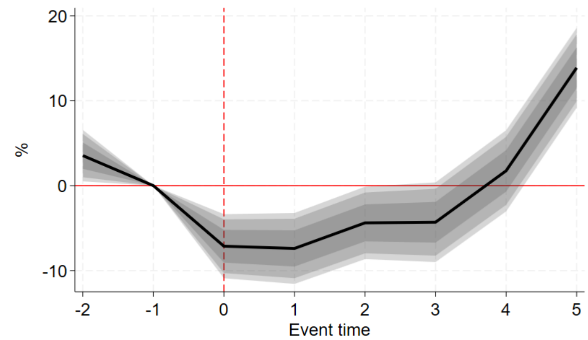
	(1)	(2)	(3)	(4)	(5)
	Dep. Var.: log Nb. of Establishment				
t-2	-0.406***	0.028	0.028+	0.032+	0.032*
	(0.057)	(0.043)	(0.025)	(0.031)	(0.016)
t	-0.577***	-0.144***	-0.144***	-0.100***	-0.100***
	(0.057)	(0.043)	(0.025)	(0.031)	(0.021)
t+1	-0.625***	-0.191***	-0.191***	-0.094***	-0.094***
	(0.057)	(0.043)	(0.025)	(0.031)	(0.024)
t+2	-0.634***	-0.200***	-0.200***	-0.083***	-0.083***
	(0.057)	(0.043)	(0.025)	(0.031)	(0.025)
t+3	-0.632***	-0.199***	-0.199***	-0.105***	-0.105***
	(0.057)	(0.043)	(0.025)	(0.031)	(0.027)
t+4	-0.667***	-0.233***	-0.233***	-0.064**	-0.064**
	(0.057)	(0.043)	(0.025)	(0.031)	(0.028)
t+5	-0.820***	-0.387***	-0.387***	0.045*	0.045+
	(0.019)	(0.032)	(0.019)	(0.023)	(0.032)
Constant	2.670***	2.464***	2.464***	2.307***	2.307***
	(0.012)	(0.016)	(0.009)	(0.011)	(0.013)
Location FE	No	Yes	No	No	No
Product FE	No	Yes	No	No	No
Location#Product FE	No	No	Yes	Yes	Yes
Year FE	No	No	No	Yes	Yes
Cluster	No	No	No	No	Yes
Observations	12,600	12,600	12,600	12,600	12,600
R-squared	0.136	0.745	0.915	0.935	0.935

Notes: Standard errors in parentheses. Clustered standard errors in Equation (5) is at location *times* product level. + p<0.33, * p<0.1, ** p<0.05, *** p<0.01

Table B.2: Event Study Regression on Log Nb. of Establishment consistent with those from the Nagoya sample. Minor discrepancies between the two are likely attributable to differences in the regions' sectoral compositions and product mixes.



(a) Log sales



(b) Log number of establishments

Notes: This figure plots the event-study coefficients estimating the dynamics of sales (Panel a) and the number of establishments (Panel b) since the outbreak of the 1995 Kobe earthquake. Event time $t = 0$ corresponds to the year 1995. The reference period is $t = -1$, corresponding to 1993, since 1994 data are incomplete due to limitations in data collection. The solid line plots the difference in log sales between firms in the treatment city (Kobe, Hyogo) and the control city (Osaka, Osaka). The shaded areas represent the 66%, 90%, and 95% confidence intervals (from darkest to lightest).

Figure B.1: The relative response of log sales and the number of establishments to the 1995 Kobe earthquake (Osaka as control group

B.3 Dynamics DID with damage intensity

In this subsection, we investigate the dynamics of sales and the number of establishments during the 1995 Kobe earthquake. We move beyond a binary treatment assignment in Section 2, to exploit the spatial heterogeneity of the disaster by allowing the treatment intensity to vary with the degree of damage sustained in each municipality. We estimate the following dynamic linear model at the municipality-product level:

$$\ln(Y_{imt}) = \sum_{\tau=-5}^{5} \beta_\tau \left[\mathbb{1}(t - t_{1995} = \tau) \times \text{Damage}_m \right] + \alpha_{im} + \lambda_t + \varepsilon_{imt}$$

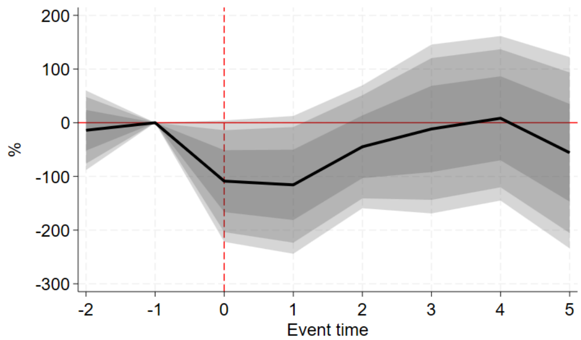
where Y_{imt} denotes the outcome of interest (either total sales or the number of establishments) for product i in municipality m at year t. The core of our identification strategy relies on an interaction term. Here, Damage_m is a continuous variable ranging from 0 to 1, capturing the degree of destruction in municipality m.

We construct this municipality-level damage index following the methodology outlined in Cole et al. (2019). We utilise Shinsai Hukkou Akaibu (archive on the damage of the 1995 Hyogo-Awaji earthquake) by the Kobe City Office and Toru Fukushima (University of Hyogo), together with Zenrin's Residential Map, Hyogo-ken Kobe city 1995, by Toru Fukushima (University of Hyogo), which provides building-level data. Specifically, we calculate the weighted percentage of damaged buildings within each municipality according to the following formula:

