Economic Activities and Regional Correlation During Economic and Natural Disasters

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Abstract

Life is characterized by risks of different features and origins. Examining the economic and natural disasters that have occurred in Japan in the past decades, we show that regional relationships strengthen during chaotic moments, such as the Lehman Brothers collapse, the Great East Japan Earthquake, and the coronavirus disease (COVID-19) pandemic. Moreover, we find that business prospects are a good predictor of labor market conditions, and employment opportunities deteriorate more severely when regions are highly correlated. Our study indicates the side effect of market integration and the relevance of regional economic centers in cushioning nationwide economic and natural shocks.

JEL classification: R1
Keywords: Lehman Brothers collapse; Great East Japan Earthquake; COVID-19; regional heterogeneity; regional correlation

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1 Introduction

Life is full of risks; however, we know that it is difficult to predict and avoid most risks because of the differences in their characteristics and origins. Since economic and natural disasters involve many issues that significantly and adversely affect people's lives, there is ample research from different academic perspectives. In this regard, economic and financial data show a tendency for economic activities to converge during and in the aftermath of disasters. Economic shocks are often transmitted initially through the banking and financial sectors and with some time lag, through the tradable sector, harmonizing business cycles globally.[1] Many countries implemented expansionary fiscal and monetary policies to boost their economies following global crises like the collapse of Lehman Brothers and the recent coronavirus disease (COVID-19) pandemic. This increase in commonality and cross-border spillovers among countries has been accelerated by the globalization of economies where traders can expect greater profit-earning opportunities.[2] As a result, presently, the shocks originating from one country have more direct and immediate impacts on other countries than before.

The shocks are known to transmit to other countries through several channels: for example, trading and investors' expectations channels (Classens, 2000; Forbes and Rigobon, 2001; Nagayasu, 2001). Deterioration in an economy typically reduces external demand for other countries, resulting in economic recession and deflation of financial assets worldwide. Moreover, during chaotic periods, investors tend to follow a leader who is believed to possess more information than others. Such a mimicking strategy is called herding behavior, which is argued to have triggered the collapse of the European Exchange Rate Mechanism (ERM) in 1992. Spillovers in global markets have been a primary research focus in the past, but contagion exists in regional economies as well.

Against this background, we study the relationship between economic conditions and regional homogeneity during economic and natural crises using regional correlation

[1] The 1997 Asian crisis that spread from Thailand to the rest of Asia is an example of a contagion in the global financial sector. Akhtaruzzaman et al. (2020) showed that conditional correlation among stock returns increased significantly at the onset of the COVID-19 pandemic, focusing on the channel of financial firms.

[2] Economic researchers often refer to cross-border influence as "contagion" during chaotic periods, and as "interdependence" during tranquil periods. Here, we do not make a clear distinction between these two terms.

as a proxy for regional homogeneity. Regional analysis is more prone to be influenced by common shocks than global studies, but it nevertheless provides relevant evidence in the global context. As summarized in the next section, some crises have more homogeneous impacts on regional economies than others, and therefore, we expect regional correlation to vary both over time and between regional pairs. We attempt to identify the uniqueness of the ongoing COVID-19 pandemic compared to other crises and argue that the effects of crises have been more devastating for homogeneous markets compared to heterogeneous markets.

2 Natural and economic disasters

Partly because of its geographical location, Japan has been confronted with many disasters over the last two decades. Prior to a formal analysis, we summarize below the three most notable crises in recent decades: the Lehman Brothers collapse, the Great East Japan Earthquake (GEJE), and the COVID-19 pandemic. The collapse of Lehman Brothers (2008) is rooted in the financial sector and thus is expected to have adverse effects primarily in metropolitan areas such as Kanto, Tokai, and Kinki; the 2011 earthquake mainly influenced the Tohoku region. In contrast, while it is not yet fully understood how COVID-19 came to existence, it appears to have affected regional economies more homogeneously than other disasters because of the resultant pandemic and the government policy to encourage all people to stay at home.

2.1 The bankruptcy of Lehman Brothers

The Lehman Brothers, a hedge-fund firm, collapsed on 15 September, 2008—the largest bankruptcy in the United States (US) history. This was originally caused by a sub-prime mortgage crisis in the US, which became prominent in 2007. The administration of the erstwhile President Barack Obama implemented a policy to assist people (including low-income consumers) to own houses, and as a result, the low quality sub-prime mortgages increased to 20% in 2006. Lehman Brothers was one of the first firms to be engaged in the mortgage business. However, the problem arose when it became apparent that poor and less creditworthy households could not pay back housing loans.

As financial markets are globally linked and European financial firms owned a significant amount of such funds, the contagious effects spread from the US to European countries and then Japan. Japanese firms owned a relatively small amount of problematic assets than its European counterparts; thus, direct damage through the financial channel was minimal. However, in the face of a weak external demand and yen appreciation (the so-called safe-haven currency), this crisis hit Japan's exporters severely. In addition, future uncertainty discouraged the households to increase personal consumption. As a result of the weak domestic and external demand, accompanied by slow but steady increases in the unemployment rate, Japan suffered from the collapse of Lehman Brothers for a considerably longer time than other advanced countries.[3]

2.2 The Great East Japan Earthquake

Japan experiences earthquakes frequently, but the one that occurred on March 11, 2011, named the Great East Japan Earthquake (GEJE), was the biggest earthquake ever recorded in Japan. This disaster is known to people not only because of the magnitude of the earthquake, but also because it was coupled with a large wave from the ocean (tsunami) and nuclear power failures. While aftershocks of the GEJE lasted for several months, damages from the initial earthquake can be attributed to the tsunami. The number of deaths exceeded 15000, while 6000 were injured and 25000 were declared missing. The tsunami had also brought about an explosion at the Fukushima nuclear power plants. Normally, the reconstruction after earthquakes begins right after the natural disaster. However, in this case, the nuclear power accident forced people to move out of the affected areas, spreading out mainly in the eastern part of Japan, and seeking jobs that could utilize their work skills in the new destinations (Kondo, 2018). The reconstruction is still in progress and there is a long way to go to deal with the collapsed nuclear power plants. In fact, a railway line linking Kanto and Tohoku (Joban-line) reopened only in March 2020.

