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Abstract

Given the increase in the importance of measuring the degree and source of resilience after great shocks, resilience has garnered researchers' attention. However, there is no generally agreed-upon measurement for resilience; the existing approach holds few industrial assessments for resilience. This study provides a structural sensitivity index to measure the industrial sources of regional employment resilience and applies it to the Japanese economy between 1980 and 2012. It presents a novel formula that quantifies the sources of regional resilience by within-sector and structural change effects and extracts how unevenly different local industries contribute to regional resilience. Exploring the industrial and quantitative aspects of employment resilience chronally and geographically reveals that Japanese prefectures gradually became resilient after the 1990s, increasing the regional heterogeneity. Moreover, the structural change effect has constantly hurt the regional resilience, offsetting some favourable within-sector effects. Finally, the increasing regional heterogeneity behind improvements in resilience accompanies industrial unevenness from different time horizons, but the overall relationship between industrial unevenness and resilience is not unique from a different spatial perspective.

Keywords

Resilience, sensitivity index, employment, industrial structural change, Japan

JEL code

B52, E24, J21, R11, R12

1 INTRODUCTION

Over the past few decades, many countries have experienced adverse economic shocks. Japan is no exception; its economy has been stagnating since the 1990s through several crises. Crises ask how resilient the economy is. Particularly, given the global financial crisis and the current COVID-19 pandemic, the concept of resilience has garnered much researcher attention.

As resilience is essentially multifaceted (Briguglio et al., 2009), the concept has been stretched to various disciplines in human and social sciences , engineering, and urban planning (Modica & Reggiani, 2015; Fröhlich & Hassink, 2018). Moreover, the evolutionary economic perspective has explored how an economic unit can withstand or absorb a shock and recover therefrom or develop a new development trajectory. It considers economic resilience an ensemble of resistance, recoverability, reorganisation, and reorientation after an adverse shock (Simmie & Martin, 2010; Martin et al., 2016; Martin & Sunley, 2020).[1] Hence, the fundamental question for regional economic resilience is 'why do some regions manage to overcome short-term or long-term economic adversity to maintain a high quality of life for regional residents while others fail?' (Christopherson et al., 2010, p. 2). Many researchers have explored the concept, measurement, and application of regional resilience via state-of-the-art empirical analyses (Bristow & Healy, 2020).

This study empirically analyses the regional employment resilience in Japan. Unlike prior studies, this study presents a novel formula for sensitivity index to simultaneously measure the spatial and industrial sources of regional resilience. It focuses on the regional employment from different industries' performance, of which it measures the resilience over recession and recovery phases. The main unit of analysis is 47 regional (prefectural) economies and their

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[1] Resilience after an adverse shock is classified via three representative conceptions: engineering, ecological, and evolutionary conceptions. The engineering concept captures the resilience of an economic unit as a bounce-back to a prior equilibrium. The ecological resilience focuses on the ability of unit to absorb shock within an existing system. Evolutionary (or adaptive) resilience defines the capacity to bounce forward and adapt via structural changes of different units (Boschma, 2015; Bristow & Healy, 2020; Evenhuis, 2020).

employment resilience over different business cycles. Thus, the study employs the Regional-Level Japan Industrial Productivity Database 2017 (R-JIP database 2017) compiled by the Research Institute of Economy, Trade and Industry. Hence, the study reveals chronal and regional characteristics of employment resilience in Japan and its industrial driving force, evolutionary property, and unevenness.

Prior studies identify the factors that principally influence regional economic resilience. As Martin and Sunley (2020) note, they focus on industrial structure (Groot et al., 2011; Brown & Greenbaum, 2017; Gardiner et al., 2013; Martin et al., 2016; 2018; Martin & Gardiner, 2021), labour market conditions (Fingleton et al., 2012; Faggian et al., 2018; Cappelli et al., 2021), financial arrangement, and governance arrangements. The role of an economic agent also matters for resistance to and recovery from shock (Bristow & Healy, 2014).

This study investigates regional employment resilience and its industrial structural sources, on which there are affluent empirical studies centred around the US and European countries. For instance, by estimating the sensitivity of sectoral GDP reaction to shocks in some EU countries, Groot et al. (2011) find that countries and regions with highly sensitive industries underwent a stronger growth decline in 2009. Brown and Greenbaum (2017) studied employment resilience in Ohio counties between 1977 and 2011 via regression analyses. They show that industrial diversification restrains the unemployment rate, but concentration raises it during national or local employment shocks. Meanwhile, Martin et al. (2018) use the decomposition technique to measure regional resilience, revealing that relative to between-sector contributions, within-sector improvements are dominant over the UK's city productivity growth rate. Using a similar technique, Martin et al. (2016) show that the regional competitiveness effect is relatively large for the UK's regional employment resilience, and most regions in the UK undergo a negative industrial structural effect over different cycles. Martin and Gardiner (2021) review the controversy on which regions with industrial competitiveness, specialisation, diversification, or related variety are more resilient. Applying these concepts to the UK cities, they show that city-specific competitiveness matters for resilience.

These studies commonly highlight that different sectoral compositions of the economy are concerned with regional resilience for the US and European countries. Despite this recognition, it is not obvious how different industry performance and structural change quantitatively contribute to regional resilience. Indeed, industrial contributions to regional resilience can be quite mixed, as per this study. Evidently, prior studies have not explored this fact.

This study presents three contributions to the existing literature. First, it builds a structural sensitivity index to quantitatively measure the industrial sources of regional resilience. The sensitivity index is originally given by Martin (2012) and has been modified to correctly measure regional resilience (Lagravinese, 2015; Giannakis & Bruggeman, 2017). It determines the regional resilience by comparing the change in an aggregate economic variable (e.g. value-added, employment rate, and productivity) of a regional economic unit with that of a benchmark unit. However, a regional economy naturally comprises different industries, and accordingly, industrial performance is crucial to building a resilient economy. However, the sensitivity index ignores this simple fact, and, consequently, the sources of regional resilience are packed in a black box. The structural sensitivity index can simultaneously measure regional resilience and its industrial sources. Unpacking the black box of the regional resilience, this study links three aspects of resilience: resistance (i.e. the degree of enduring over the general recession phase), recoverability (i.e. the degree of recovery over the general recovery phase) and an evolutionary dimension of reorganisation (i.e. continuous change in industrial structure over business cycles) in a regional economy. This study decomposes the sources of resilience into within-sector and structural change effects to measure resistance and recoverability. The new formula can generically be applied to other databases employed in this study.

Second, this study explicitly extracts the unevenness behind regional resilience quantitatively. Some industries support resilience, but others do not. The sensitivity index *per se* cannot precisely measure how different industries contribute to regional resilience for these cases, as it is defined at the aggregate level. Moreover, although regional studies have revealed regional differences in economic resilience or volatility in other ways (e.g. Duran & Fratesi, 2020, for

Italian regions; Ringwood et al., 2020, for the US county), they have not specified where the differences come from. Therefore, this study relates the sources and unevenness of industrial contributions. By disaggregating the sensitivity index into industry levels, the approach also quantifies the unevenness of industrial contributions to regional resilience. This idea is inspired by Harberger's (1998) sunrise-sunset diagram, which classified the different total factor productivity (TFP) growth patterns. The application provides useful graphical and summary statistics to consider the industrial sources and unevenness of regional resilience. It helps consider the resilience of regional employment and its uneven source.

The third contribution is empirical. The study examines the Japanese economy and considers the long-term evolution of its regional resilience. Despite many studies exploring resilience in European or the US economies, with frequent natural disasters in Japan attracting researchers' attention to its regional resilience, the subject remains limited. For instance, Aldrich (2012) compares Tokyo's 1923 and Kobe's 1995 earthquakes and shows that social community networks are vital to recovery. Fraser (2021) explores the role of social capital at a municipality level and community resilience after disasters. Using the sensitivity index, Oliva and Lazzeretti (2018) contrast employment resilience differences between strong major prefectures and weak rural ones after major earthquakes between 2003 and 2008. Todo et al. (2015) econometrically reveal that supply chain networks outside of an affected area contribute to the early recovery of production in seven Tohoku prefectures after the Great East Japan earthquake in 2011. These studies revealed how particular regions reacted to a specific disaster in Japan. However, a natural disaster is not the only serious adverse shock. The Japanese economy has long been affected by various short-term shocks, such as the bubble burst, the financial crisis in the late 1990s, and the global financial crisis of 2008. Therefore, it is pertinent to analyse the regional resilience in Japan regarding a sequence of shock and recovery processes. Generally, many studies assess resilience to only one shock, such as the global financial crisis, as Bristow and Hearly (2020) note. However, one shock alone may not drastically change a regional economic resilience, and a longer-run perspective matters, as the regional economy is a product of the history wherein its reaction to shock may have shaped its resilience to subsequent shocks. Martin and Sunley (2020, p. 32) summarise that 'the features and structures built up by a region's past development influence its resilience, and its resilience to shocks will impact back on that development path, either reinforcing it or promoting change.' Hence, the long-run focus of this study can highlight the differences and evolving nature of regional resilience and its relationship with industrial structure.

The rest of the study is organised as follows: Section 2 explains the issues of the sensitivity index and presents the structural sensitivity index. Section 3 applies this index to identify industrial sources and the unevenness of regional resilience in Japan. Section 4 concludes the study.

2 FORMULAS FOR MEASURING INDUSTRIAL SOURCES AND UNEVENNESS FOR REGIONAL RESILIENCE

2.1 Sensitivity index revisited

Martin (2012) proposed the sensitivity index to measure the UK's regional resistance to and recovery from the early 1980s recession regarding employment. It is defined by the ratio of growth rates or elasticity for economic variables, such as employment or value-added in a region to that in the country (i.e. benchmark). The original sensitivity index $\beta_{1,r}$ of a region r is given by

$$\beta_{1,r} = \frac{g_r}{g_N}, \tag{1}$$

where g_r is the growth rate in an economic variable in region r, while g_N is that in the country from the onset of a negative shock to its end. The index $\beta_{1,r}$ greater than unity over a recession period indicates that the region r shows a low resistance (or more vulnerability) to a recessionary shock. Conversely, if the index is less than unity, it has a high resistance. Martin's sensitivity index is also applied to measure recoverability. Namely, if the index is over unity for a region over the recovery process, it has a high recoverability and vice-versa.

Equation (1) implicitly supposes that the growth rates of region and country move in the same direction over the recession and recovery process. However, they can naturally move in opposite directions. When the national economy records a negative growth rate but a regional economy realises a positive growth rate (i.e. $g_N < 0$, and $g_r > 0$) over a recession, Equation (1) presents a wrong message that the regional resistance is low because the value is less than unity.