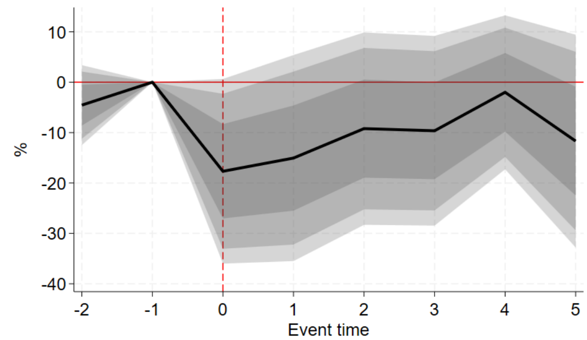
$$\text{Damage}_m = \frac{\sum_{c \in C}(w_c \times N_{mc})}{\text{Total Buildings}_m}$$

where N_{mc} is the number of buildings in municipality m classified into damage category c (Green, Yellow, Orange, Red, Pink). The weights w_c correspond to the median loss in value associated with each category: 0 for Green (no damage), 0.115 for Yellow (partial collapse), 0.35 for Orange (half collapse), 0.75 for Red (full collapse), and 1.0 for Pink (fire damage). This continuous measure allows β_τ to be interpreted as the elasticity of the local economy's response to the earthquake's intensity, rather than a simple average treatment effect. We normalise the event time relative to the earthquake year such that $\tau = t - 1995$. The coefficients of interest, $\{\beta_\tau\}_\tau$, trace the evolution of the outcome variable relative to the baseline year of 1993 ($\tau = -2$). Importantly, our model includes fixed effects to isolate the shock. Firstly, we control for municipality-product fixed effects (α_{mp}). This controls for time-invariant comparative advantages, such as the fact that any industry in a highly damaged municipality might have a permanently different scale than the same industry in a less affected area. This ensures we estimate effects solely from within-unit time variation. Secondly, we control for year fixed effects (λ_t). These absorb aggregate shocks common across regions, such as the Japanese asset price collapse, changes in national tax policy, and fluctuations in global demand. Rather than comparing aggregate sectors, we construct a balanced sample based on precise product availability. As detailed in Table 1, we identify approximately 300 distinct 6-digit products that were produced in both the affected region and the control group before the shock. By restricting our analysis to this intersection, we ensure that we are comparing firms with similar products facing identical shocks, thereby minimising bias from unobserved sector-specific heterogeneity.

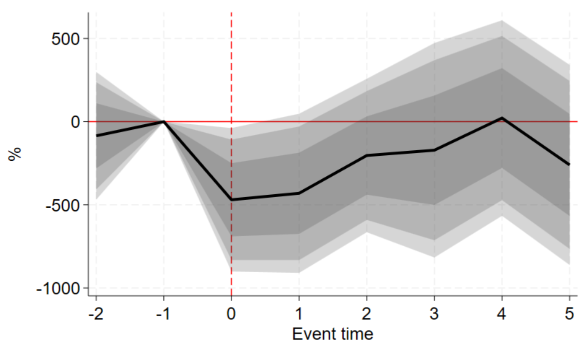
Figure B.2 presents results. We compare the results with continuous damage intensity in Panels c and d with the average treatment effects from the baseline model with binary shock (Panels a and b). The results from the continuous damage intensity indicate a larger impact of the earthquake. One plausible reason is the reallocation effect within the disaster zone. If highly damaged municipalities suffered severe declines while the aggregate suffered less, it implies that economic activity might shift from highly damaged zones to the less damaged ones. The baseline results mask this internal churn because uneven damage offsets, whereas the continuous coefficient captures the full magnitude of this divergence.



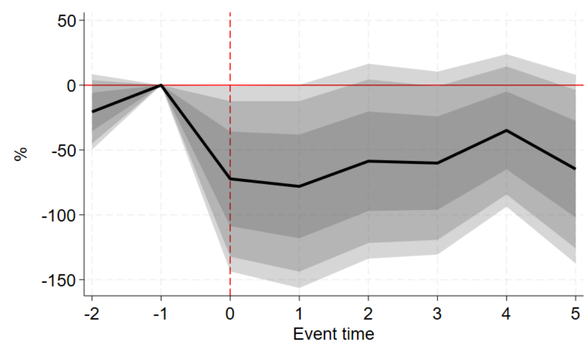
(a) Binary: Log sales



(b) Binary: Log nb. of establishments



(c) Damage intensity: Log sales



(d) Damage intensity: Log nb. of establishments

Notes: This figure plots the event-study coefficients estimating the impact of the 1995 Kobe earthquake on sales (Panel a, c) and the number of establishments (Panel b, d). Event time $t = 0$ corresponds to the year 1995. The reference period is $t = -1$, which corresponds to 1993; data for 1994 are omitted due to collection limitations. The solid line plots the difference in log sales between firms in the treatment city (Kobe, Hyogo) and the control city (Nagoya, Aichi). The shaded areas represent the 66%, 90%, and 95% confidence intervals (from darkest to lightest).

Figure B.2: The response of log sales and the number of establishments to the 1995 Kobe earthquake, assuming damage intensity

C Computing the preference weight

2-digit sector	Description	JIP Row Indices
09	FOOD	[8, 9, 11]
10	BEVERAGES, TOBACCO, AND FEED	[10, 12]
11	TEXTILE	[13, 14]
12	Lumber and Wood products	[53]
13	Furniture and fixtures	[54]
14	Pulp and paper products	[15, 16]
15	Printing	[52]
16	Chemical	[17, 18, 19, 20, 21, 22]
17	Petroleum and coal products	[23, 24]
18	Plastic products	[55]
19	Rubber products	[56]
20	Leather tanning, leather products and fur skins	[57]
21	Ceramic, stone and clay products	[25, 26, 27, 28]
22	Iron and steel	[29, 30]
23	Non-ferrous metals and products	[31, 32]
24	Fabricated metal products	[33, 34]
25	General machinery	[35]
26	Production machinery	[36]
27	Business oriented machinery	[37, 38, 39]
28	Electronic parts, devices and electronic circuits	[40, 41]
29	Electrical machinery	[42, 43, 44, 45]
30	Information and communication electronics	[46, 47, 48]
31	Transportation equipment	[49, 50, 51]
32	Other manufacturing	[58, 59]

Table C.1: Mapping of 2-digit Manufacturing Sectors to JIP Use-Table Row Indices

Table C.2: manufacturing product groups: product counts and aggregate shares

2-digit sector	Number of Products	$\sum_i \alpha_i$
9	122	0.20940
10	33	0.17928
11	235	0.07589
12	52	0.00099
13	29	0.00447
14	63	0.00507
15	18	0.00213
16	205	0.05767
17	29	0.11592
18	61	0.00883
19	53	0.00794
20	45	0.02014
21	143	0.00500
22	86	1.97×10^{-14}
23	64	0.00221
24	135	0.00711
25	92	0.00034
26	148	0.00058
27	80	0.00827
28	23	0.00556
29	99	0.05751
30	42	0.07196
31	84	0.11217
32	120	0.04158
Sum of α_i over manufacturing products		1.00000