The regions heavily affected by the tsunami were concentrated on the Pacific coast of Tohoku region (near the epicenter of the GEJE), which witnessed the destruction of its fisheries and other industries. The Kanto region was also affected (for example, due

[3]It was called the glacial age in job markets. The unemployment rate returned to its pre-Lehman-Shock level in March 2013.

to disruption of electric supply), but witnessed fewer deaths. In contrast, the GEJE did not cause damages in the western parts of Japan, although manufacturing firms in the metropolitan regions were affected because the factories that produced intermediate goods were in Tohoku. The costs incurred due to the supply chain disruptions were estimated at 0.35% of the GDP (Tokui et al., 2017).

2.3 COVID-19

The coronavirus disease (COVID-19), which spread from China, became a global pandemic in early 2020.[4] Being a neighboring country, Japan was also severely affected by COVID-19. As of July 2020, the number of deaths was reported to be around 1000 people. When this disease initially became apparent in China, a strict lockdown was imposed in order to prevent further diffusion, but was subsequently transmitted to the rest of Asia, in addition to the other continents of Oceania, Europe, and North America by early 2020. By the second quarter of 2020, it was evident that COVID-19 had become a pandemic, with the increasing number of infected patients and deaths throughout the world, including Africa and South America.

It is difficult to identify the exact date of occurrence and arrival of COVID-19. However, the Japanese government confirmed that it was transmitted to Japan in January 2020 and announced quarantine restrictions on March 6, 2020 for people coming from the severely affected regions in China (e.g., Wuhan) and Korea, subsequently extending it to other countries. Moreover, a state of emergency was declared from 8 April to 6 May in metropolitan prefectures (Tokyo, Kanagawa, Saitama, Chiba, Osaka, Hyogo, and Fukuoka) and was extended to all regions in Japan from 16 April. During this period, there was no lockdown, as was observed in other countries, due to the absence of a law to enforce such a restriction on people's movements. However, Japanese residents were encouraged to stay and work at home in order to maintain a physical distance from others in the absence of a vaccine for COVID-19.[5] As a result, the transportation industry was severely affected, and many departmental stores, restaurants, and hotels were forced to shut down their businesses temporarily or forever. In contrast, because of the increase in telework, the IT industry found a good opportunity to expand and

[4]Since it was identified in Wuhan, China, in late 2019, it is called COVID-19.
[5]The low number of the deaths in Japan without introducing a lockdown is considered a myth.

develop its business. Nevertheless, enterprises benefiting from COVID-19 are an exception. While the magnitude of the damage may differ, all consumers, regardless of residential location and income, and most industries, have been adversely affected by COVID-19.

3 Data

For an analysis of an ongoing crises, researchers have always faced a shortage of statistical information. Therefore, they have typically examined high-frequency financial data, such as stock prices and exchange rates in order to comprehend financial market conditions during and in the aftermath of crises. Our study similarly aims to analyze the effects of the crises using a limited amount of information that is disseminated in a timely manner. For this reason, we collected business projections and unemployment data (2004Q2 to 2020Q2) for nine regions: Hokkaido, Tohoku, Kanto, Hokuriku, Tokai, Kinki, Chugoku, Shikoku, and Kyushu.[6] Regions refer to a subdivision of the country, consisting of administrative areas called prefectures. Figure 1 illustrates the geographical location and the definition of these regions.

[Figure 1]

The Business Survey Index (BSI) contains information on future business prospects indicated by the firms in Japan. This survey is conducted quarterly by the Cabinet Office and the Ministry of Finance and covers a whole sector (approximately 12000 to 15000 firms in each survey). Figure 2 plots the contemporaneous business projections (i.e., business prospects for the present quarter), which reveals that the respondents have been most pessimistic about business performance during COVID-19. These business prospects were even worse than those after the Lehman Brothers collapse or the 2011 earthquakes.

Moreover, Table 1 summarizes changes in projections about business performance. NextQ is the difference between the business prospects for the succeeding quarters $(t+1)$ made in t and that for contemporaneous quarters made in $t+1$. NextQQ is the

[6]Okinawa is excluded from our analysis due to missing data during our sample periods. Furthermore, the 2016Q2 data for Kyushu are missing due to severe earthquakes witnessed in Kyushu, and thus, have been treated the same as the value in the previous quarter.

difference between business prospects for $t+2$ made in t and contemporaneous prospects at $t+2$. It is interesting to note that the average (and median) of the projection errors is positive, indicating that the initial projections were often optimistic. Furthermore, there is significant heterogeneity among regional economies, despite Japan often being considered very homogeneous by international standards.[7]

[Figure 2 & Table 1]

Quarterly unemployment data were collected from the Statistics Bureau of Japan of the Ministry of Internal Affairs and Communications, which are available for each prefecture. Regional data were compiled on the basis of prefectural data from the Labor Force Survey between 2004 and 2020. The unemployment data for Japan are compiled and disseminated more frequently than the regional GDP data, which are often used by researchers to measure the overall economic activities (but are available with a considerable time lag). Moreover, because the effects of the crises are not limited to the financial sector, the unemployment rates are more appropriate to understand the real economy that is more directly linked with the living standards in a country where consumers prefer to possess safe financial assets. Table 1 also summarizes the basic statistics of regional unemployment rates and shows that the rates, while being around 3 to 4%, varies among regions.

A poor business prospect may become a factor that triggers a layoff. Therefore, a negative relationship is expected between the BSI and unemployment rates, although it may take some time for this relationship to be effective, given the contracts and rigidity in the labor market. Christiano et al., (2016) showed that wage inertia can be brought about from a negotiation process between firms and workers. In order to verify this relationship with limited observations, we conduct panel data analyses using the standard estimation approaches: the pooled ordinary least square (POLS) and the within and random effects estimation.

Table 2 reports the results of the unemployment rate equations for three approaches. We also use a lagged explanatory variable (lagged BSI) to take into account the time lag for making employment decisions. Consistent with our expectation, the data show a clear negative relationship between these variables. A drop in the BSI by one point leads

[7]Regional disparities in Japan have been pointed out by Nagayasu (2017) with respect to inflation.

to an increase in unemployment rates by roughly 0.03%. While the size of the changes in unemployment rates appears very subtle, the influence of the BSI is statistically significant. Moreover, a slightly stronger impact is obtained from the lagged BSI, which is also shown to be a better fit to the data according to the R^2 and the adjusted R^2 values, thereby confirming that a time lag is required for business prospects to impact the implementation of employment decisions.