Thus, to avoid such a wrong determination, Lagravinese (2015) and Giannakis and Bruggeman (2017) provide the following sensitivity index:

$$\beta_{2,r} = \frac{1}{|g_N|}(g_r - g_N). \tag{2}$$

The sensitivity index $\beta_{2,r}$ is principally computed by the difference between the region and national growth rates, scaled by the absolute value of the national growth rate. The sign of the index identifies the resistance and recoverability. When the index is positive over a recession, its impact is less for the region than for the national economy, and the regional economy is regarded as high resistance. Conversely, when it is negative, its impact is harder for the region than for the national economy, and the regional economy is regarded as low resistance. When it is applied to the recovery process, the positive (negative) value indicates that the regional economy grows faster (slower) than the national economy, and the regional economy has a high recoverability. Unlike Martin's original index, Equation (2) is robust to the cases where regional and benchmark growth rates record different signs, and it has widely been employed to identify regional resilience.[2]

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[2] For example, using output growth rates, Tan et al. (2020) measured the economic resilience of resource-based cities during the Asian and global financial crises. Based on Equations (1) and (2), Lagravinese (2015) studies the resistance and recoverability of the Italian regional labour market over different business cycles from 1970 to 2007, finding that there is a positive correlation between average resistance and recoverability. Giannakis and Bruggeman (2017) employs Equation (2) to measure the regional employment resilience for EU-28 with the benchmark of EU and county and reveals heterogenous geography of the employment resilience on the impact of the global financial crisis. Moreover,

Although simple and useful, these sensitivity indices have some problems in measuring regional resilience. First and crucially, they ignore that regional and national economy comprises different industries. Consequently, they cannot measure the industrial sources of regional resilience. The sensitivity indices leave much to consider regarding the industrial structure and its different performances in regional and national economies. Second and accordingly, these indices cannot identify the impact of structural changes on regional economic resilience. Given that the sensitivity indices simply compare the magnitude of aggregate economic changes to evaluate resilience, the effect of change in industrial compositions is ignored. Moreover, regional resilience is established via contrasted contributions of different industries and structural changes. The simple sensitivity indices overlook uneven contributions and various structural changes behind different regions. Hence, to address such remaining issues, this study presents a structural sensitivity index.

2.2 Structural sensitivity index

The structural sensitivity index, denoted by β_r, emphasises the role of industrial compositions in an economy. The study employs the following equation to derive the index:

$$\beta_r = g_r - g_N, \tag{3}$$

which is identical to Equation (2) except that it is not scaled by the absolute value of the national (benchmark) growth rate. It can be scaled with it to consider the economic resilience elasticity, but the equation suffices to measure the types and degrees of resilience. The essence of the structural sensitivity index is that regional and benchmark growth rates

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sensitivity index is modified by level variables to address this issue. For example, Faggian et al. (2018) present

$$\beta_r = \frac{E_{r,t}/E_{r,t-1}}{E_{N,t}/E_{N,t-1}},$$

where $E_{r,t}/E_{r,t-1}$ is the ratio of a regional economic variable between time t and $t-1$, and $E_{N,t}/E_{N,t-1}$ is that of the national variable. Thus, if the value is over unity, the region is more resistant than the national (benchmark) economy. Oliva and Lazzeretti (2018) employ this index to measure the employment resistance of major Japanese prefectures after the major earthquakes.

are the sum of different industry contributions. Given that this approach directly uses realised values only, it does not require a counterfactual or expected value, which largely depends on statistical inference to measure the regional resilience.

Denote $g_{i,r}$ and $g_{i,N}$ as the growth rates of an economic variable in an industry i of a region r and that of the national economy N, respectively. These growth rates are standardised by the average annual rates over a business cycle phase. Moreover, let $\omega_{i,r}$ and $\omega_{i,N}$ be the shares of the economic variable in the industry i of the regional and national economies, respectively. These shares are defined at the benchmark year to calculate the contributions. The regional growth rate for the variable can then be decomposed into $g_r = \sum_i g_{i,r} \cdot \omega_{i,r}$, and, by the same token, the national growth rate is $g_N = \sum_i g_{i,N} \cdot \omega_{i,N}$. Substituting these disaggregated expressions into Equation (3) yields

$$\beta_r = \sum_i g_{i,r} \cdot \omega_{i,r} - \sum_i g_{i,N} \cdot \omega_{i,N} = \sum_i \left(g_{i,r} \cdot \omega_{i,r} - g_{i,N} \cdot \omega_{i,N}\right), \tag{4}$$

where the terms in the parenthesis can further be arranged as

$$g_{i,r} \cdot \omega_{i,r} - g_{i,N} \cdot \omega_{i,N} \equiv \left(g_{i,r} - g_{i,N}\right)\omega_{i,r} + \left(\omega_{i,r} - \omega_{i,N}\right)g_{i,N}. \tag{5}$$

Hence, the structural sensitivity index is

$$\beta_r = \sum_i \left(g_{i,r} - g_{i,N}\right)\omega_{i,r} + \sum_i \left(\omega_{i,r} - \omega_{i,N}\right)g_{i,N}\,, \tag{6}$$

which identifies the two sources of sensitivity and, accordingly, regional resilience. The first is the sum-product of differences between regional and national growth rates $(g_{i,r} - g_{i,N})$ and regional share $(\omega_{i,r})$ of each industry. If the growth rate of an industry i of a region r is higher (lower) than the country level, it positively (negatively) contributes to the regional resilience. These effects are proportionally enhanced by the share of the economic variable in the industry i of the regional economy r. Given that these dynamics work in the same industry, they are termed the 'within sector effect'.

The second is the sum-product of differences between regional and national shares $(\omega_{i,r} - \omega_{i,N})$ and national growth rate ($g_{i,N}$) of each industry. If the share of an industry i in a region r is larger than that at the national level (i.e. $\omega_{i,r} > \omega_{i,N}$), then a higher (lower) growth of the industry at the national level raises (lowers) the regional resilience. However, if that share is lower than the national level (i.e. $\omega_{i,r} < \omega_{i,N}$), then a higher (lower) growth of the industry at the national level lowers (raises) the regional resilience. Thus, the industrial composition and macroeconomic trend matter for the second effect. Importantly, given that $\omega_{i,r}$ and $\omega_{i,N}$ reflect the degree of regional and national concentration of an industry i, its ratio $\frac{\omega_{i,r}}{\omega_{i,N}}$ is the so-called location quotient measuring the relative degree of regional specialisation in industry i. In the formula, if their difference is positive and larger, the region r can be said to be specialised in industry i. When the specialisation goes with a pro-trend of industrial growth at the national level, it positively contributes to regional resilience by raising regional contribution over national contribution. Conversely, if the specialisation exhibits an anti-trend, it negatively contributes to regional resilience. Thus, how specialisation affects regional resilience depends on the macroeconomic trend of each industry.[3] Given that these dynamics originate in the structural aspect (i.e. the industrial composition) of regional and national economies, they are termed the 'structural change effect'.

The structural sensitivity index identifies within-sector and structural change effects as the sources of resilience for a region, the sum of which is the 'total effect'. Summing the total effect at a regional level measures the sensitivity index of that region.[4] Unlike the bounce-back approach, the index does not *a priori* suppose any single equilibrium

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[3] Dauth and Suedekum (2016) reveal that some regions in German grow at a higher pace even though the regional economy is strongly based on nationally declining industries. Urso et al. (2019) find that the global financial crisis promoted a change in industry composition of inner areas in Italy, though their local industry composition does not accord with the nationally booming sectors.

[4] The formula can also be regarded as an application of the shift-share analysis for regional economic growth, of which the economic geography has long been recognised as useful. For instance, Knudsen (2000), Nazara and Hewings (2004), Giannakis and Bruggeman (2017), and Martin and Gardiner (2021) present several shift-share formulas for regional growth rate decompositions, whereas Ray et al. (2012) and Gardiner et al. (2013) extend this formula to the

or return to it after a shock. It allows for different trajectories of each unit's behaviour under consideration as the ecological conception does. The most important advantage of the index is that the structural change effect sheds light on an evolutionary aspect of resilience in the sense of how resilience is associated with structural changes in regional and national economies (Evenhuis, 2020).

2.3 Measuring industrial unevenness behind resilience

The disaggregate approach is also helpful to understand the industrial unevenness of resilience in each region. Equation (6) can be rearranged as follows:

$$\beta_r = \sum_i \left\{ \frac{\left(g_{i,r} - g_{i,N}\right)\omega_{i,r} + \left(\omega_{i,r} - \omega_{i,N}\right)g_{i,N}}{\omega_{i,r}} \right\} \omega_{i,r}, \tag{7}$$

where the terms in the curly bracket represent the total effect per regional industrial share. Equation (7) can graphically be described as Harberger's (1998) sunrise-sunset diagram to measure how regional resilience is industrially even or uneven.

The diagram for a region is depicted by taking the share of each industry's economic variable on the horizontal axis in descending order for the total effect per regional industrial share. The vertical axis measures the cumulative contributions of the total effect. It gives useful summary statistics and characterises the regional resilience as 'yeast' and 'mushroom' types. The yeast type resilience means that most industries broadly contribute to regional resilience, whereas the mushroom one reflects that only a limited number of industries contribute to it.[5]

Using the Harberger diagram, Figure 1 illustrates contrasted configurations of sensitivity index for Fukushima (Panel A) and Okinawa (Panel B) over the recession in the 14th cycle (2008 to 2009). The former (latter) was the

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multi-factor partitioning model. However, as these formulas specify the regional growth by subtracting different growth rates, they do not consider the role of industrial compositions or structural changes in sectoral shares.

5 The terms are metaphors. Harberger (1998) considers the yeast type when most sectors expand evenly and mushroom type when growth unevenly stems from different sectors. For a graphical illustration of Harberger's diagram and its TFP growth pattern application, see Harberger (1998) and Inklaar and Timmer (2007).

least (most) resistant. The red solid line with dot plots presents the cumulative industrial contributions to the sensitivity index. The slope of each plot depends on the total effect per regional industrial share, and the cumulative share of industries with a positive total effect per regional industrial share indicates the pervasiveness of regional resilience. Meanwhile, the black solid line shows the cumulative average contribution to regional resilience, computed via $\sum_i \beta_r \cdot \omega_{i,r}$. Each term is a hypothetical contribution by each industry when it realises the average sensitivity. Thus, the distance between the cumulative (red) and average (black) contributions creates the surface of the Harberger diagram. If most industries in a region equally contribute to the sensitivity index, then the distance between the two lines is short, and the surface is small. Conversely, if each industry differently contributes to the regional sensitivity index, the distance is long and the surface is large. By dividing this area by the total area beneath the diagram, the study can measure the industrial unevenness of regional resilience.[6] It is zero when all industries have equal sensitivity; however, when industrial contributions diverge, this value is close to unity. If the value is close to unity, the resilience is concentrated among a few industries, which Harberger (1998) termed mushroom-type, whereas if the value is close to zero, the resilience formation is more industrially broad-based (i.e. yeast-type). Note that these classifications are not absolute but are relative.

[Insert Figure 1 here]

Figure 1 shows that resilience stems from different industries in the regions. In Fukushima, 12.68% (87.32%) of employment positively (negatively) contributes to resistance. Thus, the pervasiveness of regional resilience is low. Consequently, the sensitivity index takes a negative value; thus, Fukushima is low resistant. The industrial unevenness of regional resilience from the diagram is 0.4302 for Fukushima. Relative to the national average of 0.6952 for this period, Fukushima can be characterised as 'yeast-type' low resistant. However, 67.96% (32.04%) of employment positive-

[6] This method is also applicable for negative sensitivity index like Fukushima's case in Figure 1's panel (A), because the surface made by the red and black lines is symmetric with regard to the black line.

ly (negatively) contributes to resistance in Okinawa. Thus, the pervasiveness of regional resilience is high. The sensitivity index takes a positive value, and Okinawa is highly resistant for this period. Further, most industries almost positively contribute to the regional resistance, and the industrial unevenness of regional resilience is 0.4269. From the national average, Okinawa is 'yeast-type' high resistant.