D Estimations of Median products

Table D.1: Median Kobe Products (Common Products)

2-digit code	6-digit code	Industry group	# Products
Panel A: Overall Median (Common Products)			
24	244692	fabricated_metal_products	300
Panel B: Median by 2-digit sector (Common Products)			
9	91312	food	42
10	101110	beverages_tobacco_and_feed	6
11	119410	textile	14
12	123210	lumber_and_wood_products	4
13	139920	furniture_and_fixtures	9
14	149990	pulp_and_paper_products	14
15	151390	printing	9
16	166210	chemical	12
17	174110	petroleum_and_coal_products	1
18	183410	plastic_products	13
19	193320	rubber_products	8
20	204110	leather_tanning_leather_products_fur_skins	1
21	211120	ceramic_stone_and_clay_products	4
22	225110	iron_and_steel	12
23	235190	nonferrous_metals_and_products	7
24	244690	fabricated_metal_products	32
25	259920	general_machinery	28
26	265320	production_machinery	29
27	273310	business_oriented_machinery	8
28	281120	electronic_parts_devices_and_circuits	3
29	297210	electrical_machinery	16
30	303110	information_and_communication_electronics	2
31	312210	transportation_equipment	15
32	326220	other_manufacturing	11

The method we employe is ismorphique the one used in XX and XX.