[Table 2]

4 Empirics

4.1 Regional correlation during crises

Regional homogeneity, measured by correlation, is likely to be time-varying; similarly, firms' reactions to crises is likely to differ by the type of firm. We therefore classify our samples into the following: 1) manufacturing and non-manufacturing firms, and 2) large and small & medium firms. Large firms are corporations with capital of more than three billion yen and generally possess significant internal reserves to protect themselves against crises. Among the different types of firms, the non-manufacturing industry has been directly affected by the COVID-19 pandemic, which has forced people to reduce economic activities. Out of 500 firms that have gone bankrupt due to COVID-19 since 29 February, 2020, 69 were restaurants, followed by 53 hotels, 34 apparel and general stores, 33 construction firms, and 29 food wholesalers (Teikoku Database, September 8, 2020).

We initially calculated time-varying correlation using the rolling estimation method to examine regional homogeneity. With nine regions under investigation, we obtained 36 pairs of regional correlation for the BSI and unemployment rates, with a window size of 3 and 4, respectively.[8] Figure 3 depicts the national average of time-varying regional correlation based on BSI, and the crisis periods are denoted by the shaded areas. Regional correlation is very volatile and approaches one on a number of occasions. A sharp correlation curve during the GEJE indicates that the shocks were initially scattered across the country, but regional heterogeneity dominates soon after

[8] We attempt to set a short window size that allows us to estimate such a model.

the occurrence of the earthquakes. In contrast, the shocks from the Lehman Brothers collapse were more pervasive throughout the country. While a formal analysis is required, regional correlation seems to be high in the aftermath of the crises.

[Figure 3]

Using the estimates of the time-varying regional correlation ($Corr_{it}$), we first determine if regional correlation, which can be interpreted as regional homogeneity, is higher during economic and financial disasters. The sensitivity to crises at time t is estimated against the constant term (α) and dummy variables to capture the effects of the Lehman Brothers collapse (*Lehman*), the GEJE (*Earthquake*), and the COVID-19 pandemic ($COVID$).

$$Corr_{it} = \alpha + \beta_1 Lehman_t + \beta_2 Earthquake_t + \beta_3 COVID_t + \epsilon_t \tag{1}$$

where $Corr$ is a matrix of 36 pairs of regional correlation, and $\epsilon \sim N(0, \sigma^2)$. The constant term, α, represents the average level of regional correlation, and βs become significantly positive when regional heterogeneity weakens during crises. The effects of crises are captured by the dummy variables defined below. However, the definition may not be exactly consistent with the crisis periods due to the low frequency and availability of the data. Although COVID-19 was prevalent in early 2020, we assume that its effect began in April, given that life was almost normal in Japan until March 2020.

$$\begin{aligned}
&Lehman{=}1 \text{ for 2008Q4-2009Q1}, && \text{otherwise } 0;\\
&Earthquake{=}1 \text{ for 2011Q2-Q3}, && \text{otherwise } 0;\\
&COVID = 1 \text{ for 2020Q2}, && \text{otherwise } 0.
\end{aligned}$$

Table 3 reports the correlation analysis for all firms based on the POLS and the within (fixed effects) estimation methods. The average BSI correlation is approximately 0.65, and the regional correlation is highest for COVID-19, which suggests that its effects were prevalent across the country. Moreover, there is relatively little difference between the estimates for the effect of the crises from the POLS and within models, confirmed by a similarity in the average value of regional correlation. These results are interesting when compared with those of the regional correlation of unemployment rates and show that such correlation in the labor market is relatively more stable over time. That is, a shock will be reflected in expectations immediately, but actual changes in employment policy requires considerable time and are smoothened to the level close to the normality as the shock does not necessarily result in changes in all firms' employment decisions.

[Table 3]

The BSI correlation analysis for different sectors is summarized in Table 4. There is evidence of an increase in regional correlation during crisis periods; however, such correlation for the manufacturing sector drops in response to the GEJE. This may be due to some regions that are not popular locations for manufacturing firms. In this case, regional discrepancies may arise due to the supply chain linkages with Tohoku and the geographical concentration of manufacturing firms in metropolitan areas, which is said to increase knowledge spillovers and improve productivity (Fujita and Thisse, 2013). Among the three crises, the COVID-19 pandemic has the largest positive impact on regional correlation for non-manufacturing firms. This confirms that these firms have been universally and severely affected by the pandemic; their correlation increased significantly in response to the government policy to close businesses in the service sector.

[Table 4]

Table 5 reports the results by firm size, which also reveals a tendency for regional correlation to increase during the crises, regardless of firm size. However, the collapse of Lehman Brothers did not affect regional correlation for small & medium firms. This seems to confirm that large manufacturing firms (that are often global enterprises and are concentrated in metropolitan regions) suffered severely from the failure of Lehman Brothers, whereas small & medium non-manufacturing firms were more evenly affected.

[Table 5]

4.2 Unemployment rates and regional BSI correlation

We investigate the relationship between regional BSI and economic conditions to determine if the increases in regional correlation would explain a deterioration in economic activities. Table 6 presents a preliminary analysis of the dynamic relationship between regional unemployment rates, regional correlation, and economic variables. Here, the dynamic analysis is conducted using lagged economic variables such as the BSI correlation, sales, and regional firms' profits obtained from the Ministry of Finance. The lagged variables were used not only to account for the time required for making employment decisions by firms, but also to deal with potential endogeneity in the specification. To check the robustness of our findings to the model specification, we use the economic variables with different combinations of lag lengths.

We discovered a strong and negative relationship between the unemployment rates and profits. The unemployment rates increase along with a fall in profits of firms, consistent with the standard economic theory, and this effect is immediate. On the other hand, sales are often insignificant, and the BSI correlation requires time to have a statistically significant impact on unemployment rates. In the model with 3 lags of the BSI correlation, which is the best model according to the goodness-to-fit measures, the lagged BSI correlation becomes statistically positive and significant.[9] This positive relationship of regional BSI correlation is in line with the increasing unemployment rates during times of natural and economic disasters, when regional ties tend to strengthen.