3 REGIONAL EMPLOYMENT RESILIENCE IN JAPAN

3.1 Regional-Level Japan Industrial Productivity Database 2017 and Business cycles in Japan

The study employs the R-JIP 2017 database to analyse the industrial sources of regional resilience and its unevenness over time. It contains 23 different industries comprising 13 manufacturing and 10 non-manufacturing sectors for 47 regions (prefectures) in Japan over the 1970–2012 period (calendar year). Three principal reasons for using this database are as follows. First, the R-JIP database is most suitable for this study as it simultaneously covers regional and time dimensions to analyse the regional economic performance for a long period. Second, given that the industrial classification in the R-JIP database is much wider than conventional ones, such as agriculture, manufacturing, and service, it allows for identifying the industrial origin of regional resilience in detail. Third, the R-JIP 2021 database is the latest, covering the 1994–2018 period but does not include the data to calculate the number of workers. It includes total man-hour labour, which is the product of the number of workers and annual hours worked. Using the man-hour labour variable, the research outcome is largely affected by the working hours. However, the R-JIP 2017 database directly contains the number of workers, suitable to measure employment resilience.[7]

[7] For details on the R-JIP database and the original data employed in this study, see https://www.rieti.go.jp/en/database/R-JIP2017/index.html. Additionally, Tokunaga (2018) is a comprehensive study for the regional productivity and price differences using the R-JIP database. It also explains the characteristics of this database. However, resilience is not the scope of the studies included in this volume.

Value-added and (un)employment have been frequently employed to measure regional economic resilience; this study considers regional employment. Regional employment is measured by the 'number of employed persons (persons)' in the labour input account of the R-JIP database. Relative to the value-added, it has merits in measurement when analysing from a time-series perspective because employment data does not have to be deflated by some price indices, avoiding challenges associated with inflation or deflation (Cellini & Cuccia, 2019). Naturally, employment is relevant for the regional economic resilience because labour is essential to producing the value-added and the associated income. Further, the wage income reception determines the living standard of local people.

The study alternatively employs prefecture (prefectural) and region (regional) to analyse the regional resilience below unless some particular attention is necessary. By applying the structural sensitivity index to this database, the study explores how employment in 47 prefectures reacted to recession and recovery processes. According to *The Reference Dates of the Business Cycle* by the Cabinet Office, the Japanese economy has undergone 16 business cycles since the 1950s, of which this study analyses the regional resilience from the peak of the 9th cycle to that of the 15th cycle. Table 1 briefly shows an overview of the period examined in this study.

[Insert Table 1 here]

Based on this reference date, suppose a shock hits the Japanese economy at the peak of a cycle, leading to a recession phase. The degree of resistance in each region is measured for this period. Suppose the recovery process starts at the trough of the cycle; thus, this study investigates the degree of recoverability in each region. Notably, although the turning points for recession and recovery are determined by month and year, the study approximates these points based on the annual data because of the data limitation. However, the overall change in employment at the nationwide level seems to roughly follow the turning points, as in Figure 2.

[Insert Figure 2 here]

Figure 2 shows the time series of the number of employed persons in each prefecture according to the Japanese areas. Each panel includes the nationwide (Total) variables as a reference, and the black and red vertical lines indicate the trough and peak years, respectively. Accordingly, first, as the nationwide series reflects, the overall trend of employment increases until the end of the 1990s and decreases ever since. Naturally, the overall trend is affected by factors other than the growth cycles. For example, the Japanese labour force population began to fall as early as 1995. Although the study considers the resilience affected by business cycles, the overall trend may also be affected.[8] Second, the employment trend varies per area. For instance, the prefectures located in the Kanto area perform better than nationwide, as the series in Panel (B) shows, whereas those located in the Chugoku and Shikoku areas perform worse than those in Panels (E) and (F). Third, it also varies among different prefectures even within the same area. For instance, in the Chubu area, some series are higher than nationwide (e.g. Aichi), but others are not (e.g. Niigata), generating the Crocodile's mouth (or K-shape) dynamics, as in Panel (C). Kinki and Kyushu and Okinawa areas (Panels D and G, respectively) show a similar evolution, where the change in employment generates an increasing gap.

Against these heterogenous regional employment dynamics, with an emphasis on its industrial foundations, this study identifies how different types of regional resilience are shaped. It calculates the sensitivity index based on Equation (6) for recession and recovery phases. From the signs of the index, the study characterises the resilience of each region in the following ways:

- If the value of the sensitivity index for a region is negative over the recession phase, it is considered low resistance; if the value is positive, it is high resistance. Similarly, if the value of the sensitivity index for a region is negative over the recovery phase, it is considered low recoverability; if the value is positive, it is high recoverability. Thus, the study can obtain four types of regional resilience: high resistance and high recoverability, high resistance or low recoverability, low resistance and high recoverability, and low resistance and low recoverability.

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[8] The sensitivity index takes the nationwide dynamics as a benchmark in measuring resilience. Therefore, the approach can control for common trends as overall fall in labour force and depopulation to some extent.

- Alternatively, for a region throughout a cycle, the study defines the region with high resistance and high recoverability as the most resilient. Conversely, the study defines the region with low resistance and low recoverability as the least resilient. The other two cases (i.e. high or low resistance and low or high recoverability) are labelled as moderate resilient.

3.2 Evolving regional resilience in Japan: Overview

The maps in Figure 3 show the geographical configuration of regional employment resilience over the different cycles between 1980 and 2012. It classifies each prefecture into four types of resilience based on the structural sensitivity index (Equation 6) for recession and recovery periods. The number in the parentheses in the legend of each map indicates the frequency of resilience type.

[Insert Figure 3 here]

The maps show that between 1980 and 1985, 11 prefectures with high resistance and high recoverability concentrate around the three biggest prefectures of Tokyo, Nagoya, and Osaka. The high resilient areas can mostly be found in the Kanto area, while some of the Chubu areas follow low resistance and high recoverability. Consequently, 31 prefectures are in low resistance and low recoverability modes. From 1985 to 1991, the overall configuration does not change drastically. The resilient prefectures can be observed in the three biggest prefectures and their neighbouring areas, while 30 prefectures remain with low resistance and low recoverability.

From 1991 to 2008 after the bubble burst, the regional resilience gradually began to be geographically diverse. During these periods, the number of low resistance and low recoverability prefectures decreased by 4 or 5, whereas that of the moderate resilience regions increased by as much. Although the number of each resilience type was relatively stable during these periods, the spatial distribution is more divergent, except for the Shikoku area. Indeed, the geographical configuration of resilience is the most diverse between 2008 and 2012, which includes the post-global-financial-crisis (2008) and the Great East Japan earthquake (2011) periods. Precisely, the number of the least resilient prefecture particularly decreased to 19, and that of the moderate resilient increased by as much, comprising nine prefectures with high resistance and low recoverability and 11 prefectures with low resistance and high recoverability. The rest of the eight prefectures were the most resilient.

The regional resilience was low particularly in the rural areas along the Sea of Japan coast and Shikoku until the late 1990s. However, it became somewhat resilient since then, increasing regional heterogeneity. Thus, resilience is not a static equilibrium but a dynamic process. How then does regional resilience evolve from one type to another? By calculating a transitional probability matrix, which shows the probability of transition from one state to another over two different cycles, the study investigates the dynamic nature of resilience.

[Insert Table 2 here]

From the transitional probability matrix for resilience states in Table 2, two salient points emerge. First, based on the two highest probabilities, the Japanese prefectures have a persistent character for the most and least resilient states. For instance, once a region initially undergoes a period of being in the least resilient state, it remains in the same state with a probability of 78.99% in the next cycle. If a region experiences being the most resilient state, it may enjoy the same state in the next cycle with a probability of 64.29%. The probability of remaining in the least resilient state over two cycles is higher than that of being in the most resilient one. Indeed, the least resilient state also has the character of attracting different states the most. Regardless of the initial state, the Japanese regions may undergo a period of being in the least resilient state in the next cycles with a probability of 53.62%. Meanwhile, high resilience is the second most attracting state with a probability of 22.55%.

Second, although resilience evolves, it is not so drastic from one cycle to another. Rather, it is a gradual process. For example, if a least resilient region changes its state, it is more likely to be in a moderate resilience state in the next cycle; the probability is 17.39%. However, the probability that the least resilient region becomes the most resilient is only 3.62%. Similarly, if a most resilient region changes its state, it is also more likely to be in a moderate resilient state in the next cycle, with a probability of 28.57%. It is only by 7.14% of probability that a high resilient region changes into a least resilient state in the next cycle. Thus, the probability that the least or the most resilient region drastically transforms to be in the opposite state is generally low. Comprehensively, moderate resilient states attain the most or least resilience with almost equal probability (i.e. 29.27% to the former and 31.71% to the latter).[9]

In summary, the Japanese regional resilience has a particular persistence in the least resilient state first and the most resilient one second. Additionally, if it is to change, the process is not so radical as to quickly experience the least resilient state after a most resilient one or vice versa. Rather, it is a gradual process, as the least or most resilient state becomes a moderate resilient one.

3.3 Industrial sources of regional resilience

Based on Equation (6), the study examines the chronal configuration of resilience (i.e. over cycles) first and investigates its geographical configuration (i.e. across prefectures). The sample has 47 prefectures wherein each includes 23 industries, for which the study considers the regional resilience over different cycles. It straightforwardly considers the overall characteristics in mean value.

Figure 4 shows the mean values of the sensitivity index over different phases of business cycles, presenting its decomposition into the within-sector and structural change effects. The following characteristics emerge. First, the mean value of the sensitivity index is generally negative, but its degree nearly varies per decade. It was particularly low during the cycles in the 1980s. Consequently, most Japanese prefectures were least resilient in such periods, as in Figure 2. The value of the sensitivity index gradually began to rise from the beginning of the 1990s, reflecting that some prefectures withstood or recovered from overall shocks. From Figure 2, the number of the low resistance and low re-

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[9] The probability for the transition of moderate resilience can be obtained by summarising the number of observations. The number of total observation for the moderate resilience at the initial cycle is 41, of which the most resilience case in the next cycle is 12, whilst the least resilience case is 13. Thus, the probability for the former (latter) is 12/41 (13/41).

covery prefectures decreased from 1991 to 2008, whereas that of the moderate resilient ones increased as much. While recording lower values over the recession to 2002 and 2009, the sensitivity index was higher in the 2000s than in the 1980s, showing that fewer prefectures underwent the least resilient state.

[Insert Figure 4 here]

Second, regarding decomposition, the within-sector effect differs, whereas the structural change effect is constantly negative. From 1983 to 1991, both effects negatively impacted the sensitivity index. By contrast, the within-sector effect generally had a positive impact from 1993, except for the recession by the global financial crisis. The positive within-sector effect is driven by the mechanism that the growth rate of an industry of a region is higher than that of the country level, which improves the regional resilience.

Meanwhile, Figure 5 shows the mean values for each prefecture's sensitivity index throughout all cycles and its decomposition in ascending order for the sensitivity index. On average, the sensitivity index is below zero in most prefectures. Only 14 prefectures (i.e. prefectures rightward Shizuoka) enjoy positive sensitivity on average, of which only four prefectures (i.e. prefectures rightward Kanagawa) exclusively enjoyed positive impacts of these effects. However, the rest of the 33 prefectures recorded a negative sensitivity index. No less than 24 prefectures exclusively underwent negative impacts of both effects, and the rest of the nine prefectures experienced mixed impacts of positive and negative effects.

