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Networks in Japanese regional agro-food economies: an empirical exploration of the network linkage model

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Abstract

Network linkage is important in evaluating macroeconomic performance since input–output networks across industries are asymmetric and respond differently to external shocks. While most studies implicitly assume elastic substitution between intermediates and factors using Cobb–Douglas models, this is often improbable since the input–output structure may change due to the shocks, which would be observed as non-linearities in macroeconomic impacts on sectoral shocks. Additionally, considering regionally located sectors such as the agriculture and food-processing industries, the propagation of sectoral shocks can be interregionally correlated. This study employs the network linkage model to empirically verify the interaction of agro-food sectoral shocks in regional outcomes. By comparing the network effects influencing the national economy and regional economy, the superiority of considering intraregional networks among agro-food sectors is empirically verified; thus, productivity shocks arising in these industries propagate more intensively within their own region.

Keywords: Network linkage model, Interregional input–output table, Agro-food supply chain, Regional economy

1 Introduction

In Japan, demand for processed foods is growing, with extensive use of agricultural products supplied for these industries (Shimowatari 2003; Takayanagi 2006; Akune 2004). In 1980s, as farming costs increase, the food processing industries started to relocate its supply chain to East Asian and Southeast Asian countries, outsourcing the stable and bulk procurement of ingredients abroad. Under the globalization, however, domestic produces are still supplied to processed foods for its better quality, safety and transparency of origins or due to the constraints of perishability and transportation costs. Consequently, the food processing industries, not fully fragmented unlike the other manufacturing sectors, mostly consist of those firms that locate between agricultural production and local consumption areas, except some items that agglomerate in the metropolitan area for proximity to large-scale consumption and port facilities, such as beverage industries and wheat processing industries, respectively (Akune 2004). On the other hand, following a global trend, the supply chains destined for a major market

are turning into more complex system as food processing firms are strongly connected and even vertically integrated to its metropolitan customers (i.e., large-scale retailers) for fresh food quality control, transaction cost reduction, and information utilization for efficient logistics (Rong et al. 2011; Hobbs and Young 2000; Prajogo and Olhager 2012). Agro-food supply chain network is rather asymmetric across regions, and therefore, regional perspectives are important when evaluating economic impacts from sectoral idiosyncratic shocks.

For example, the vertical integration is subject to criticism on its vulnerability to supply chain interruption such as transport delays and cost increases after the Covid-19 pandemic (Nagurney 2021). In this regard, self-sufficient supply chains turned out robust to such risks and resilient even if disrupted since they are less distanced to production and local consumers. This suggests that the structure of minor sectors, such as agro-food sectors that account for only 10 percent of GDP in Japan, might matters in the wake of macroeconomic tail risk. The question is generally whether such a regional difference is attributed to these industries' characteristics that locate in specific regions to input geographically irreplaceable production factors (i.e., land and climate) and intermediates locally reproducible (i.e., perishable local produces) and supply to local consumers with preferences diversified in each region.

This study provides asymmetric input–output network linkages in agricultural and food industries across nine domestic regions. The study first propose a network linkage model generalized with the nested CES function system with modifications such that the interregional input–output structure is incorporated, and second, empirically examine the direction of propagation of sectoral shocks by comparing its intensity toward regional output and national output. This study incorporates two crucial parameters in this regard: elasticities of substitution, namely, the degree to which factors and intermediates are substituted between sectors and regions, and an input–output multiplier that scales the ripple effect that arises from the presence of intermediates in a region (e.g., raw materials from agriculture to food-processing industries). If those parameters significantly vary between regions and do not converge into a common trend in a long term, it will be a concern that even if each region gains from unitary productivity growth, the outcomes to regional economies are not equal because of the asymmetric property of ripple effect.

The results are summarized as below. Unit productivity shocks only in the agro-food sectors propagate more intensively toward regional economy than toward national economy. This can be attributed to the network linkage model employed in this study that allows endogenous changes in input–output structure (i.e., changes in expenditure share of input). For example, assuming positive productivity growth in agricultural sector, food processing sector in downstream adopts the technology to use local produces in its own region more intensively. Even when productivity falls temporally, the negative impact on regional economy is mitigated if the products is elastically substitutable among related industries. The source of superiority of intraregional linkage is that these industries trade most of intermediate goods with the counterpart located in the same region. Intuitively, the primary reason for intense intraregional network is a greater share of intermediate goods and factor from the own region within and between agricultural and food processing industries.