[Table 6]

The previous analysis is dynamic, but is limited to a time span of one or three quarters. To conduct a more dynamic analysis, we estimate the relationship between unemployment rates and BSI using impulse response functions. These functions can be estimated from the panel vector autoregression (PVAR) model, which is a popular statistical approach in economic and financial studies. The VAR model is a convenient statistical model to summarize a dynamic relationship in time-series data and is a useful method to deal with a potential endogeneity issue in economic variables. PVAR is an extension of VAR designed for panel data analyses, and the standard PVAR(p) for a $m \times 1$ vector of endogenous variables (y) can be stated as:

$$y_{i,t} = \left(I_m - \sum_{l=1}^{p} A_l \right) \mu_i + \sum_{l=1}^{p} A_l y_{i,t-l} + \epsilon_{i,t} \tag{2}$$

where I is a $m \times m$ identity matrix, μ_i is a fixed effect, and ϵ is a random error. We estimate the generalized impulse response functions or GIRFs (Pesaran and Shin,

[9]This model excludes the third lag of sales and profits that are found to be insignificant.

1998) from PVAR(6).[10] This model specification appears to be appropriate for the relationship between unemployment rates and BSI correlation as well as between unemployment rates and BSI. The Hansen test of over-identification restrictions examines the validity of the parameter identification under the null hypothesis, which cannot be rejected for both cases. The GIRF for a shock to variable j (δ_j) can be obtained as:

$$GIRF(j) = E[y_{i,t+h}|\epsilon_{i,t,j} = \delta_j, \Sigma_\epsilon] - E[y_{i,t+h}|\Sigma_\epsilon] = A^h \Sigma_\epsilon (\sigma_{j,j})^{-1/2} \tag{3}$$

where $\sigma_{j,j}$ is the jth element in $\Sigma_{\epsilon,j,j}$. Figure 4 shows that a dynamic response of unemployment rates to the BSI is consistent with the conventional expectations. We calculate the GIRFs of $h = 6$, extended from the time-series model, which are invariant to the level of exogeneity (i.e., the order) of variables in the PVAR. Figure 4 (a) shows the positive relationship between unemployment rates and BSI correlation. A high regional correlation would worsen the labor market conditions by increasing unemployment rates. Figure 4 (b) shows the negative relationship between unemployment rates and the BSI (in levels). Thus, the worsening business prospects of firms are associated with the increases in unemployment rates. These two graphs suggest that a certain amount of time is required for the employment condition to change after the projections are made, with BSI being a good predictor of employment conditions in general.

[Figure 4]

4.3 Asymmetric responses of unemployment rates to changes in BSI forecast errors

Moreover, we consider possibilities of asymmetric responses of unemployment rates because labor markets are known to be sensitive to macroeconomic conditions (Levin, 2013; Christiano et al., 2016). Therefore, we calculate threshold impulse response functions closely following a methodology proposed by Aberbach and Gorodnichenko (2013). They proposed a threshold panel model by extending Jorda's (2005) impulse response functions (known as local projections). His methodology differs from the stan-

[10]The PVAR was estimated using the panelvar function in R (Sigmund and Ferstl, 2017). We used forward orthogonal data transformation.

dard impulse responses based on the VAR or PVAR in that defines structural shocks by imposing restrictions on parameters and residual covariance. The local projection approach can easily accommodate nonlinear behaviors and circumvent the problem of the curse of dimensionality.

We use the two-regime models (Low and High correlation periods), which allow different parameters and variances during regimes and where the regime is determined by the BSI correlation. For a vector of y comprising unemployment rates and the BSI, such a model can be summarized as:

$$y_t = (1 - F(z_{t-1})) + \Pi_H(L)y_{t-1} + F(z_{t-1})\Pi_L(L)y_{t-1} + u_t \tag{4}$$

where $u_t \sim N(0, \Sigma_t)$ and $\Sigma_t = \Sigma_H(1 - F(z_{t-1})) + \Sigma_L F(z_{t-1})$. Π is parameters for high and low correlation periods that are denoted as subscripts H and L, respectively. (L) is a lag operator. Moreover,

$$F(z_t) = \frac{exp(\gamma z_t)}{1 + exp(-\gamma z_t)} \tag{5}$$

where $\gamma > 0$ that determines threshold points in the system. The threshold variable is normalized as $E(z_t) = 0$ and $var(z_t) = 1$. Eq. (5) incorporates a smooth transition process between high and low periods, which has often been used in univariate threshold time-series analyses. As discussed by Aberbach and Gorodnichenko (2012), while it is possible to estimate all parameters simultaneously, it involves nonlinear estimation and results are sensitive to the sample size. Therefore, we impose a value of γ prior to the estimation, and check the sensitivity of the results to γ afterwards.

Furthermore, we use a definition of economic shock that is different from that in our previous analysis. Here, economic shock is defined as NextQ, which is a difference between business prospects for next quarters $(t + 1)$ and prospects for contemporaneous quarters made in $t + 1$. Therefore, a revision in business prospects for the same quarter should reflect increases in information brought about between t and $t + 1$, and this information is assumed to influence firms' employment decisions. Therefore, we examine responses of unemployment rates to an economic shock that leads to errors in firms' business prospects. NextQ equal to zero indicates the accuracy of business prospects, and the positive NextQ represents over-optimistic views.[11] The effect of the shock in regimes can be written as Eq. (6) and will be incorporated into Eq. (4), such that we can easily accommodate nonlinear properties and circumvent the curse of dimensionality problem.

$$F(z_{t-1})\Theta_H Shock_t + (1 - F(z_{t-1}))\Theta_L Shock_t \tag{6}$$

[Figure 5]

Figure 5 presents asymmetric responses of unemployment rates between high and low periods that are defined by quantiles of the BSI correlation (25, 50, and 75% quantiles and the medium value). The left side of each figure (a to d) corresponds to high BSI correlation periods, and the right to low correlation periods. We find that there is a clear positive response of unemployment rates at times of high BIS correlation, implying that during chaotic moments, over-optimistic views of business prospects lead to employees being laid off in the following quarters. In contrast, this effect is insignificant in periods of low BSI correlation. It follows that unexpectedly worse business events that occurred between t and $t+1$ made firms reduce the number of workers at a greater scale during higher correlation periods than low correlation periods. This conclusion remains generally the same regardless of the threshold points to determine the regimes. However, the effect of the shock on unemployment rates becomes more significant when γ increases. In other words, consistent with the conventional expectations, layoff is a more likely scenario during economic and natural disasters.