[Insert Figure 5 here]

Figures 4 and 5 show that the structural change effect negatively affects the sensitivity index in all periods and most prefectures. Whether the structural change effect in an industry in a region is positive or negative depends on the combination of regional specialisation and its macroeconomic trend (i.e. $\frac{\omega_{i,r}}{\omega_{i,N}} \gtrless 1$ and $g_{i,N} \gtrless 0$). In the formula, this effect is negative when an industry's share of a region is smaller than that of a country, and the industry grows at a faster pace at the country level, termed as the 'pro-trend negative' pattern. It is also negative when an industry's share of a region is larger than that of a country but the industry is shrinking at the country level, termed as the 'anti-trend negative' pattern. Similarly, the opposite mechanisms generate a positive structural change effect through 'pro-trend positive' and 'anti-trend positive' patterns. Thus, the evolutionary perspective highlights the effects of reorganisation through continuous structural changes over business cycles (Simmie & Martin, 2010; Martin et al., 2016; Martin & Sunley, 2020). Such an evolutionary dimension can also be observed through the lens of decomposition.

Table 3 shows the frequency of the causes for the structural change effect for each phrase. The frequency of negative impacts (i.e. pro- or anti-trend negative patterns) was dominant from 1983 to 1991, being more than 50%. However, the anti-trend negative pattern began to exceed 30% in the late 1990s, whereas the pro-trend negative pattern began to decrease. That is, the negative structural change effect is induced by the regional industries declining at a macroeconomic level. Simultaneously, the frequency of positive causes became slightly more dominant until 2008, principally led by the anti-trend positive pattern. However, the pro-trend positive pattern has decreased and stagnated over time, although it was high until the beginning of the 1990s. Only a few regional industries match the overall industrial growth trend. Generally, even if the frequency of positive structural change patterns increases, it follows from Figure 2 that their contributions are not large enough to create an overall positive effect.

[Insert Table 3 here]

The transitional probability matrix (Table 4) is useful to explore the evolution of structural change patterns, by which two features emerge. First, the diagonal observation in Table 4 shows that each pattern has a persistent character. For instance, when the regional industry initially experiences an anti-trend negative pattern, it realises the same pattern in the following cycle with a probability of 81.93%. The pro-trend positive pattern is the least persistent, but once it is realised the same pattern follows with a probability of 56.74%.

[Insert Table 4 here]

Second, when the pattern transforms, it is basically because of changes in industrial growth patterns at the national level rather than those in the relative degree of regional industrial specialisation. For example, pro-trend negative patterns are realised by having a relatively lower share of the regional industry, whose macroeconomic growth rate is rising. Thus, if structural change largely occurs and the region has a relatively higher share of that industry (i.e. from $\omega_{i,r} < \omega_{i,N}$ to $\omega_{i,r} > \omega_{i,N}$), it should become an anti-trend negative or a pro-trend positive pattern depending on the overall trend of industrial growth. However, either type is hardly realised in the next phase because, as the probability indicates, the former (latter) is 1.27% (2.13%). Instead, given the existing industrial share, an anti-trend positive pattern is more likely to happen with a probability of 35.43%. These characteristics also apply to other patterns. Thus, if the pattern of structural change effect transforms, it is more dependent on the industrial growth pattern at the national level than the change in the relative degree of regional industrial specialisation. The anatomy of the structural change effect shows that the regional structural change does not occur so drastically.

In summary, the gradual dispersion in regional resilience observed in Figure 2 accompanies the following properties. First, the mean value of the sensitivity index was particularly low until the beginning of the 1990s but gradually rose since then; some of the Japanese regions moderately attained regional employment resilience. Second, when the sensitivity index is decomposed, the structural change effect has constantly had a negative impact. The effect depends on the direction of the industrial growth pattern at the national level. The within-sector effect began to have a positive impact on the sensitivity index in the 1990s, but its impact is not large enough to offset the negative structural change effect, which is also true for most prefectures. No less than 24 prefectures underwent negative impacts of effects exclusively, whereas only four prefectures enjoyed positive impacts of these effects. Consequently, throughout the cycles, the sensitivity index has been generally negative.

3.4 Industrial unevenness of regional resilience

Even if a region shows a positive sensitivity index, some industries may negatively contribute to it. Based on the Harberger diagram, this study measures the pervasiveness and unevenness of industrial contributions to regional resilience. The former is calculated by the industrial shares of which the total effect is positive, while the latter is given by the relative area of the Harberger diagram.

Figure 6 shows the time series of pervasiveness for regional resilience in mean values. The mean values of pervasiveness remained in the 30% values in the 1980s. These values were lower than in the following periods, implying that the prevalence of least resilience in the 1980s was because of the low pervasiveness. Meanwhile, the dispersion of regional resilience from the 1990s accompanies an increase in pervasiveness. The mean values have been over 40% on average between 1993 and 2009. More industries had a positive total effect on the regional resilience behind the expansion of moderate resilience during these periods.

[Insert Figure 6 here]

Figure 7 shows the unevenness of resilience in mean values. It was relatively low during the 1980s, reflecting that the overall regional resilience is close to a yeast-type. As noted, the sensitivity index and pervasiveness were also low during this period. Meanwhile, the unevenness rose during the 1990s when the regional resilience started to geographically disperse and the pervasiveness of industrial contributions also expanded. Although the unevenness temporally decreased towards 2008, it remained higher than in the 1980s and the average.

[Insert Figure 7 here]

Therefore, the Japanese low regional resilience until the 1990s was broad-based, backed by both low pervasiveness and unevenness. Accordingly, it can be characterised as yeast-type low resilience. Moreover, the gradual dispersion in regional resilience after the 1990s accompanies the overall rise in unevenness and overall pervasiveness, generally higher than average. Hence, the type of resilience during these periods can be characterised as somewhat mushroom-type resilience.

The pervasiveness and unevenness can also be observed from the regional perspective. Figure 8 shows the mean values of the pervasiveness over different prefectures in ascending order, with the average value over them.

There is a considerable gap between the bottom and top prefectures regarding the pervasiveness. For instance, the mean value of the total prefectures is 39.7%, whereas those of Yamaguchi and Saitama are 14.9% and 86.6%, respectively. The gap ratio between the top and bottom is approximately 5.80. Additionally, taking the two highest and lowest mean values of pervasiveness, for instance, Yamaguchi and Kochi prefectures have never experienced the most resilience state over time, whereas the Saitama and Chiba prefectures have never undergone the least resilience state, as in Figure 2. Thus, establishing industrial structures that generate pervasiveness supports regional resilience.

[Insert Figure 8 here]

Figure 9 presents the mean values for the unevenness from a regional perspective in ascending order with the average value over them. Relative to the pervasiveness, the gap ratio for unevenness between the bottom and top prefectures is twice at best and therefore small. For instance, the mean value of all prefectures is 0.6578 whereas those of Saitama (the most even) and Tochigi (the most uneven) are 0.4154 and 0.8424, respectively. Notably, the pervasiveness of Saitama is the highest, whereas that of Tochigi takes approximately over 50%; thus, the industrial contributions are mixed.

[Insert Figure 9 here]

Comparing the sensitivity index (Figure 5), pervasiveness (Figure 8), and unevenness (Figure 9) to the changes in resilient states (Figure 2) presents an intriguing fact on the type of regional resilience. As noted, Yamaguchi and Kochi prefectures have never experienced the most resilient state. These prefectures underwent the two lowest pervasiveness. However, Saitama and Chiba prefectures have never gone through the least resilient state. They attained the two highest pervasiveness. These four prefectures also realised the least unevenness. Interestingly, there are two yeast-type prefectures for the formation of regional resilience: yeast-type low and high resilience prefectures. Moreover, the prefectures realising high values of unevenness include Tochigi, Gunma, and Gifu. The pervasiveness of these prefectures is close to 50%, their sensitivity index is relatively close to zero, and they tend to change their states of resilience frequently. These examples suggest that prefectures with close-to-zero sensitivity index or frequently changing resilient states mostly follow the mushroom-type resilience.

Indeed, these characteristics can be generalised to the overall configuration of regional resilience in Japan. Figure 10 plots the relationship between unevenness and sensitivity index by pooling all prefectures' data over all periods. The plots are separately shown per the sign of sensitivity index to see how high or low the type of resilience is associated with unevenness.

[Insert Figure 10 here]

Based on these plots, the relationship between sensitivity index and unevenness is non-linear, and there are yeast-type low resilience prefectures, yeast-type high resilience prefectures, and mushroom types for both resilience prefectures. It clearly shows that for the negative sign (i.e., low resistance or low recovery) resilience is positively related to unevenness, while it is negatively related to unevenness for the positive sign (i.e. high resistance or high recovery). For instance, the left side panel shows that the unevenness is small for large negative sensitivity values. It reflects that some of the low resistance and low recovery prefectures are realised by the fact that broad industries evenly and negatively contribute to the sensitivity index. Simultaneously, the right-side panel shows that some of the high resistance and high recovery prefectures, although fewer than the low cases, are also realised by the fact that broad industries evenly and positively contribute to the sensitivity index. Thus, yeast-type high and low resilience prefectures exist, where positive or negative industrial contributions are balanced. Additionally, Figure 10 shows that the unevenness increases as the sensitivity index approaches zero from the positive and negative sides. These areas are most dense, mirroring that industrial contributions to regional resilience are mostly blended. The disaggregate approach reveals that when the sign is close to zero, regardless of the sign, the industrial contributions to the regional resilience are mixed, shaping the mushroom-type resilience. These patterns are the most uneven where positive and negative industrial contributions almost offset each other within a region.

4 CONCLUSION

This study builds a structural sensitivity index, applying it to the employment resilience in the Japanese regional economy over the business cycles from the 1980s. By decomposing the sensitivity index into within-sector and structural change effects, this study's formula sheds new light on the role of industrial sources in regional resilience. It measures the sources and types of regional resilience and how it is unbalanced from an industrial structure perspective. The key findings are as follows.

First, employment resilience varies chronally and geographically. The least resilient state was the most prevalent in Japan until the beginning of the 1990s; however, it became somewhat resilient since then, increasing the regional diversity. Namely, some regions are resistant and recoverability to a certain shock but the others are not. Additionally, regional resilience persists in the least and most resilient states. When it is to change, the process is not as radical as experiencing a least resilient state after a most resilient state or vice versa. Rather, it is a gradual process from the least or most resilient state to a moderate state in the subsequent cycle. Thus, resilience is not a static phenomenon but gradually evolves in Japan.

Second, the structural change effect has constantly negatively impacted regional resilience, whereas the within-sector effect had a positive impact on the sensitivity index from the 1990s. Given that the latter is not large enough to offset the negative impact of the former, the sensitivity index has been negative. The negative structural change effect since the 1990s is principally associated with a high share of anti-trend negative patterns; thus, regional resilience is restrained by a relatively higher share of regional industries whose overall growth is declining. Even when its effect is positive, it is supported by an anti-trend positive pattern. Pro-trend positive patterns by which regional resilience is enhanced through a high share of regional industries with a rising overall growth are very few. Hence, regional industrial compositions do not fit well with the overall macroeconomic industrial growth.