A major contribution of this paper is the application of the network linkage model of Baqaee and Farhi (2019a) to an interregional input–output scheme. The model is successfully generalized with the nested-CES function system so that it captures nonlinearities in macroeconomic impacts on sectoral shocks, which are derived from the aforementioned parameters.

The outline of this paper is organized as follows. Section 2 discusses the contributions of the related literature on the network linkage model and clarifies their limitations. Then, Sect. 3 reviews the generalized network linkage model of Baqaee and Farhi (2019a) and provides an interpretation to fit in the interregional scheme. Section 4 introduces an estimation strategy for the crucial parameters and data structure. Finally, Sect. 5 presents the quantitative implications of the results.

2 Related literature

Studies that focus on supply chain have developed to deal with a couple of issues in the contemporary food supply chains, and a considerable number of them employ the concept of network in order to analyze the complexity of extensive supply chains. In the early 2000s, the performance of food supply chain was measured by five key indicators: product availability, product quality, responsiveness to demand, distribution reliability and total cost of production and distribution, according to Vorst (2005). Originally, the interactions between food channel members (i.e., farms, manufacturers, retailers and logistics firms) emerged from vertical integration in order to minimize the transaction costs though technological, regulatory and socio-economic characteristics with each commodity drive them differently (Hobbs and Young 2000). Bourlakis (2008) indicates, as food supply chains become more complex through spatial extension in material procurement and product distribution, outsourcing decision in logistics have been common among EU member states. In fact, Hsiao et al. (2006) empirically examines that the degree of complexity in food supply chain of dairy and veal sectors is associated to degree of outsourcing. Additionally, Prajogo and Olhager (2012) reveals that information technology capability and information sharing with supply chain partners have significant effects on logistics integration and indirectly on operational performance with data from Australian firms. Today, there are multiple options of collaboration other than buyer–seller relationships such as foreign direct investment to original equipment manufacturers abroad, outsourcing logistics to specialized firm that provide distribution center and information sharing throughout the food supply chain.

Recently, supply chain management is more likely to be discussed in the context of network optimization as criteria on decision-making are more diversified due to uncertainty. Apte (2010), for instance, investigates the contributing factors to vulnerability of supply chain disruption such as topological structure, traceability and product communication, following a specific case of *E. coli* contamination in packaged spinach in the US. Rong et al. (2011), on the other hand, provide a linear programming model used for production and distribution planning that integrates quality degradation of fresh foods since designing an optimal supply chain requires both food quality and cost criteria. Theoretically, Baghalian et al. (2013) develop a stochastic formulation model used for selecting robust supply chain network under supply-side uncertainties, providing with a real-life case study for rice distribution. According to Davis et al. (2021), environmental

shocks such as extreme rainfall and temperatures are now potential risks in food production and distribution as it is more frequent to observe these variabilities, and its propagation to supply chains and response from supply chain actors determine resilience to those shocks.

After experiencing a couple of natural or epidemiological disasters in this decade, supply chain studies pay more attention to economy-wide phenomena that affect the entire supply chain network through propagation. Inoue and Todo (2019) and Todo et al. (2015) put emphasis on indirect effects of the Great East Japan Earthquake in 2011 that affect firms that locate outside of the earthquake-devastated area but have business relationship with directly damaged firms. Todo et al. (2015) also suggests that networks with firms outside of the impacted area contributed to the earlier resumption of production as a general effect among manufacturing industries. Hobbs (2020) reports a wide range of COVID-19 impacts to Canadian food supply chains from labor shortages in long-haul truckers by movement restriction to isolation/quarantine regulations in the Canadian–US border, which simultaneously caused short-run disruption of food transportation and distribution networks. Nagurney (2021) especially focuses on the labor availability among perishable food supply chain under the COVID-19 pandemic. It proposes a general network optimization model that incorporates labor availability at every node of supply chain: production, processing, storage and distribution and quality deterioration as well. It is subject to further research what factors contribute to vulnerability or resilience of food supply chain and to what extent they have an impact on the economy, but Hobbs (2020) and Renting et al. (2003) refer to a potential benefit of local food supply chain or short food supply chain.

Although the literatures on network optimization are rich, they are not incorporating the feature to agro-food sectors: immobility of input and output, which is a primary source of regional or sectoral differences in economic impacts observed in the previous studies. Besides, responsiveness of agro-food sectors to macroeconomy are not compared to other manufacturing and service sectors, considering tail risks propagate regardless of sectoral division. Such an incorporation can provide useful insight for policymakers in the wake of economy-wide disaster since they need to prioritize regions and industries to be supported.