5 Conclusion

As proposed in standard economic theory, market globalization has had many positive impacts in our life, and presently, it is difficult to imagine life without any imported goods. We do not intend to refute this assertion but argue that market integration has a side effect, which becomes prominent during nationwide crises and disasters. More precisely, our findings imply that regional homogeneity strengthens during economic

[11] Aberbach and Gorodnichenko (2013) used differences between forecasts of government expenditures and actual data as an economic shocks in the study of fiscal multipliers.

and natural disasters and is positively associated with unemployment rates with time lags. Notably, the relationship between regional correlation and unemployment rates is stronger during disasters like COVID-19 that has more homogeneous effects on regions than other crises. It implies that regional homogeneity would hinder economic recovery, since no other regions can become an engine of economic growth in the country.

This finding has relevant economic policy implications for the future of Japan, which is one of the most aged countries in the world. The proportion of people older than 65 years increased from 4.9% to 28.4% between 1950 and 2020. Along with this demographic change, both the population and the labor force has been declining. Moreover, people tend to relocate to the Kanto region (Tokyo prefecture). A concentration of population and firms (economic agglomeration) may bring economic benefits through increasing returns, thus widening regional heterogeneity, which, according to our results, acts as a cushion against various disasters. However, this cushioning effect may not function in the absence of a modest scale of regional economic centers. Therefore, we caution that the disappearance of local economic centers in Japan, along with changes in demography and lifestyle, could be problematic during disasters and provide a justification against the geographical over-concentration of population and economic activities in a country.

Similarly, our conclusion may contradict the conventional economic theory that advocates a very high level of (or perfect) regional homogeneity in a single currency market. One very notable example is the Maastricht convergence criteria to ensure the homogeneous Euro-wide area. In calm periods, heterogeneity in member countries is often considered a negative factor for a single currency area, but diversified markets with a certain level of economic centers in member countries buffer Euro-wide shocks during chaotic times.

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Table 1: Errors in business projections and regional unemployment rates

Region	Mean	SD	Median	Min	Max	Skew	Kurtosis	SE
BSI (NextQ)								
Hokkaido	7.05	7.28	5.25	-1.40	46.30	2.67	11.07	0.91
Tohoku	6.91	7.70	5.65	-7.20	46.70	2.37	9.48	0.96
Kanto	6.27	7.55	4.00	-1.70	43.80	2.77	9.24	0.94
Hokuriku	6.02	9.29	4.15	-6.50	52.30	2.24	8.04	1.16
Takai	5.82	9.37	3.65	-12.20	52.10	2.36	8.31	1.17
Kinki	7.02	7.83	5.65	-1.70	50.00	2.96	12.46	0.98
Chugoku	6.31	8.01	4.30	-3.70	51.30	3.17	13.97	1.00
Shikoku	6.40	7.37	4.85	-5.00	43.10	2.25	8.06	0.92
Kyushu	5.92	8.01	4.10	-12.00	45.00	1.83	7.07	1.00
BSI (NextQQ)								
Hokkaido	9.04	8.82	7.10	-4.50	48.90	1.61	4.77	1.11
Tohoku	9.59	9.32	8.10	-3.20	49.60	1.83	4.52	1.17
Kanto	8.98	9.96	6.70	-4.40	49.10	2.31	6.28	1.25
Hokuriku	9.59	11.24	7.80	-5.10	57.70	1.84	4.43	1.42
Takai	9.24	11.34	8.00	-6.00	58.20	2.23	6.10	1.43
Kinki	9.88	9.96	8.10	-4.40	55.90	2.44	7.69	1.25
Chugoku	9.07	10.44	8.20	-5.30	57.80	2.32	7.64	1.32
Shikoku	8.78	9.21	6.60	-5.50	46.70	1.72	4.25	1.16
Kyushu	7.98	9.80	6.80	-9.70	53.00	2.00	6.29	1.23
Unemployment rates								
Hokkaido	4.71	1.14	4.95	2.10	8.30	-0.10	-0.05	0.12
Tohoku	4.17	1.14	4.30	2.10	6.30	-0.17	-1.06	0.12
Kanto	3.90	0.84	3.95	2.10	5.40	-0.43	-0.75	0.09
Hokuriku	2.91	0.74	3.00	1.50	4.20	-0.38	-0.83	0.08
Tokai	3.11	0.80	3.10	1.50	4.70	-0.11	-0.89	0.08
Kinki	4.70	1.22	4.80	2.30	7.20	-0.10	-0.85	0.13
Chugoku	3.36	0.73	3.50	1.90	4.50	-0.39	-0.86	0.08
Shikoku	3.71	0.91	3.90	1.50	5.20	-0.55	-0.55	0.09
Kyushu	4.33	0.99	4.50	2.30	6.00	-0.51	-0.78	0.10

Note: The sample period is from 2004Q2 to 2020Q2. NextQ refers to projection differences between t and $t+1$, and NextQQ to those between t and $t+2$. Regions comprises the following prefectures stated in parentheses. Hokkaido (Hokkaido), Tohoku (Aomori, Akita, Iwate, Miyagi, Yamagata, Fukushima), Kanto (Tokyo, Kanagawa, Saitama, Chiba, Ibaraki, Tochigi, Gunma, Niigata, Yamanashi, Nagano), Hokuriku (Toyama, Ishikawa, Fukui), Tokai (Gifu, Shizuoka, Aichi, Mie), Kinki (Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama), Chuugoku (Tottori, Shimane, Okayama, Hiroshima, Yamaguchi), Shikoku (Kumamoto, Oita, Miyazaki, Kagoshima).