Finally, the study extracted the industrial unevenness behind regional resilience. From different time horizons, the Japanese regional resilience until the 1990s is characterised by yeast-type low resilience, as sensitivity, pervasiveness, and unevenness were historically low. Meanwhile, apart from a temporal up and down between 2002 and 2008, there is an increasing regional heterogeneity behind improvements in resilience after the 1990s. During these periods, the sensitivity index increased within a negative range, whereas pervasiveness and unevenness increased and were higher than the average value. Thus, these periods were mushroom types. Moreover, from the regional perspective, the overall relationship between unevenness and resilience is not unique, with both high and low yeast-type resilience prefectures and mushroom-type resilience. Some of the high and low resilient prefectures experienced yeast-type patterns, where most industries positively (negatively) contribute to the sensitivity in the former (latter). The mushroom type resilience is mostly found when the sensitivity index is close to zero; thus, many prefectures' resilience comprises industries with contrasted performers.

Hence, this study exclusively identified the industrial sources of employment resilience and their unevenness over time and region, which is the most important contribution to the existing literature. However, the study scope also has some limitations. Although the analysis sheds light on resilient regional employment, it does not answer why it is resilient. For example, prior studies explore the features of the labour market to identify the determinants of resilience and present skilled human capital as critical to enhancing adaptation and resilience (Kitsos & Bishop, 2016; Giannakis & Bruggeman, 2017; Cappelli et al., 2021). Based on the classification in this study, future studies can employ an econometric analysis to specify the determinants of resilience.

Additionally, this study focused on regional resilience regarding employment. Employment resistance and recovery are essential elements of regional resilience, but they are not exhaustive. Other variables such as value-added, labour productivity, and the unemployment rate may show different aspects of regional resilience. Even if a region is resilient in one variable, it may not so in other variables as resilience is multifaceted. Hence, further research and comparison with the results in this study are necessary to understand regional resilience more precisely in Japan.

Finally, an empirical analysis with higher frequency dates is preferable. The R-JIP 2017 database is the most suitable, as it simultaneously covers regional and chronal dimensions to analyse the long-run regional employment performance. However, the data frequency is annual and, consequently, cannot help investigating the regional and industrial performances with lead and lag between different months. Although the study approximates the turning points for recession and recovery based on the annual data, it is more desirable to relate them to monthly points on which the Japanese business cycles are determined. This limitation is not the problem of the approach but of the nature of available data. Considering increasing research contributions to the regional resilience analyses in European and north-American countries and the economic shocks from the COVID-19 pandemic, Japan also needs nowcasting-like regional data. Of course, the analyses can be appropriately applied to a more frequent dataset. Moreover, it applies to revisiting regional resilience in other countries as far as the dataset has a similar structure to the R-JIP database.

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Tables and Figures

TABLE 1 Business cycles and main short-term shocks in Japan

Business cycles	Trough	Peak	Main short-term shocks
9th–10th: 1980–1985	1983, Feb.	1985, Jun.	Sudden yen appreciation
10th–11th: 1985–1991	1986, Nov.	1991, Feb.	Bubble burst
11th–12th: 1991–1997	1993, Oct.	1997, May.	Financial crisis
12th–13th: 1997–2000	1999, Jun.	2000, Nov.	IT bubble burst
13th–14th: 2000–2008	2002, Jun.	2008, Feb.	Global financial crisis
14th–15th: 2008–2012	2009, Mar.	2012, Mar.	Post-great earthquake

Source: *The Reference dates of business cycle* by the Cabinet Office

TABLE 2 Transitional probability matrix for resilience states

		Next phase			
		H-Resis./H-Recov.	H-Resis./L-Recov.	L-Resis./H-Recov.	L-Resis./L-Recov.
Initial phase	H-Resis./H-Recov.	64.29%	10.71%	17.86%	7.14%
	H-Resis./L-Recov.	16.67%	11.11%	16.67%	55.56%
	L-Resis./H-Recov.	39.13%	17.39%	30.43%	13.04%
	L-Resis./L-Recov.	3.62%	10.87%	6.52%	78.99%
	total	22.55%	11.49%	12.34%	53.62%

TABLE 3 Frequency of causes for structural change effect

Year (Phase)	Pro-trend negative	Anti-trend negative	Pro-trend positive	Anti-trend positive
1983 (9th trough)	41.44%	16.93%	19.43%	22.20%
1985 (10th peak)	38.48%	19.70%	18.04%	23.77%
1986 (10th trough)	28.95%	23.31%	14.52%	33.21%
1991 (11th peak)	49.49%	8.97%	28.77%	12.77%
1993 (11th trough)	28.12%	20.63%	19.70%	31.54%
1997 (12th peak)	16.56%	31.82%	9.53%	42.09%
1999 (12th trough)	8.70%	37.37%	4.35%	49.58%
2000 (13th peak)	16.74%	32.01%	9.34%	41.91%
2002 (13th trough)	6.66%	39.59%	2.04%	51.71%
2008 (14th peak)	18.87%	35.43%	7.22%	38.48%
2009 (14th trough)	15.45%	37.84%	6.29%	40.43%
2012 (15th peak)	21.46%	31.64%	13.32%	33.58%
Total	24.24%	27.94%	12.71%	35.11%

Note: Pro-trend negative counts the number of regional industry with $g_{i,N} > 0$ and $\omega_{i,r} < \omega_{i,N}$, Anti-trend negative counts the number with $g_{i,N} < 0$ and $\omega_{i,r} > \omega_{i,N}$, Pro-trend positive counts the number with $g_{i,N} > 0$ and $\omega_{i,r} > \omega_{i,N}$, and Anti-trend positive counts the number with $g_{i,N} < 0$ and $\omega_{i,r} < \omega_{i,N}$.

TABLE 4 Transitional probability matrix for causes of structural change effects

		Next phase			
		Pro-trend negative	Anti-trend negative	Pro-trend positive	Anti-trend positive
Initial phase	Pro-trend negative	61.17%	1.27%	2.13%	35.43%
	Anti-trend negative	0.40%	81.93%	15.54%	2.13%
	Pro-trend positive	1.86%	40.27%	56.74%	1.13%
	Anti-trend positive	20.85%	2.60%	0.31%	76.23%
	total	22.68%	28.94%	12.10%	36.28%

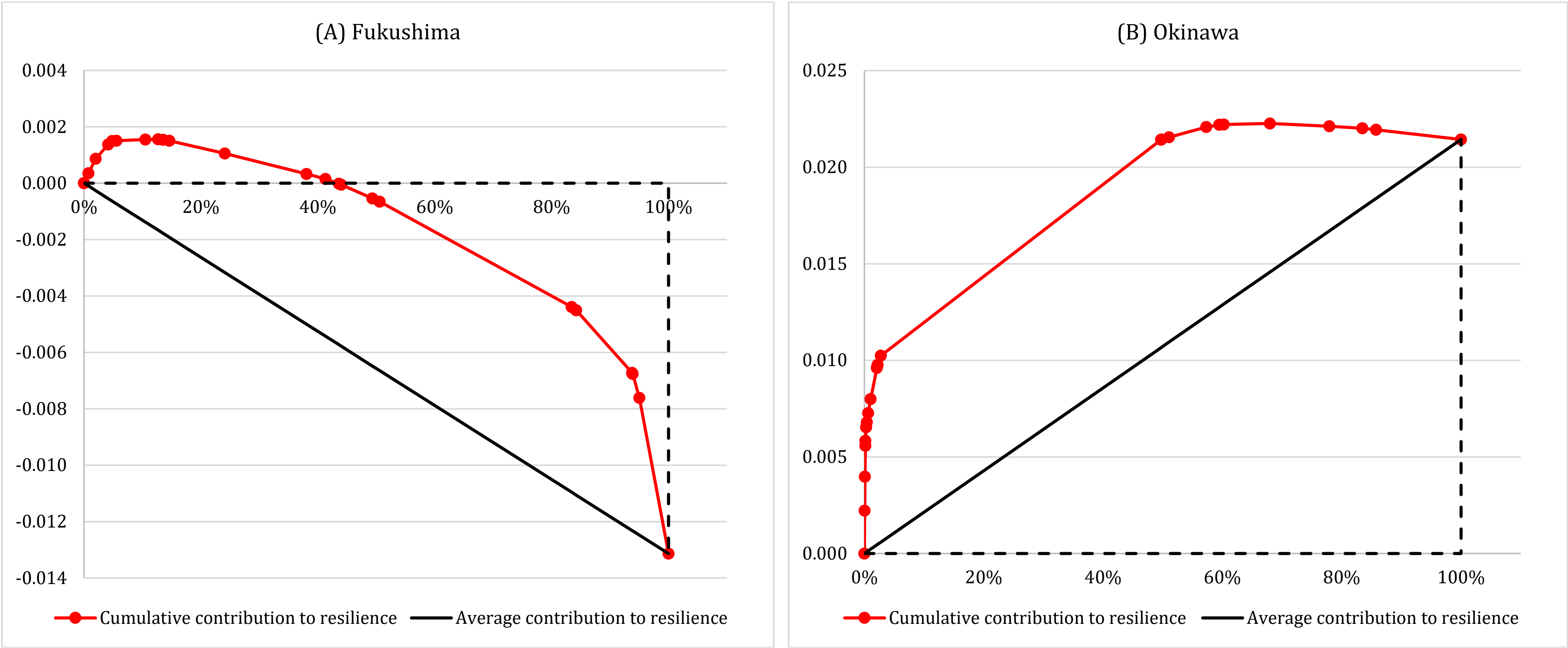

FIGURE 1 Harberger diagram examples for Fukushima and Okinawa (Recession in 14th cycle)