By the way, the multisector general equilibrium framework, first developed by Long and Plosser (1983), show that input–output linkages can neutralize the force of the law of large numbers; idiosyncratic shocks in a sector are not negligible and can translate into aggregate fluctuations in macroeconomic variables if the sector is particularly important as a supplier to other sectors. Then, Acemoglu et al. (2012) proposes the modern network linkage model and, in the theoretical framework, shows that macroeconomic volatility comes from sectoral idiosyncratic shocks if the scale of the firm in the center of the vast production network is significantly large. Their work is based on a Cobb–Douglas model following the context of Long and Plosser (1983).

Following this framework, a series of empirical contributions arose, targeting idiosyncratic tail risks. Carvalho et al. (2021) identify the role of input–output linkages among disaster-stricken firms affected by the Great East Japan Earthquake in 2011, which accounted for a 1.2 percentage point decline in Japan's gross output. As another example, Barrot and Sauvagnat (2016) find that US firms affected by natural disasters have negative effects on

their customers and that this effect translates into other downstream suppliers. As a relevant study, Acemoglu et al. (2017) theoretically imply that a large-scale economic downturn can emerge under two conditions: sufficient heterogeneity in sectoral Domar weights (or asymmetric distribution of sectoral output share in GDP) and sectoral shocks that exhibit tail risks.

The studies above focus on the nature of the network in the input–output structure, while they mostly use the Cobb–Douglas production function that allows perfect substitution between intermediates and factors. In turn, Baqaee and Farhi (2019a) argue that Cobb–Douglas models, where the input–output matrix is constant and can be treated as exogenous, are a very special case in which Hulten's theorem globally holds; more generally, the input–output matrix responds endogenously to shocks. For this reason, they establish a second-order approximation of Hulten's theorem in which the macroeconomic impact of sectoral shocks is nonlinear and its source is microeconomic details of the production structure shaped by the nested CES function system. In relation to the original framework, as noted in the literature, one can experience macroeconomic tail risk without either fat-tailed shocks or fat-tailed Domar weights resulting from the second-order impact of sectoral shocks.

Among the few works that study endogenous changes in industrial structures, Acemoglu et al. (2016) empirically examine propagation based on the conventional Cobb–Douglas type framework, including *geographic overlay* as a consequential effect of industrial agglomeration. For example, as their paper notes, the more an enterprise procures production factors and intermediate goods from local suppliers, the propagation of surplus value added is through an intensive increase (or decrease) in the employment of its suppliers and other industries located upstream. This impact of industrial agglomeration is verified by other empirical analyses, such as those of Autor et al. (2013) and Mian et al. (2013). Although Acemoglu's framework treats geographic overlay as an ad hoc effect that is not necessarily incorporated into the theoretical model (partly explained in Acemoglu and Azar (2020)), it is possible to consider it as a special case of Baqaee's generalized network model (perhaps this is a reason why it is named 'generalized') since the geographical overlay, i.e., nonlinear changes in value added over local industrial clusters, is very similar to what Baqaee calls the sectoral change in Domar weights.

This study applies the theoretical framework of the generalized network linkage model to make the following contributions:

1. Incorporate the heterogeneity of goods produced by different regions and modify the model into one with a regional network.
2. Empirically estimate the elasticity of substitution, a crucial parameter in the generalized network model.
3. Compare regional propagation (i.e., impact on the regional economy) with its national counterpart for agro-food sectors among the other manufacturing and service sectors.

3 Network linkage model

3.1 Review of generalized network linkage model

The framework developed by Baqaee and Farhi (2019a) is based on transitions from one state to another in general equilibria just as conventional network models, although the transition period varies in empirical approaches from the annual to the quadrennial, which is as long as the standard business cycle. The general framework is therefore normal as described in Sect. 3 of their paper. The core of their work is the second-order approximation of Hulten's theorem (Hulten (1978)):

$$\frac{d\log Y}{d\log A_i} = \lambda_i \tag{1}$$

where Y is the aggregate output function, A_i is Hicks-neutral technology in the production of good i, and $\lambda_i = p_i y_i / GDP$ is the sales of producer i as a fraction of GDP or the Domar weight. The second-order approximation of the aggregate output with respect to productivity is written as:

$$\log Y \approx \log \overline{Y} + \frac{d\log Y}{d\log A_i}\log A_i + \frac{1}{2}\frac{d^2\log Y}{d\log A_i^2}\left(\log A_i\right)^2 \tag{2}$$

where $\overline{Y}$ is the aggregate output evaluated at the steady-state technology values. The coefficient of the second-order term in the approximated equation is interpreted as the source of nonlinearities in macroeconomic impacts on sectoral shocks.