E Estimation of Parameter values for Nagoya

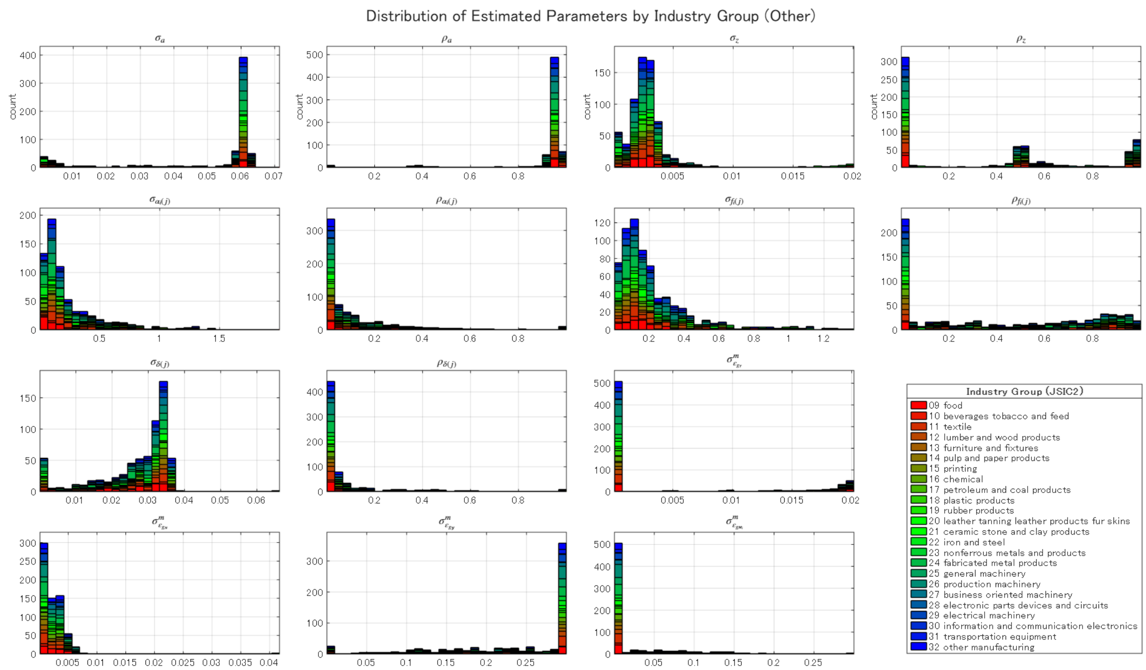


Figure E.1: Parameter Distribution for Nagoya

F Variance Decompositions

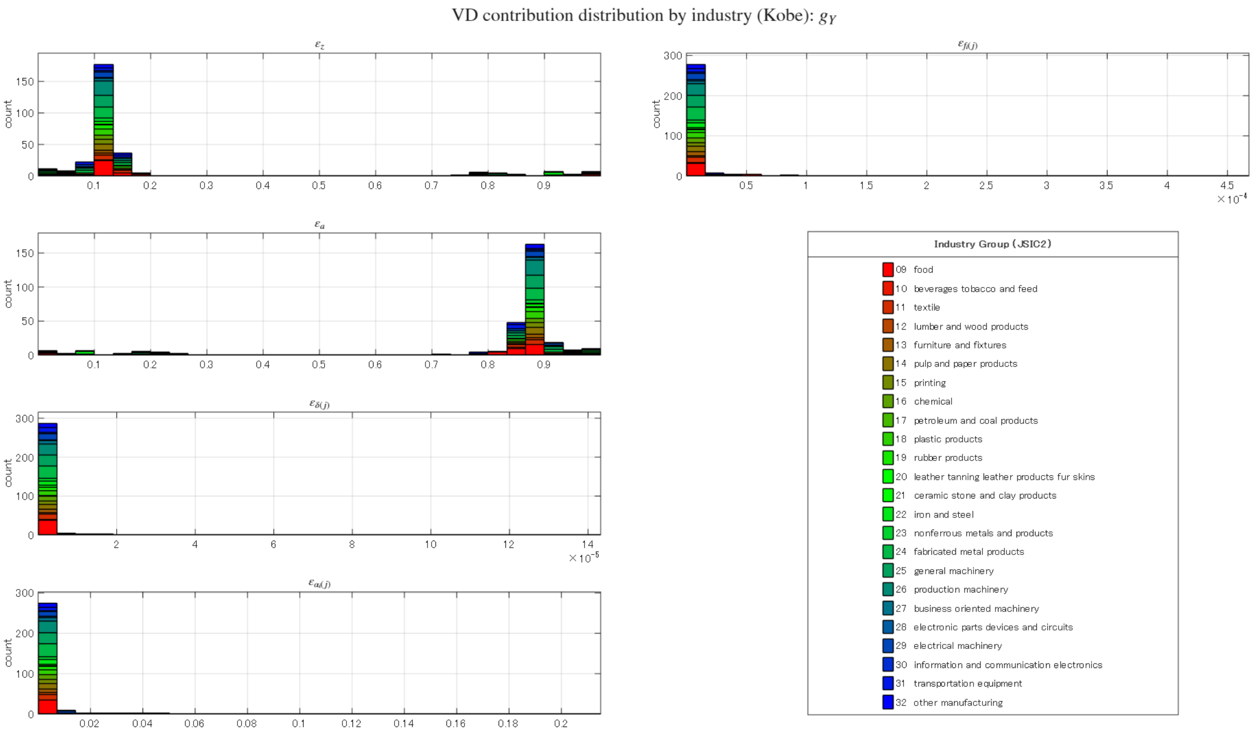


Figure F.1: Variance decomposition of the growth rate of GDP

Note: The figure presents the distribution of the variance decomposition of GDP growth. In each panel, the horizontal axis shows the relative contribution of each shock.

VD contribution distribution by industry (Kobe): $g_{N(j)}$

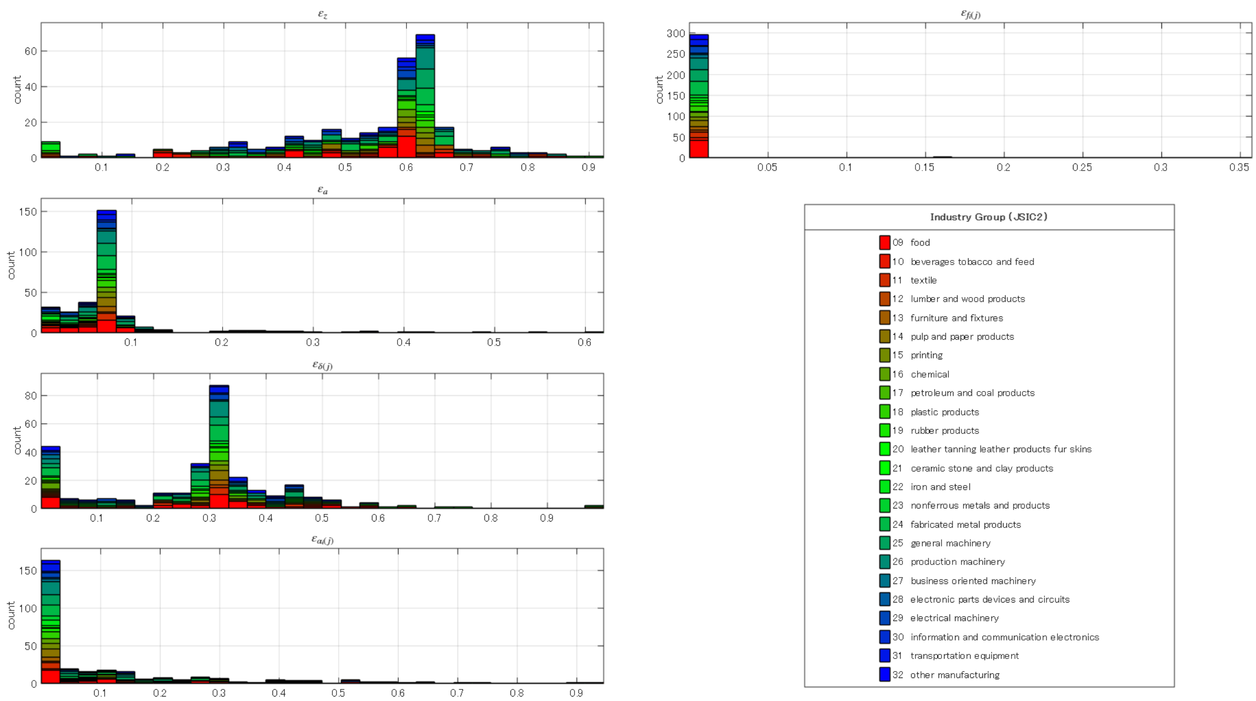


Figure F.2: Variance decomposition of the growth rate of the number of establishments in Kobe

Note: The figure presents the distribution of the variance decomposition of the growth rate of the number of establishments. In each panel, the horizontal axis shows the relative contribution of each shock.