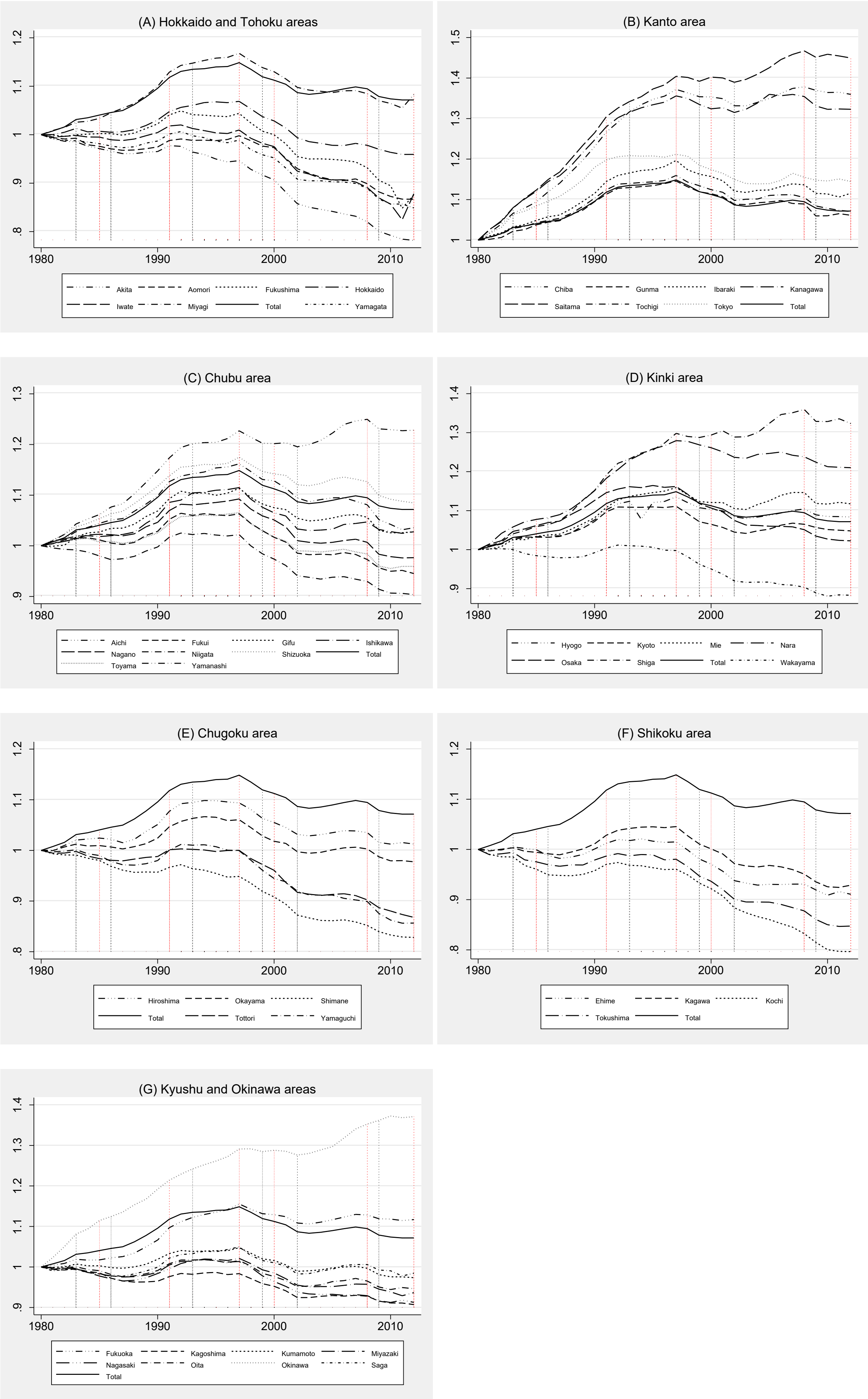

FIGURE 2 Index for the number of employed persons (1980=1)

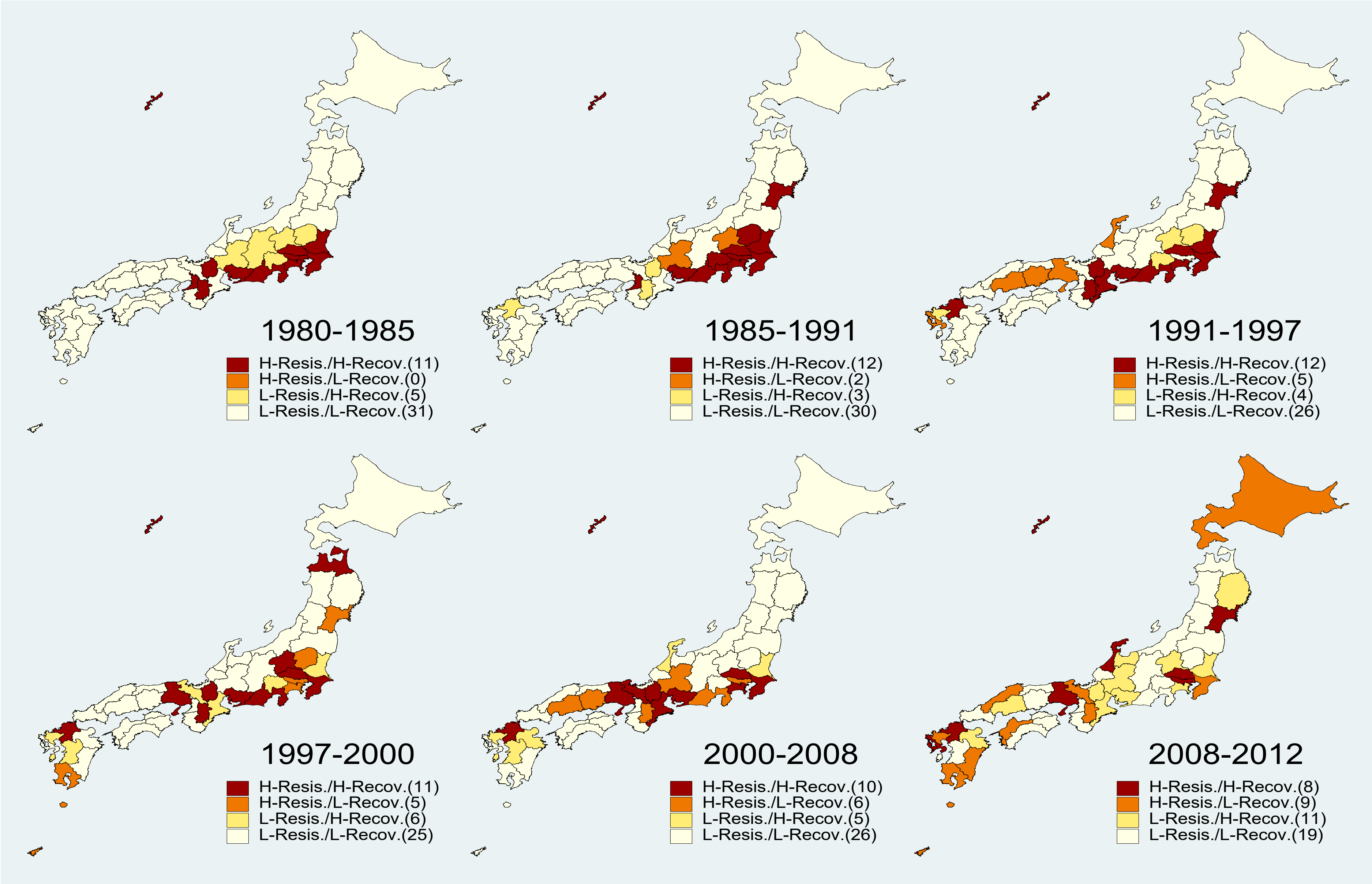

FIGURE 3 Geographical configuration and evolution of regional resilience

Note: H-Resis. and H-Recov. represents high resistance and high recoverability, respectively, while L-Resis. and L-Recov. represents low resistance and low recoverability, respectively. The number in the parentheses in the legend of each map indicates the frequency of resilience type

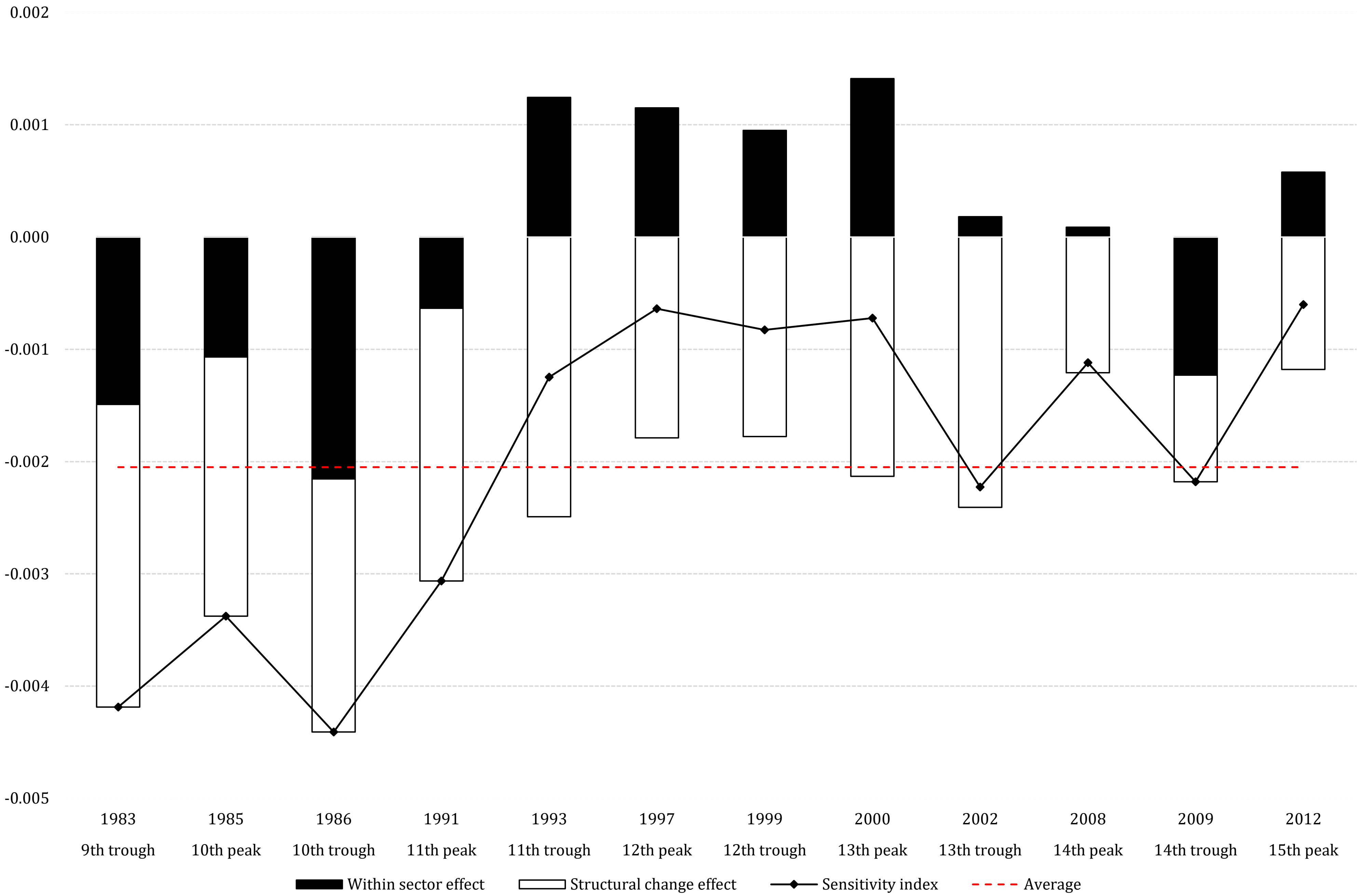

FIGURE 4 Mean values of sensitivity index and its decomposition from the time perspective