To evaluate the second-order term, they define two crucial parameters: first, the *general equilibrium pseudo elasticities of substitution* ρ_{ji} in reciprocal form is defined as:

$$\frac{1}{\rho_{ji}} \equiv \frac{d\log\left(MRS_{ji}\right)}{d\log A_i} = \frac{d\log(Y_j/Y_i)}{d\log A_i} = 1 - \frac{d\log(\lambda_j/\lambda_i)}{d\log A_i} \tag{3}$$

where Y_i is the first derivative of the aggregation function with respect to A_i. It measures the percentage change in the relative Domar weight of j and i in response to a unitary change in the technology of i by the different notion of Hulten's theorem $Y_i A_i = \lambda_i$.

The second parameter is the *input–output multiplier* ξ defined as:

$$\xi \equiv \sum_{i=1}^{N} \frac{d\log Y}{d\log A_i} = \sum_{i=1}^{N} \lambda_i \tag{4}$$

If $\xi > 1$, the sum of each sector's output is larger than GDP, which indicates that there are intermediate inputs. ξ captures the percentage change in aggregate output in response to unitary changes in each technology; therefore, as they note in their paper, it is a notion of returns-to-scale at the aggregate level.

By a simple derivation with the parameters above, the coefficient of the second-order term can be rewritten as follows (Theorem 2 in Baqaee and Farhi (2019a)):

$$\frac{d^2\log Y}{d\log A_i^2} = \lambda_i \frac{d\log\lambda_i}{d\log A_i} = \frac{\lambda_i}{\xi}\left[\sum_{j\neq i}\lambda_j\left(1 - \frac{1}{\rho_{ji}}\right) + \xi\frac{d\log\xi}{d\log A_i}\right] \tag{5}$$

where the first term in parentheses is the total change in relative Domar weights in sector j other than i and the second is a change in the return-to-scale of aggregate output, weighted by λ_i/ξ that is the output share of sector i.

Hulten's theorem globally holds if one assumes a Cobb–Douglas model. Intuitively, the value of elasticities of substitution is one for every sector by definition; thus, the first term is zero. In turn, the input–output multiplier is interpreted as a notion of constant returns-to-scale since a change in a Domar weight is always offset by another if sectoral output is perfectly substitutable in aggregation.

3.2 Data structure

The parameters defined above play crucial roles both in quantitatively evaluating macroeconomic impacts by the second-order term and gaining implications from microeconomic characteristics in the sector of interest. While the former is already shown above, the latter requires the data structure used in the empirical approach.

A nested CES economy in standard form is defined by the share parameter ω and elasticity of substitution θ for intermediates N and factors F. ω corresponds to the input–output matrix $(NR+1+FR)\times(NR+1+FR)$ in share form, which consists of the first row and column as final demand, the next NR rows and columns as N goods for R regions, and the last FR rows and columns as F factors for R regions. Production factor y_{fs}, assuming inelastic supply, are modeled as the production function in share form,[1]

$$\frac{y_{fs}}{\overline{y_{fs}}} = 1.$$

The goods are modeled as nodes of nested CES production functions in share form,

$$\frac{y_{ir}}{\overline{y_{ir}}} = A_{ir}\left(\sum_{s=1}^{R}\sum_{j=1}^{N}\omega_{ir,js}\left(\frac{x_{ir,js}}{\overline{x_{ir,js}}}\right)^{\frac{\theta_{ir}-1}{\theta_{ir}}}\right)^{\frac{\theta_{ir}}{\theta_{ir}-1}} \tag{6}$$

where $x_{ir,js}$ are intermediate inputs from sector j in region s used by i in r and $\omega_{ir,js}$ are the share parameters for this pair of input and output. Output sector 0 represents final demand, and its production function in share form is the aggregator:

$$\frac{Y_r}{\overline{Y_r}} = \frac{y_{0r}}{\overline{y_{0r}}},$$

where Y_r is the aggregate output and y_{0r} is the final demand in region r.

The market clearing condition for goods and factors with respect to jsth output is,

$$y_{js} = \sum_{r=1}^{R}\sum_{i=0}^{N} x_{ir,js}.$$

The share parameter ω is imposed with restrictions such as:

[1] In share form of production function, overline symbols such as $\overline{y_{fs}}$ refer to the amount in steady state.