G Historical Decomposition of Median Products

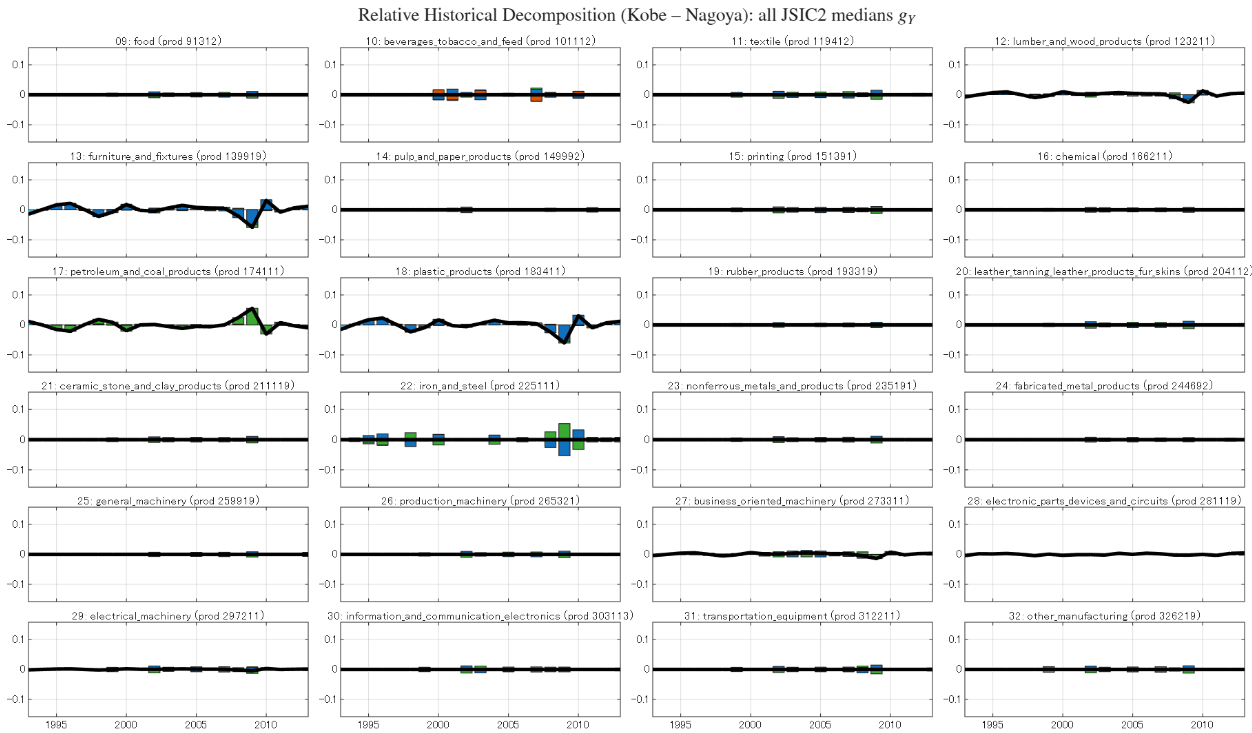


Figure G.1: Relative historical decomposition of real GDP growth

Note: The figure presents the historical decomposition of real GDP growth for the median product in each two-digit sector, relative to Nagoya.

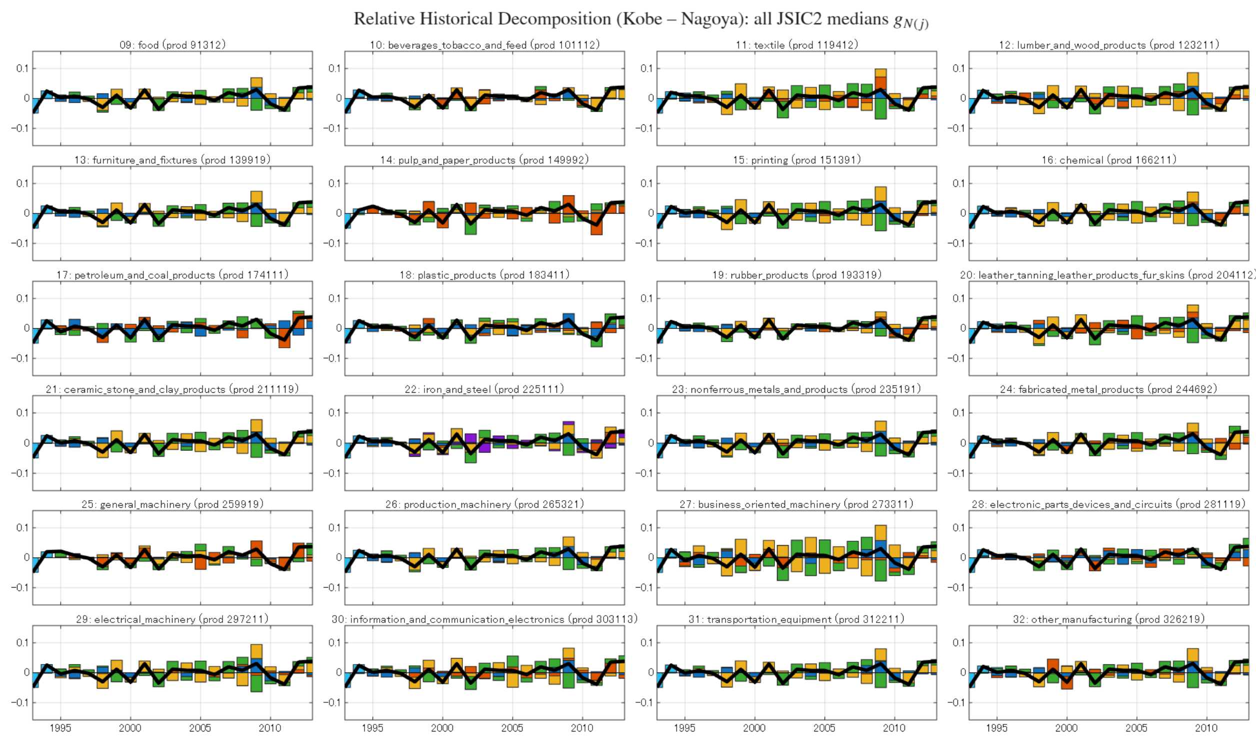


Figure G.2: Relative historical decomposition of the growth rate of the total number of local establishments

Note: The figure presents the historical decomposition of the growth rate of the total number of local establishments for the median product in each two-digit sector, relative to Nagoya.