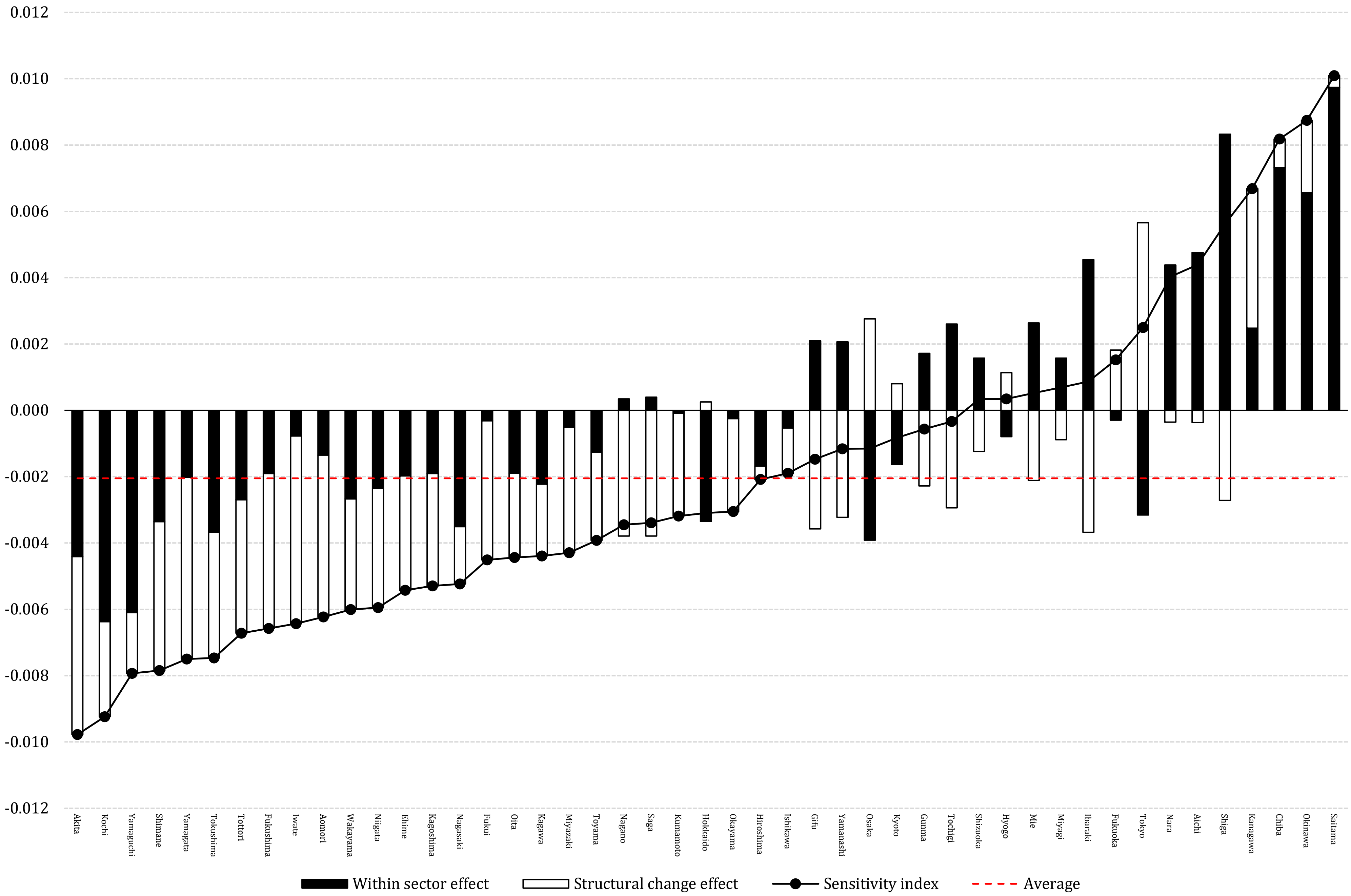

FIGURE 5 Mean values of sensitivity index and its decomposition from the regional perspective