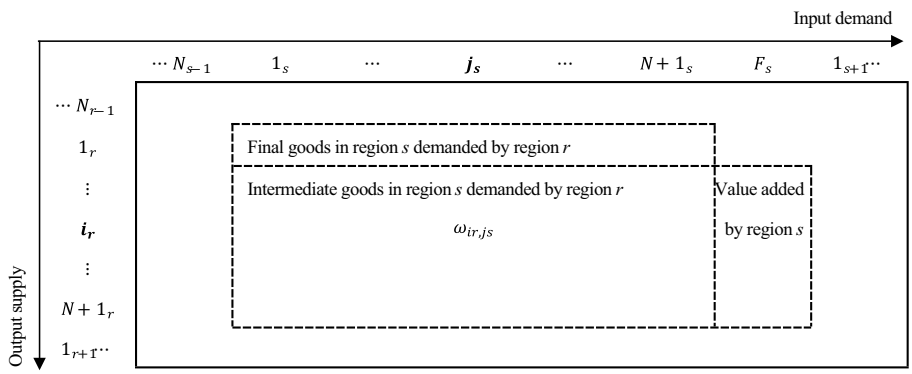

Fig. 1 Regional input–output table

$$\sum_{s=1}^{R}\sum_{j=1}^{N+F}\omega_{ir,js}=1 \text{ and } \omega_{ir,js}\in[0,1].$$

Figure 1 illustrates these properties above in an input–output table. Let us clarify that the input–output notations are opposite to the conventional, for the model strictly following that of Baqaee and Fahri (2019a). In this figure, a row corresponds to factor and intermediate inputs demanded by the row sector while a column corresponds to outputs supplied to the column sector.

In addition, let us introduce the *input–output covariance* defined by Baqaee and Farhi (2019a) as the correspondence with interregional input–output tables. It is defined with an input–output matrix in share form whose (*ir*,*js*) element is equal to the steady-state value:

$$\Omega_{ir,js}=\frac{p_{js}x_{ir,js}}{p_{ir}y_{ir}}$$

and the Leontief inverse matrix:

$$\Psi=(I-\Omega)^{-1},$$

where the (*ir*,*js*) element is a measure of producer *ir*'s total reliance on supplier *js*.

Then, the input–output covariance in interregional input–output tables is defined as:

$$Cov_{\Omega_{kv}}\left(\Psi_{ir},\Psi_{js}\right)=\sum_{u}\sum_{l}\Omega_{kv,lu}\Psi_{lu,ir}\Psi_{lu,js}-\left(\sum_{u}\sum_{l}\Omega_{kv,lu}\Psi_{lu,ir}\right)\left(\sum_{u}\sum_{l}\Omega_{kv,lu}\Psi_{lu,js}\right).$$

It is the covariance between the *ir*th and *js*th raw of the Leontief inverse matrix for an arbitrary *kv*th node of nested CES production functions as distribution. Since Ω are the correspondence with ω and sum to 1 with respect to column, a pair of raw elements (*ir*, *js*) in *kv*th column can be regarded as variables distributed on the *kv*th production. As intuitive implication, another *lu*th input supplier may be affected when there is a unitary increase in output of *ir*th or *js*th sector, which can be normalized for expenditure shares between *lu*th and *ir*th or *js*th sectors by *kv*th production. If the distribution of (*ir*, *js*) is positively (or negatively) correlated, the pair of sectors (*ir*, *js*) are complementary (or substitutes).

3.3 Corresponding parameters

With the input–output covariance defined above, one can numerically evaluate the coefficient of the second-order term (Baqaee and Farhi (2019a), Proposition 7):

$$\frac{d^2 \log Y}{d\log A_{js} d\log A_{ir}} = \lambda_{js} \frac{d\log \lambda_{js}}{d\log A_{ir}} = \sum_{v=1}^{R} \sum_{k=0}^{N} (\theta_{kv} - 1) \lambda_{kv} Cov_{\Omega_{kv}} \left(\Psi_{ir}, \Psi_{js}\right) \tag{7}$$

where its sign and scale are determined by three subparameters:

I. Substitutability/complementarity of a pair of sectors: $Cov_{\Omega_{kv}} \left(\Psi_{ir}, \Psi_{js}\right)$,
II. Production technology of an arbitral sector kv:θ_{kv} and
III. Domar weight of an arbitrary sector kv: λ_{kv}.