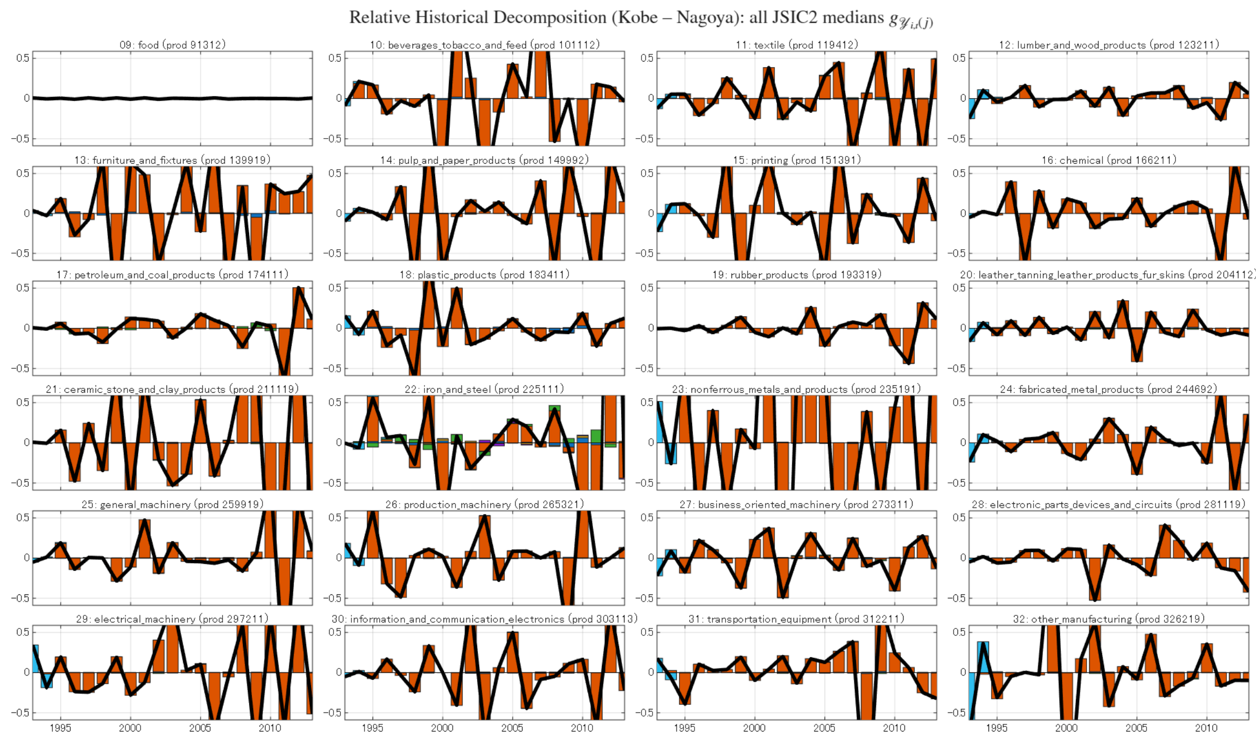


Figure G.3: Relative historical decomposition of the growth rate of real product sales

Note: The figure presents the historical decomposition of the growth rate of real product sales for the median product in each two-digit sector, relative to Nagoya.

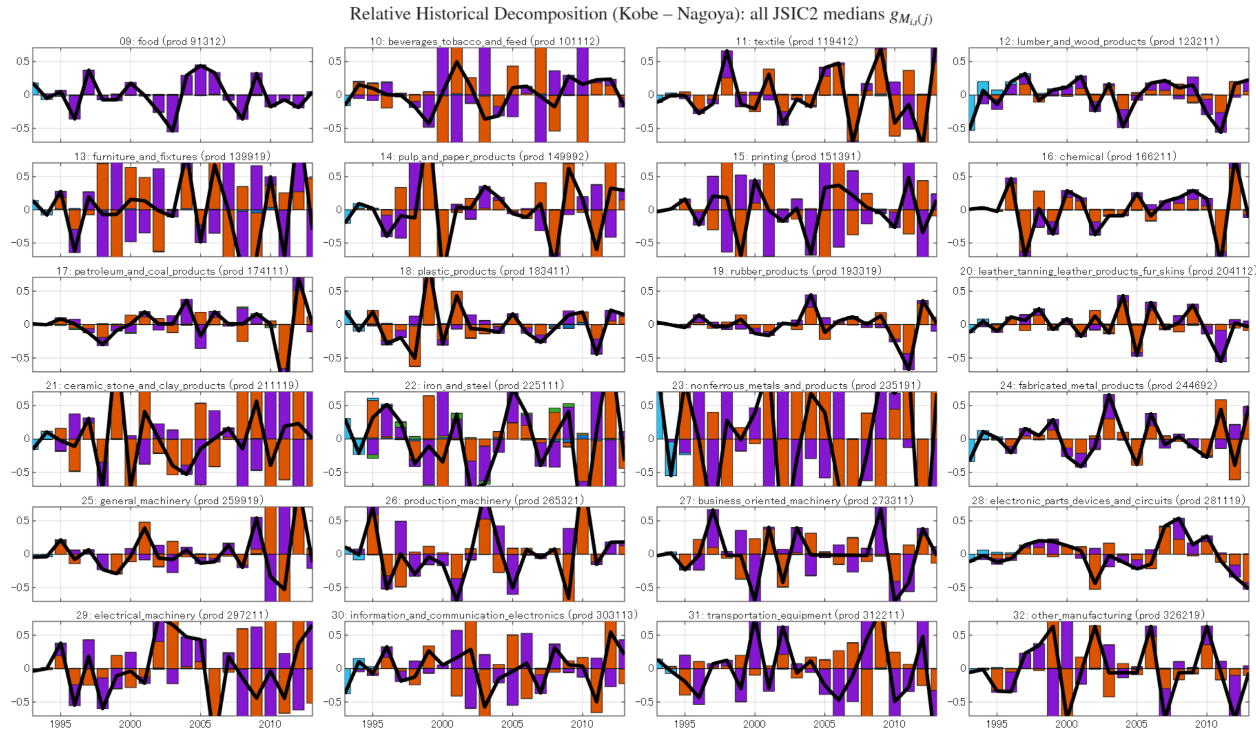


Figure G.4: Relative historical decomposition of the growth rate of the number of product-producing establishments

Note: The figure presents the historical decomposition of the growth rate of the number of product-producing establishments for the median product in each two-digit sector, relative to Nagoya.