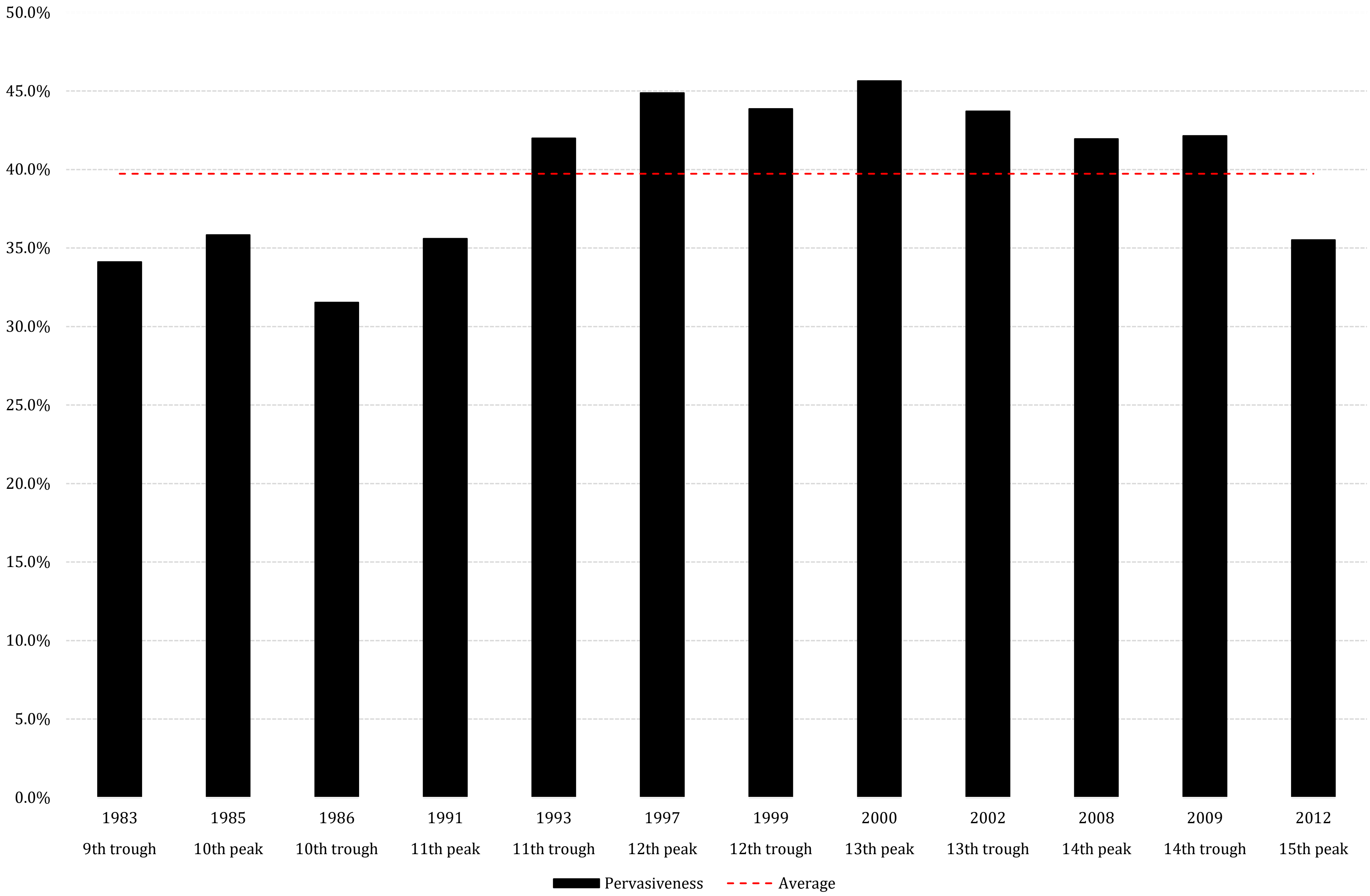

FIGURE 6 Mean values of pervasiveness for resilience

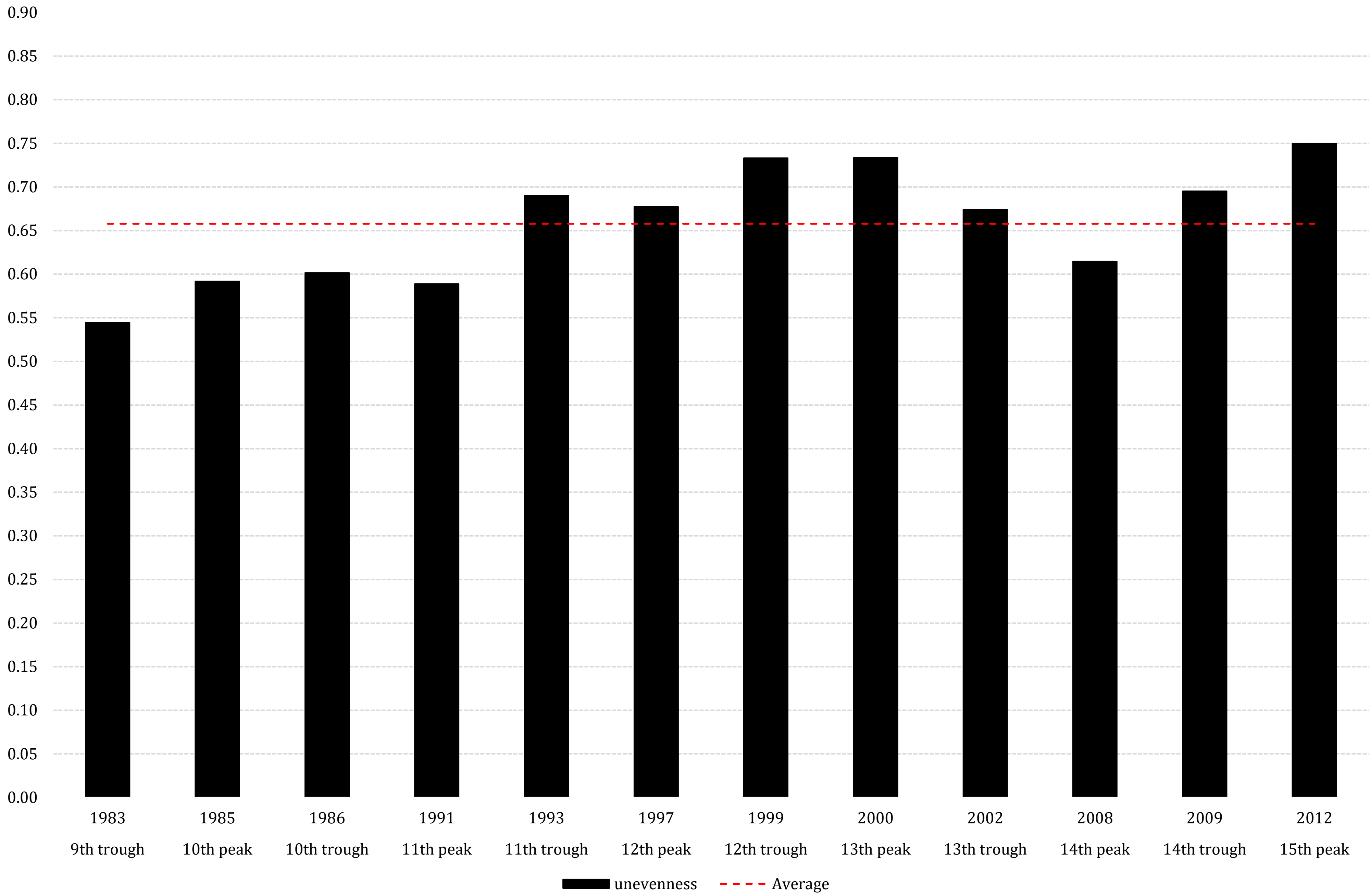

FIGURE 7 Mean values of unevenness for resilience

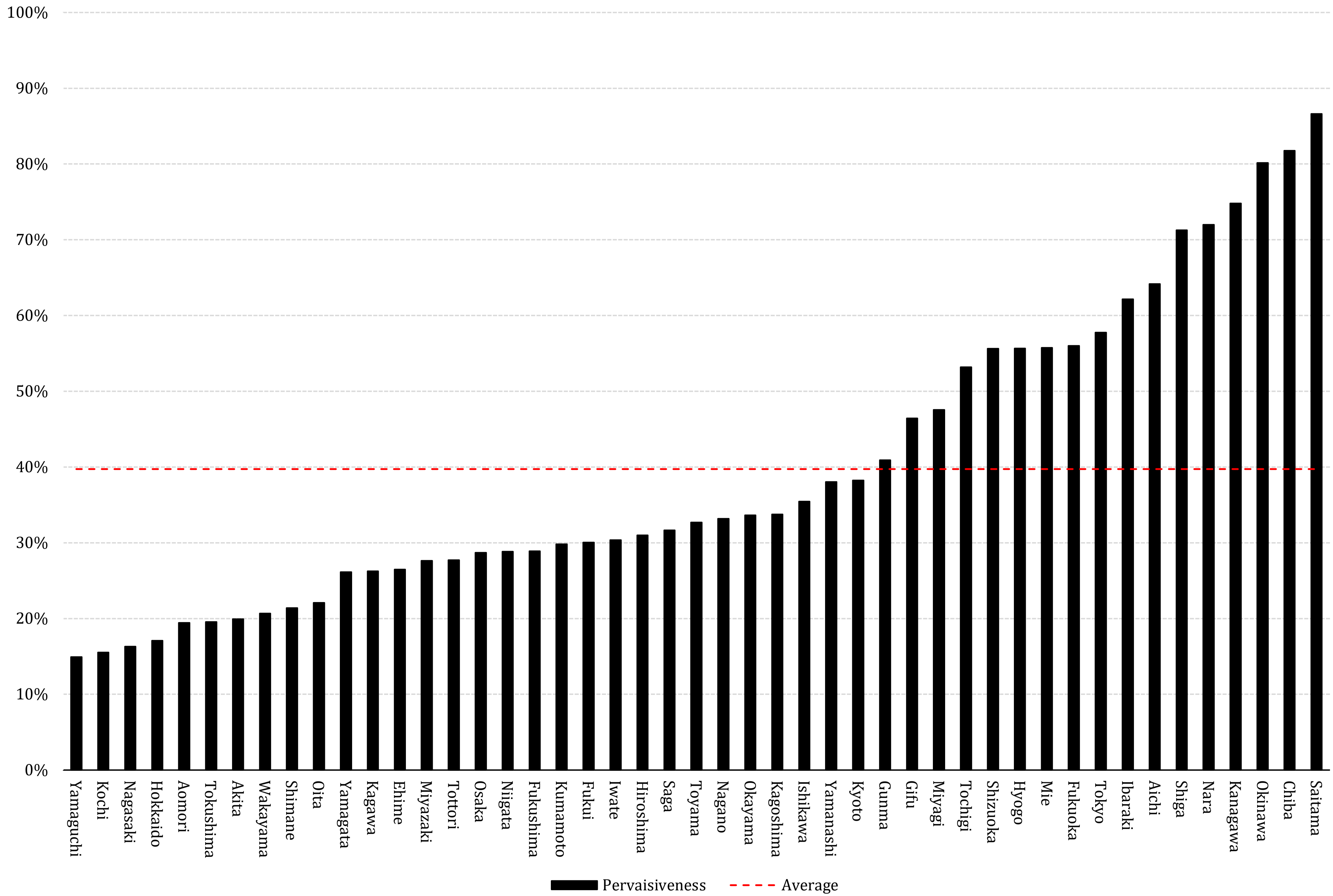

FIGURE 8 Mean values of pervasiveness for resilience from different regional perspectives

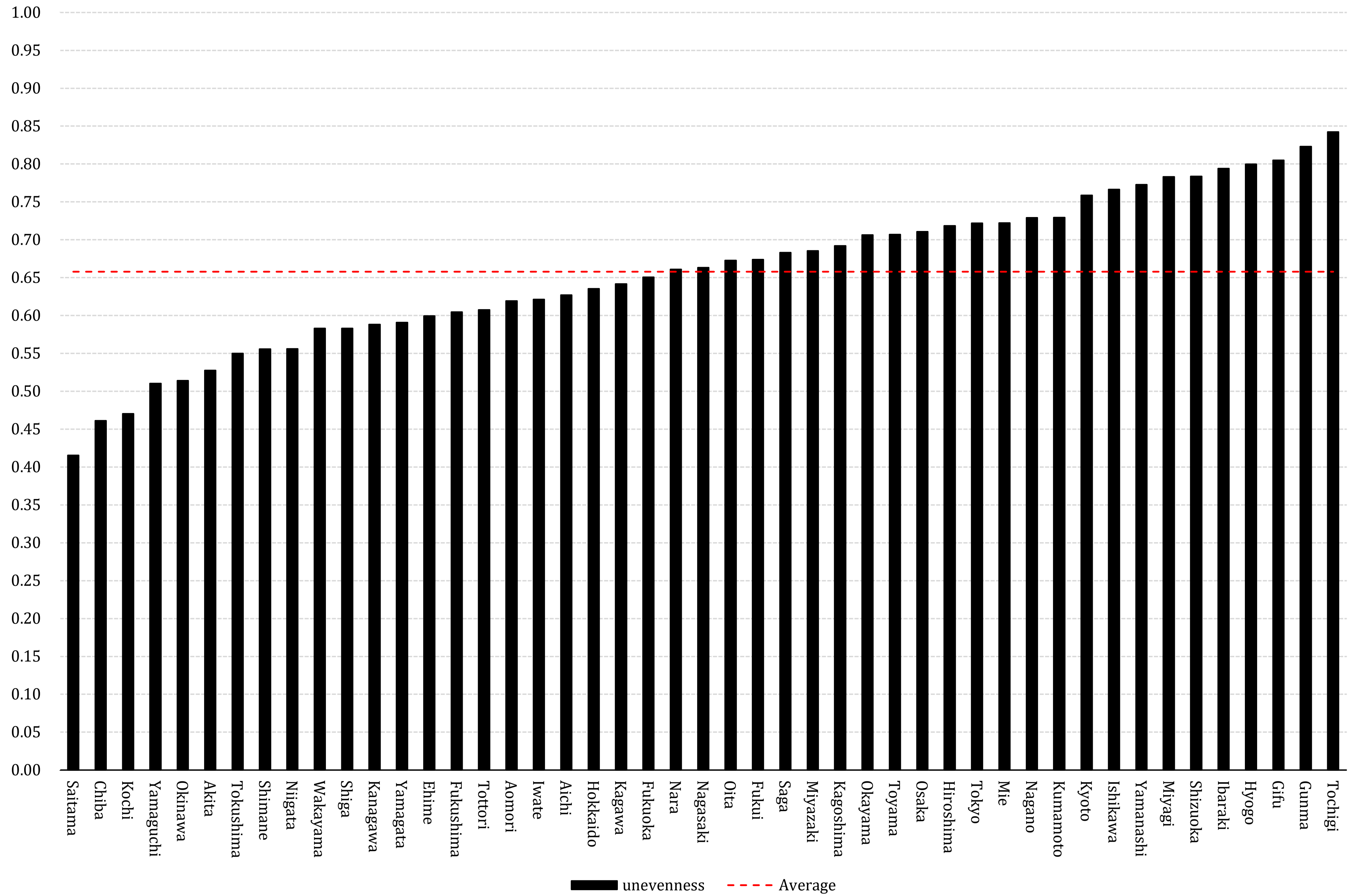

FIGURE 9 Mean values of unevenness for resilience from different regional perspectives

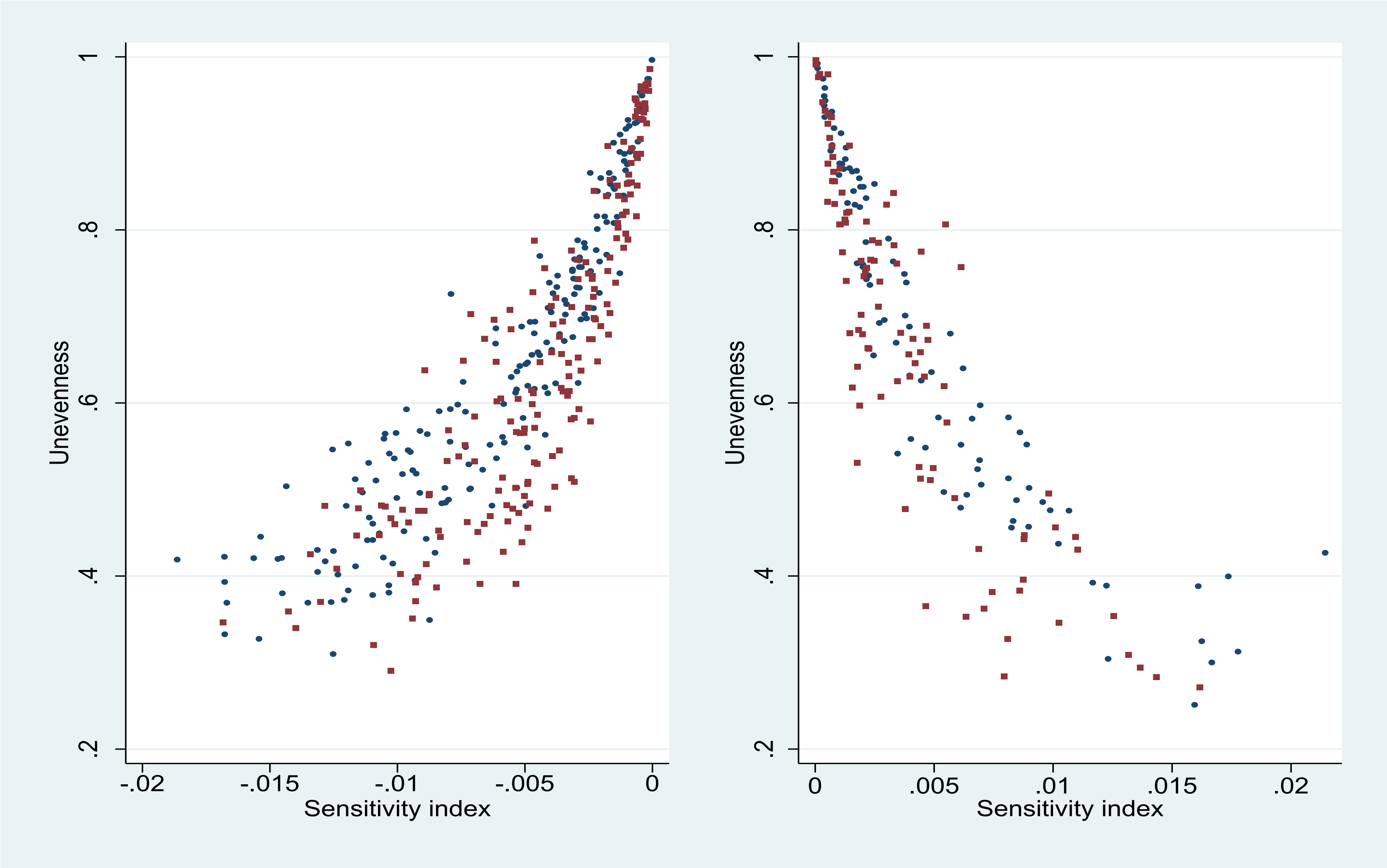

FIGURE 10 Mean values of unevenness and sensitivity index

Note: The left panel is for the negative sensitivity index, whereas the right panel is for the positive sensitivity index. The blue circle indicates recession and the red square, recovery.