The first determinant is a change in industrial structure that arises on the demand side; namely, when an arbitrary enterprise kv increases its expenditure share on an intermediate good ir by one unit; it measures the correlation with another intermediate js's expenditure share in kv's production. The second determinant, on the other hand, is a change in industrial structure that arises on the supply side; when the relative price of intermediate goods changes, it measures the elasticity by which the expenditure share of enterprise kv will change. Finally, the third determinant is the weight of enterprise kv's production, which determines the scale of impact when a productivity shock arises. By summing these factors for all enterprises in the supply chain between ir and js, the nonlinear impact of shock in sector ir propagated to sector js is evaluated. This coefficient is also described as the variation in the sector's Domar weight to another sector's productivity change, as described in Eq. (7).

In Eq. (5), the coefficient of the second-order term consists of two effects: the change in the relative Domar weight among other industries and the variation of the input–output multiplier after being affected by the productivity shock in sector ir. Since the input–output multiplier captures the percentage change in aggregate output in response to unitary productivity change in sector ir, the latter effect can be interpreted as how much more (or less) intensively all the other sectors in the supply chain will procure ir's product as an intermediate. As shown in Eq. (8), the elasticity of the input–output multiplier can be rewritten as the sum of the variation in other sectors' Domar weights. Hereinafter, let us focus on the change in the input–output multiplier and define it as the *network effect* ν_{ir}, which represents the aggregate change in industrial structure centered on the productivity shock in sector ir:

$$\frac{d \log \xi}{d \log A_{ir}} = \frac{1}{\xi} \sum_{s} \sum_{j} \lambda_{js} \frac{d \log \lambda_{js}}{d \log A_{ir}} \equiv \nu_{ir} \tag{8}$$

3.4 Model specification

The preliminaries under the derivation of Eq. (8) is identical to that of Baqaee and Farhi (2019a). In this sense, there are two important caveat to the implication of this equation: (i) regionally differentiated inputs are tradable over regions without any varriers or costs, and (ii) the CES technology is quite simplified in which intermediate goods and a single factor is aggregated into output under nonnested production functions.

The first concern can be paraphrased that the model is not fully specified open economy. Any transportation costs or trade varriers over regions are not considered. Although the input–output data employed for empirical approach in the later section incorporate the transportation and distribution margins as inputs to the corresponding industries, it does not formally constrain the change of input–output structures specified by Eq. (7) or (8). Since the model is applied to Japan's regional production networks, instead of international trades, the theoretical defect might cause only limited distortions. Nevertheless, it should be noted for future studies that the share of transportation cost is relatively high for some agro-food products if they are distributed by cold chain logistics, and that some raw produces are not distributable over long distances due to perishability. To incorporate such conditions, Caliendo et al. (2018) and Baqaee and Fahri (2019b) suggest a trade-oriented network model with iceburg trade costs.

Though the CES technology is common to related studies, this study employs non-nested CES production functions for a single factor and a variety type and origin of inputs. Simplification highlights the dynamics of input–output structures at expense of intuitive implications. Namely, the subparameter θ plays an important role in measuring network effects, yet it might be difficult to find its analogy to production practices in the reality. The framework by Nakano and Nishimura (2023) and Atalay (2017) propose the nested CES model consistent with empirical approach, which is subject to implementation for further research.

4 Empirical approach and data

Following the theoretical derivation in the former section, network effects are evaluated by three subparameters, two of which (i.e., input–output covariance and Domar weight) can be calculated from interregional input–output tables. These are the steady-state parameters at each observation of the industrial structure; thus, they are time-varying. On the other hand, the other subparameter, θ, as the production technology of an arbitrary enterprise, is the elasticity of substitution in the nested CES function system, which is unaffected by productivity shocks or time trends; thus, it is time-invariant. As described in Eq. (7), θ is an important parameter that determines the sign and scale of the coefficient of the second-order term, similar to the case of network effects (in a special case, as θ converges to 1, the function system becomes Cobb–Douglas; therefore, the second-order term is zero). This section estimates the value of θ for all sectors, assuming regional differences within the same industry, to calculate network effects in the next section.

The elasticity of substitution represents a change in intermediate demand in accordance with a unitary change in its relative price, which affects the intensity of propagation of productivity shocks into the economy. Additionally, it is a sector-specific time-invariant parameter and needs to be predetermined as an exogenous variable to the generalized network linkage model. Therefore, the model requires the parameter to be estimated using an econometric method for calculating robust coefficients; however, Baqaee and Fahri (2019a; b) ultimately employ an analytical approach, with a dozen variations for the parameter to simulate the impact of second-order terms.