H Additional Results from Counterfactual Analyses

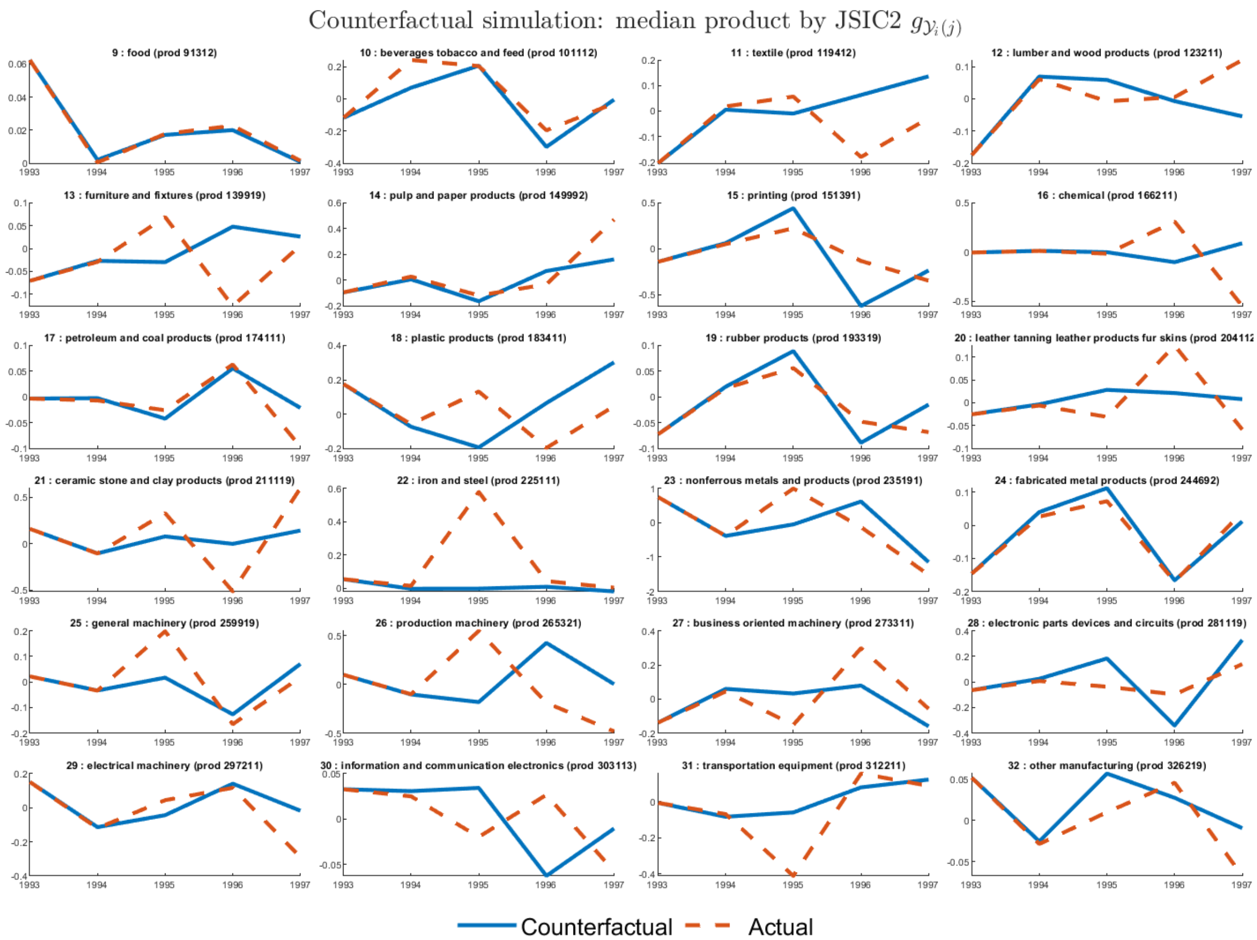


Figure H.1: Counterfactual simulation

Note: The figure plots actual and counterfactual series of real product sales growth during 1993 to 1997 for median product within each two-digit sector. Solid and dashed lines correspond to the actual (Kobe shocks) and counterfactual (Nagoya shocks), respectively. All series are expressed in level. Measurement errors are ignored in the simulation.

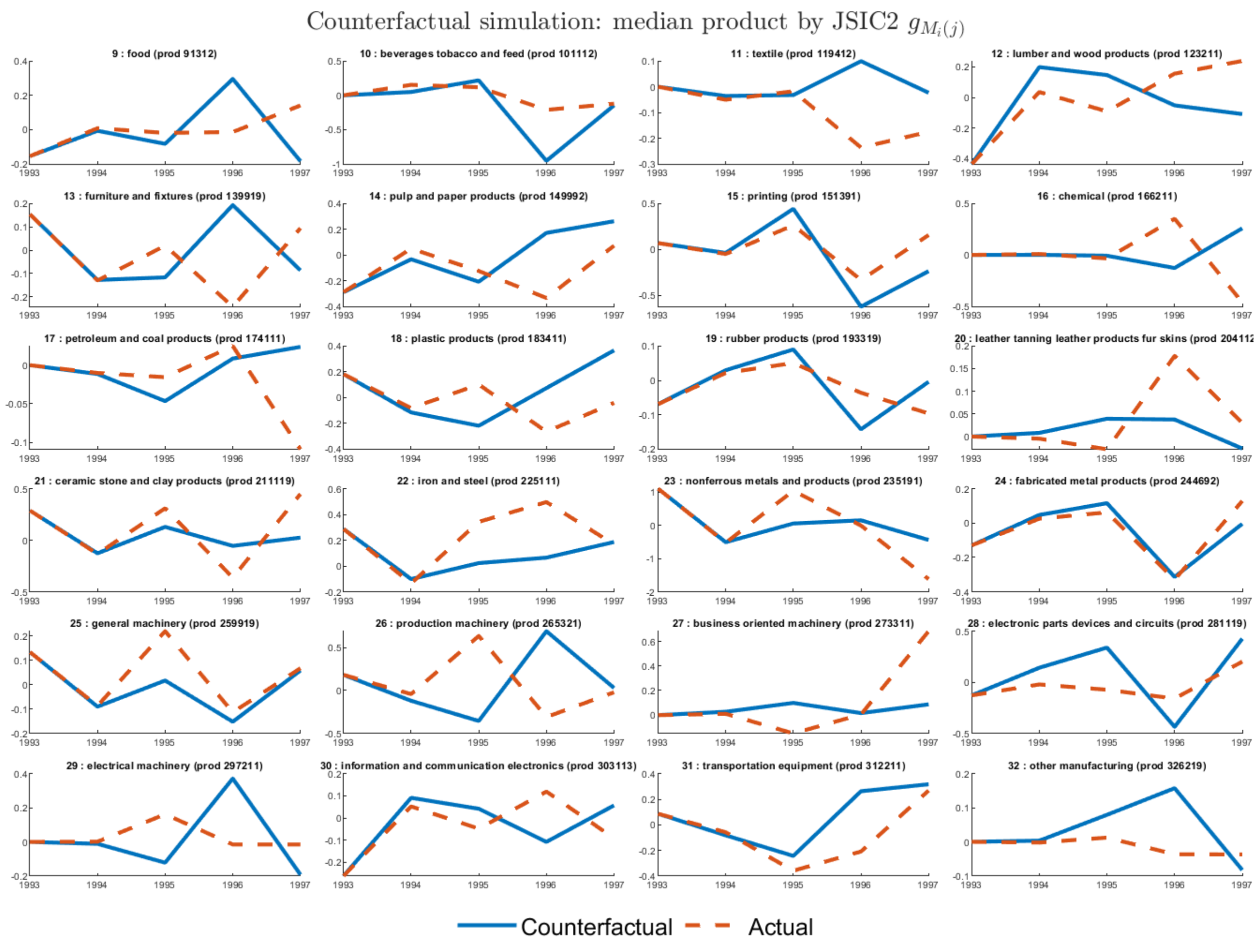


Figure H.2: Counterfactual simulation

Note: The figure plots actual and counterfactual series of growth of the number of producing establishment during 1993 to 1997 for median product within each two-digit sector. Solid and dashed lines correspond to the actual (Kobe shocks) and counterfactual (Nagoya shocks), respectively. All series are expressed in level. Measurement errors are ignored in the simulation.