Table 2: Panel estimations for unemployment rates

Estimation methods	POLS	Within	Random	POLS	Within	Random
Intercept	3.412^{***}		3.402^{***}	3.281^{***}		3.267^{***}
	(0.055)		(0.216)	(0.053)		(0.214)
BSI	-0.020^{***}	-0.021^{***}	-0.021^{***}			
	(0.003)	(0.003)	(0.003)			
lag(BSI, 1)				-0.034^{***}	-0.036^{***}	-0.036^{***}
				(0.004)	(0.003)	(0.003)
R^2	0.057	0.085	0.084	0.137	0.200	0.198
Adj. R^2	0.055	0.070	0.082	0.136	0.187	0.196

Note: Unemployment rates are endogenous variables. The POLS stands for the pooled ordinary least square. The sample period is from 2004Q2 to 2020Q2.

Table 3: Regional correlation levels during crises

	POLS				Within
End. variable	BSI correlation (All sectors)				
Intercept	0.663^{***}	0.656^{***}	0.647^{***}	0.641^{***}	
	(0.010)	(0.010)	(0.010)	(0.010)	
Lehman		0.236^{***}	0.245^{***}	0.251^{***}	0.251^{***}
		(0.058)	(0.057)	(0.057)	(0.056)
Earthquakes			0.277^{***}	0.283^{***}	0.283^{***}
			(0.057)	(0.057)	(0.056)
COVID				0.354^{***}	0.354^{***}
				(0.080)	(0.079)
R^2	0.000	0.007	0.017	0.026	0.027
Adj. R^2	0.000	0.007	0.017	0.024	0.010
Num. obs.	2268	2268	2268	2268	2268
End. variable	Unemployment rate correlation				
Intercept	0.442^{***}	0.443^{***}	0.445^{***}	0.443^{***}	
	(0.011)	(0.011)	(0.011)	(0.011)	
Lehman		-0.024	-0.027	-0.024	-0.024
		(0.061)	(0.061)	(0.061)	(0.058)
Earthquake			-0.077	-0.075	-0.074
			(0.061)	(0.061)	(0.058)
COVID				0.119	0.120
				(0.085)	(0.082)
R^2	0.000	0.000	0.001	0.002	0.002
Adj. R^2	0.000	-0.000	-0.000	0.000	-0.016
Num. obs.	2224	2224	2224	2224	2224

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Explanatory variables are dummies and are expected to capture crisis effects.

Table 4: Regional correlation during crises II

	POLS				Within
End. variable	BSI correlation (Manufacturing sector)				
Intercept	0.642^{***}	0.631^{***}	0.636^{***}	0.625^{***}	
	(0.011)	(0.011)	(0.011)	(0.011)	
Lehman		0.337^{***}	0.332^{***}	0.343^{***}	0.343^{***}
		(0.060)	(0.060)	(0.059)	(0.058)
Earthquake			-0.152^{*}	-0.140^{*}	-0.140^{*}
			(0.060)	(0.059)	(0.058)
COVID				0.340^{***}	0.340^{***}
				(0.059)	(0.058)
R^2	0.000	0.014	0.017	0.031	0.033
Adj. R^2	0.000	0.013	0.016	0.029	0.016
Num. obs.	2268	2268	2268	2268	2268
End. variable	BSI correlation (Non-manufacturing sector)				
Intercept	0.566^{***}	0.561^{***}	0.549^{***}	0.534^{***}	
	(0.012)	(0.012)	(0.012)	(0.012)	
Lehman		0.136^{*}	0.149^{*}	0.164^{*}	0.164^{*}
		(0.068)	(0.067)	(0.067)	(0.066)
Earthquake			0.392^{***}	0.407^{***}	0.407^{***}
			(0.067)	(0.067)	(0.066)
COVID				0.439^{***}	0.439^{***}
				(0.067)	(0.066)
R^2	0.000	0.002	0.016	0.035	0.037
Adj. R^2	0.000	0.001	0.016	0.033	0.020
Num. obs.	2268	2268	2268	2268	2268

Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Explanatory variables are dummies and are expected to capture crisis effects.

Table 5: Regional correlation during crises III

	POLS				Within
End. variable	BSI correlation (Large firms)				
Intercept	0.505***	0.492***	0.476***	0.463***	
	(0.013)	(0.013)	(0.013)	(0.013)	
Lehman		0.415***	0.431***	0.443***	0.443***
		(0.073)	(0.072)	(0.072)	(0.070)
Earthquake			0.478***	0.490***	0.490***
			(0.072)	(0.072)	(0.070)
COVID				0.376***	0.376***
				(0.072)	(0.070)
R^2	0.000	0.014	0.033	0.045	0.048
Adj. R^2	0.000	0.014	0.032	0.044	0.032
Num. obs.	2260	2260	2260	2260	2260
End. variable	BSI correlation (Small & medium firms)				
Intercept	0.615***	0.614***	0.609***	0.596***	
	(0.011)	(0.011)	(0.011)	(0.011)	
Lehman		0.021	0.027	0.039	0.039
		(0.062)	(0.062)	(0.062)	(0.060)
Earthquake			0.178**	0.191**	0.191**
			(0.062)	(0.062)	(0.060)
COVID				0.371***	0.371***
				(0.062)	(0.060)
R^2	0.000	0.000	0.004	0.019	0.021
Adj. R^2	0.000	-0.000	0.003	0.018	0.004
Num. obs.	2268	2268	2268	2268	2268

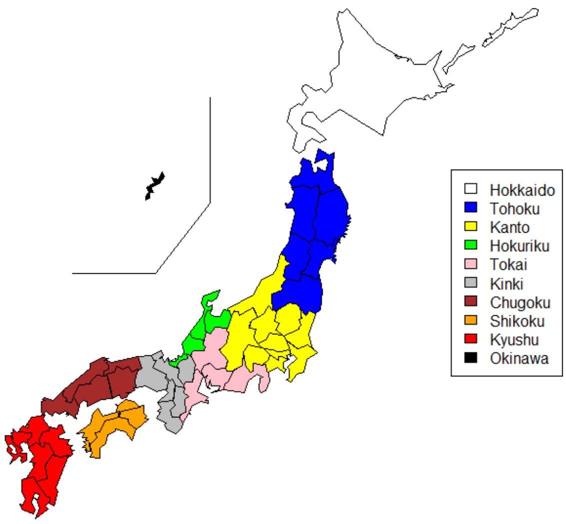
Note: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Explanatory variables are dummies and are expected to capture crisis effects.