In the literature on spatial computable general equilibrium (SCGE), assuming the same nested CES system as under the Armington approach, some studies estimate spatially differentiated elasticities of substitution.[2] A similar empirical approach can be employed in this study, but assuming asymmetric propagation in the interregional trade of intermediate goods (i.e., assuming different production technologies across regions enables different propagation even if shocks arising in every region are identical) requires estimation for each industry and region. In a previous study that estimated the elasticity of substitution for the network model, Atalay (2017) estimates the elasticity of substitution for a network model covering 30 industries, including agriculture and food processing, in the United States. The present work employs an empirical method to estimate the elasticity of intermediate goods across 9 regions in Japan.

4.1 Estimation of elasticities of substitution

For simplicity, let us assume an economy with a single aggregated production factor, nonnested CES production function and no capital formation (consumption, investment and inventory are aggregated into a single final demand). Additionally, let us assume Hicks-neutral productivity that is exogenous to trade and allow net exports in international and interregional trade to be aggregated into the single final demand.[3]

Under these assumptions, the CES production function in sector ir can be written with the time-series notation t,

$$\widetilde{y_{ir}^t} = A_{ir}^t \left(\sum_s \sum_j \left(\omega_{ir,js}\right)^{\frac{1}{\theta_{ir}}} \left(\widetilde{x_{ir,js}^t}\right)^{\frac{\theta_{ir}-1}{\theta_{ir}}} \right)^{\frac{\theta_{ir}}{\theta_{ir}-1}} \tag{9}$$

where $\widetilde{y_{ir}^t}$ and $\widetilde{x_{ir,js}^t}$ are quantities of output and input, respectively, and ω represents the cost shares of factor and intermediate inputs in steady state, which are assumed to depend only on productivity shocks and variations in relative prices.

Following the derivation by Atalay (2017), by minimizing the cost of the representative enterprise in sector ir, the equation to be estimated is in log-linear form of the expenditure share $p_{js}^t \widetilde{x_{ir,js}^t} / p_{ir}^t \widetilde{y_{ir}^t}$, its relative price p_{js}^t / p_{ir}^t and Hicks-neutral productivity A_{ir}^t, with $1 - \theta_{ir}$ as a coefficient, as shown in Eq. (10). Since $p_{ir}^t \widetilde{y_{ir}^t}$ and $p_{js}^t \widetilde{x_{ir,js}^t}$ are identical to the values of output and input, respectively, they are y_{ir} and $x_{ir,js}$ in the notation of regional input–output tables defined in the previous section.

$$\Delta log \frac{p_{js}^t \widetilde{x_{ir,js}^t}}{p_{ir}^t \widetilde{y_{ir}^t}} = -(\theta_{ir} - 1) \Delta log \frac{p_{js}^t}{p_{ir}^t} + (\theta_{ir} - 1) \Delta log A_{ir}^t + \epsilon_{ir}^t \tag{10}$$

This equation suggests that $\theta_{ir} - 1$ can be regarded as the elasticity of the expenditure share in response to changes in relative prices and productivities. For instance, if any of the relative prices of intermediate inputs increase, then the enterprise will minimize its expenditure by reducing the share of the input. In this regard, the response will be elastic

[2] For studies that estimated the elasticity of substitution of agricultural and food products while allowing for regional differentiation of goods and interregional trade, see Koike et al. (2012), Koike and Naka (2014), and Ishikura and Ikeda (2018); their estimates are introduced in a later section for comparison and validation of my estimates.

[3] Nevertheless, trade and productivity are usually considered mutually correlated (e.g., a decrease in TFP might allow for expanded imports), but this assumption will be empirically examined in future work.

(inelastic) if θ_{ir} is greater than 1 (smaller than 1). In the Cobb–Douglas case (θ_{ir} converges to 1), an increase in price is perfectly offset by a decrease in quantity so that the expenditure share remains constant.

4.2 Data

For the estimation of θ, this research employs multiple published statistics, with some estimation of missing figures and extension of input–output tables (summarized in Table 1), to create an annual dataset for the period 1970–2015 on a fiscal year basis. Statistics and associated publishing agencies are Prefectural Accounts (Cabinet Office), R-JIP (RIETI), Interregional Input–Output table (METI), Distribution Census (MLIT) and Consumer Price Index (MIC). While prefectural data are available in Prefectural Accounts, R-JIP and the Distribution Census, the Input–Output tables are based on their own regional classification as shown in Table 2 and Fig. 2, so the rest of the statistics need to be aggregated to match this classification.