Rank	Product Code	Cumulative difference
1	259311	-1.6162
2	253211	-1.4116
3	265222	-1.2834
4	259214	-1.2723
5	249219	-1.1933
6	92411	-1.1273
7	119191	-1.0536
8	252332	-0.9917
9	266229	-0.9361
10	266411	-0.8761
11	97191	-0.8325
12	144919	-0.7478
13	193312	-0.6605
14	165111	-0.6422
15	151212	-0.6396
16	265231	-0.5241
17	253412	-0.5206
18	116213	-0.5178
19	244311	-0.5124
20	116511	-0.5105
21	166115	-0.4833
22	252121	-0.4557
23	96111	-0.4225
24	292221	-0.4152
25	183319	-0.3731
26	265321	-0.3690
27	269491	-0.3676
28	119412	-0.3407
29	259691	-0.3269
30	248191	-0.3141

Table H.1: Ranking according to the impact of earthquake

Note: The table presents the list of 30 products that experienced the largest impacts of the earthquake on the real product sales growth according to the counterfactual simulation. The cumulative difference defined as the actual minus counterfactual values from 1995 to 1997 are reported. Negative differences implies that the product sales growth is suppressed by the impact of the earthquake in these years.

I Implication for Global Financial Crises

To

Counterfactual series around the Global Financial Crises are obtained by simulating the model parameterized with Kobe estimates with smoothed shocks, while the series of smoothed shocks from 2007 to 2009 are replaced by those from Nagoya estimates. Figure I.1 shows the histograms of cumulative differences between actual and counterfactual values of each variable from 2007 to 2009.

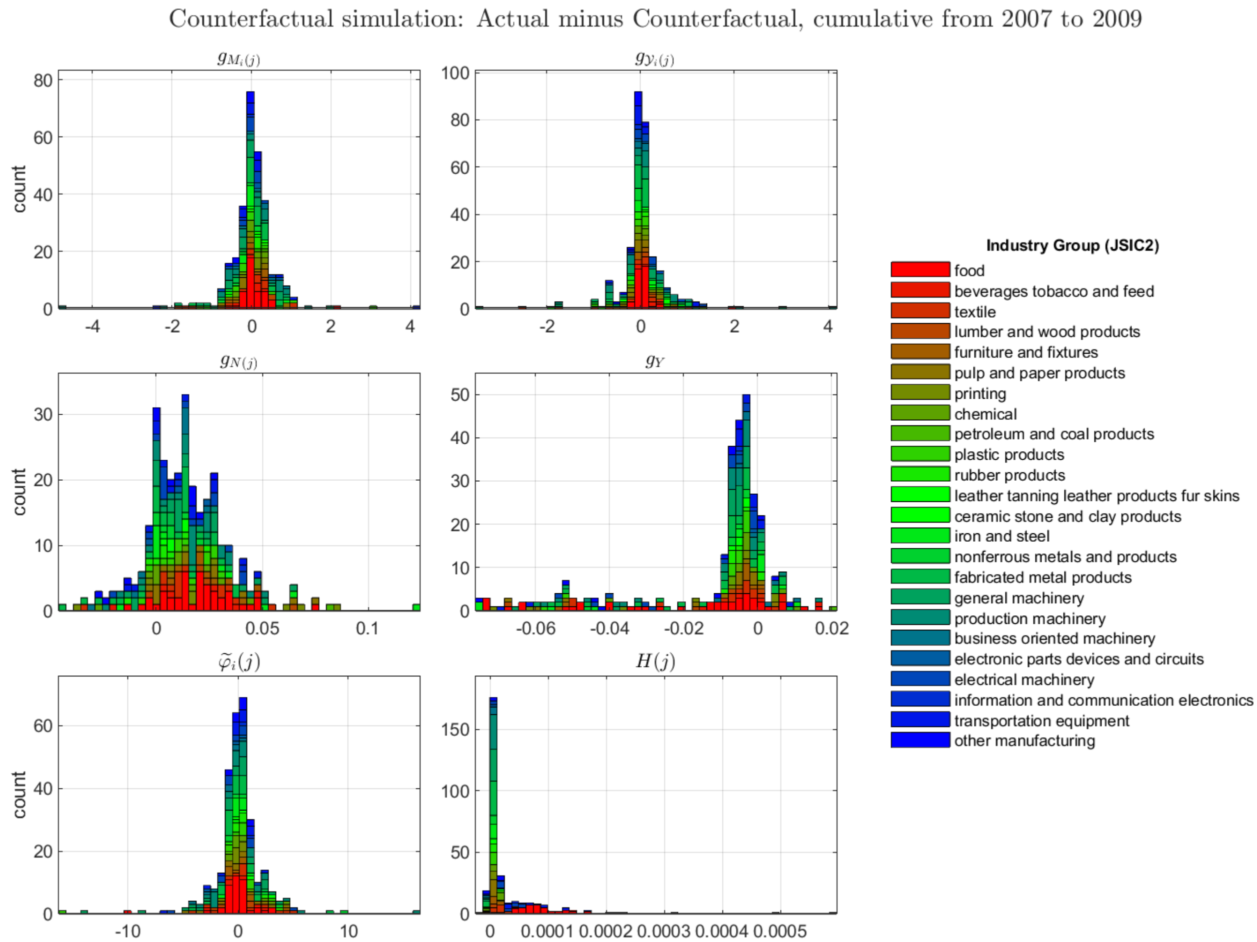


Figure I.1: Counterfactual simulation

Note: The figure plots histograms of cumulative differences, defined as actual (Kobe smoothed shocks) minus counterfactual (Nagoya smoothed shocks), for each variable over the period 2007–2009.