Table 6: The ADL model for unemployment rates

	POLS	Random	Within
Intercept	2.860***		2.892***
	(0.106)		(0.155)
BSI corr	−0.111	−0.108	−0.110
	(0.134)	(0.116)	(0.116)
Sales	0.043*	0.017	0.020
	(0.021)	(0.018)	(0.018)
Profits	−0.038***	−0.023**	−0.024**
	(0.008)	(0.008)	(0.008)
R^2	0.085	0.034	0.038
Adj. R^2	0.075	−0.007	0.028
Intercept	2.785***		2.816***
	(0.101)		(0.154)
lag(BSI corr, 1)	−0.007	−0.006	−0.008
	(0.129)	(0.109)	(0.109)
lag(Sales, 1)	0.025	0.002	0.004
	(0.021)	(0.018)	(0.018)
lag(Profits, 1)	−0.041***	−0.028***	−0.029***
	(0.008)	(0.008)	(0.008)
R^2	0.109	0.065	0.069
Adj. R^2	0.099	0.024	0.058
Intercept	2.210***		2.206***
	(0.160)		(0.230)
lag(BSI corr, 1)	0.206	0.246*	0.241*
	(0.133)	(0.110)	(0.109)
lag(BSI corr, 2)	0.298*	0.336**	0.331**
	(0.135)	(0.110)	(0.109)
lag(BSI corr, 3)	0.199	0.227*	0.223*
	(0.128)	(0.106)	(0.105)
lag(Sales, 1)	0.041	0.021	0.021
	(0.031)	(0.024)	(0.024)
lag(Sales, 2)	0.019	−0.012	−0.011
	(0.030)	(0.025)	(0.025)
lag(Profits), 1)	−0.039**	−0.021	−0.022
	(0.014)	(0.012)	(0.012)
lag(Profits, 2)	−0.026	−0.004	−0.006
	(0.014)	(0.012)	(0.012)
R^2	0.146	0.115	0.114
Adj. R^2	0.121	0.056	0.087

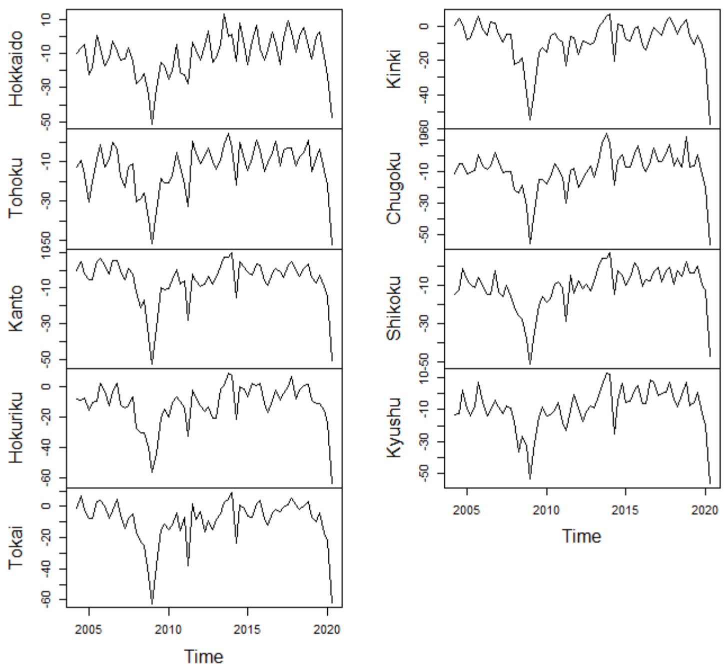
Note: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.010$. BSI corr presents regional correlation.

Figure 1: Japanese regions



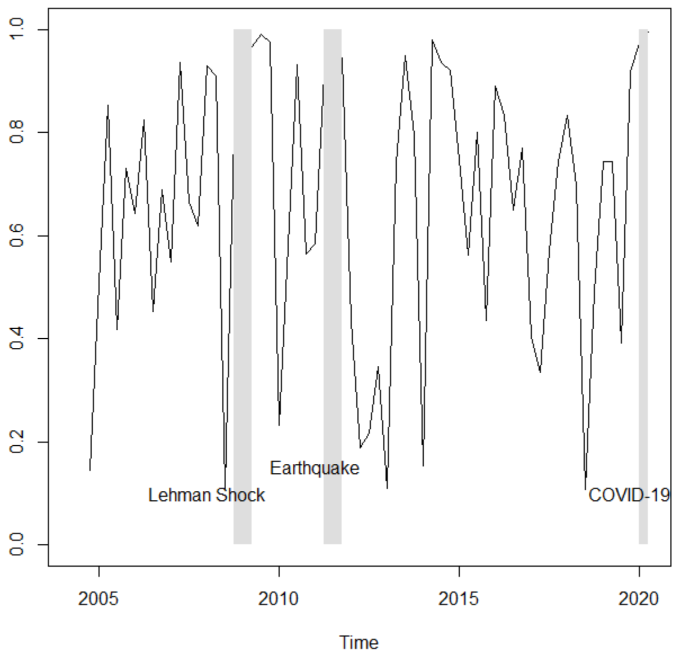
Note: See Table 1 for the definition of regions.

Figure 2: Business Survey Index



Note: The sample from 2004Q2-2020Q2. Increases in the BSI shows that businessman see a bright future.

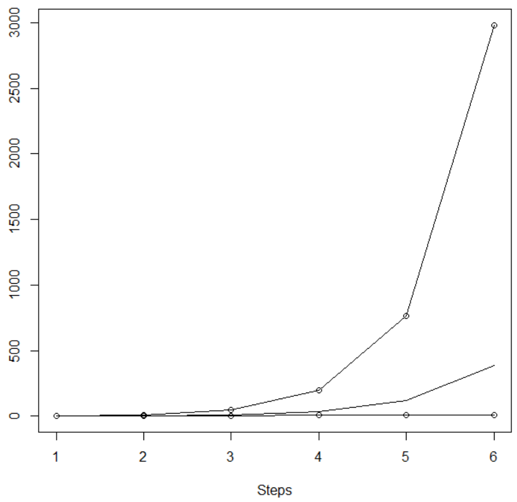
Figure 3: Regional correlation



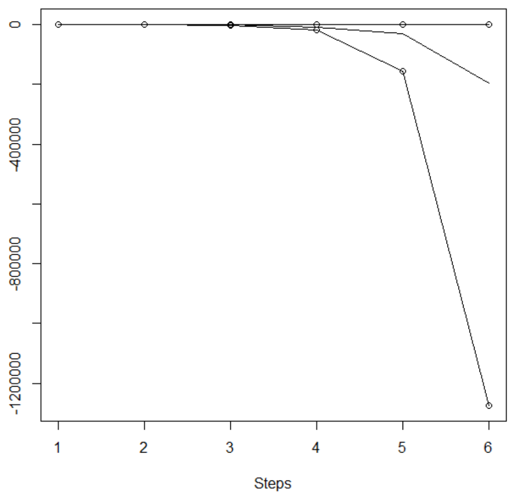
Note: The national average of regional BSI correlation.

Figure 4: Impulse response functions from the PVAR

(a) Unemployment rates in response to a shock in BSI correlation



(b) Unemployment rates in respose to a shock in the BSI

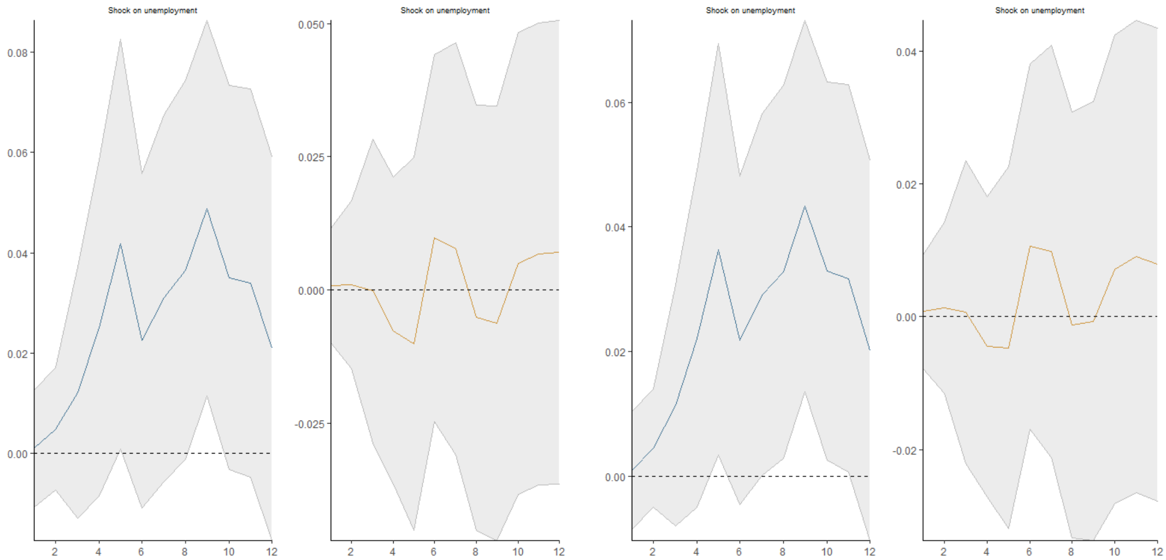


Note: The generalized impulse response functions are obtained from the PVAR(6). Lines with circles show a 95% confidence interval, which is obtained by the bootstrap method with 1000 draws. Hansen test of overidentification restrictions: $\chi^2(1076) = 0.001$ for (a) and $\chi^2(1116) = 0.001$ for (b).

Figure 5: Threshold Impulse response functions: Unemployment rates in response to changes in BSI forecast errors

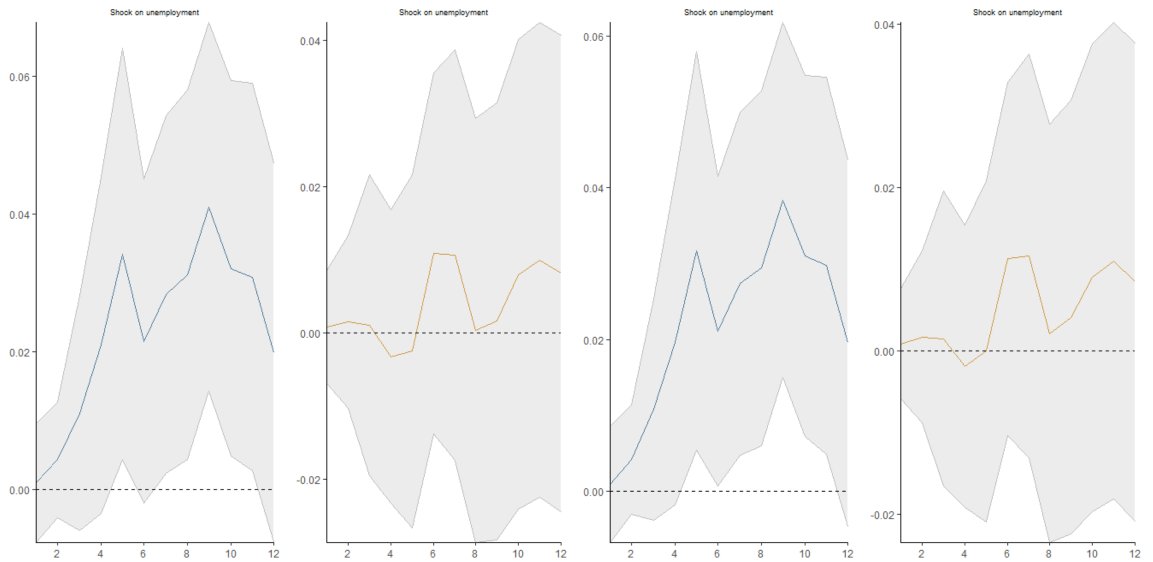
(a) Threshold=1st quantile (25%) of BSI correlation

(b) Threshold=2nd quantile (50%) of BSI correlation



(c) Threshold=medium of BSI correlation

(d) Threshold=3nd quantile (75%) of BSI correlation



Note: The left side of each graph (a,b,c,d) shows responses of unemployment rates during periods of high BSI correlation and the right side is those during low BSI correlation periods. Generally, high BSI correlation corresponds to chaotic periods. The BSI shock is defined as NextQ, which is a difference between business prospects for next quarters ($t+1$) and prospects for contemporaneous quarters made in $t+1$. The shaded area is a 95% confidence interval.