Table 1 Variables and corresponding data

Variables		Data	Publications	Year
A_{ir}	Factor neutral productivity in sector *ir*	Time dummy variables	R-JIP (as reference)	1970–2015
y_{ir}	Output value in sector *ir*	Sectoral output values (JPY)	Prefectural accounts	1970–2015
$x_{ir,js}$	Factors and intermediate input values from sector *js* to sector *ir*	Factors and intermediate input values (JPY)	Interregional input–output table	1970–2005 (every 5y)
$\widetilde{x_{ir,js}}$	Factors and intermediate input quantities from sector *js* to sector *ir*	Transported or distributed quantity (MT)	Distribution census	1970–2015 (every 5y)
p_{js}	Consumer price of factors and intermediate input *js*	Nonservice: value/quantity Service: CPI	Consumer price index	1970–2015

(1) For pre-1990 data in prefectural accounts, food processing classification is aggregated into manufacturing and decomposed by this study

(2) Interregional input–output table is extended for unpublished 2010 and 2015 years by RAS

Table 2 Regional classification

id	Region	Corresponding prefectures
hok	Hokkaido	Hokkaido
toh	Tohoku	Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima
kan	Kanto	Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, Kanagawa, Niigata, Nagano, Shizuoka
chb	Chubu	Toyama, Ishikawa, Gifu, Aichi, Mie
kin	Kinki	Fukui, Shiga, Kyoto, Osaka, Hyogo, Nara, Wakayama
chg	Chugoku	Tottori, Shimane, Okayama, Hiroshima, Yamaguchi
sik	Shikoku	Tokushima, Kagawa, Ehime, Kochi
kyu	Kyusyu	Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima
oki	Okinawa	Okinawa

Classification is that used in the interregional input–output table

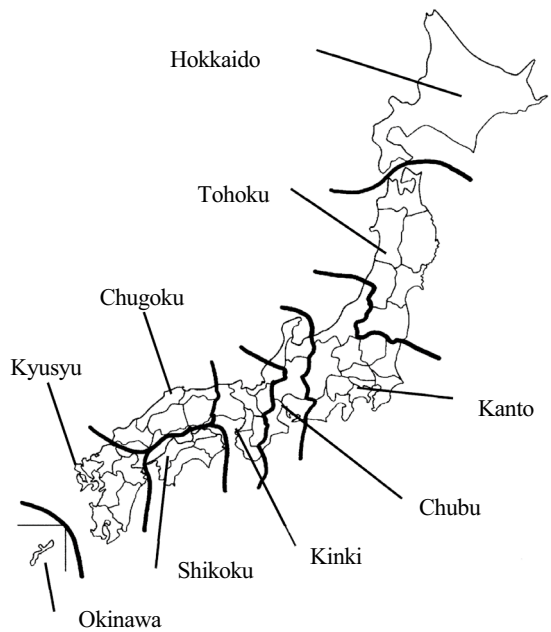

Fig. 2 Regional classification

Table 3 refers to the industrial classification. It is employed from the Prefectural Account and Interregional Input–Output table and aggregated into 21 sectors since it is in the least detailed form than those of the others.

Corresponding to the estimation model, sectoral output y_{ir}, factors and intermediate inputs $x_{ir,js}$ are extracted from the Prefectural Account and Interregional Input–Output table, respectively, and Hicks-neutral productivity (or factor neutral productivity according to Atalay (2017)) A_{ir}^t is taken as time dummy variable. However, publications on the price index on a sectoral basis are limited, so they are calculated following the outline below. For nonservice industries, let us generate a price vector by dividing sectoral input values[4] by corresponding transported and consumed quantities obtained from the Distribution Census. For service industries, since no quantity data are available, let us use the corresponding CPI (Consumer Price Index) as a proxy.[5]

- Nonservice industries

$$p_{ir}^t = \frac{y_{ir}^t}{\widetilde{y_{ir}^t}}, p_{js}^t = \frac{x_{ir,js}^t}{\widetilde{x_{ir,js}^t}},$$

[4] Let us consider the sectors in the Interregional Input–Output Tables equivalent to the products produced in corresponding industries.

[5] Therefore, all price vectors are on a consumption basis.

Table 3 Industrial classification

id	Industry (abbreviation)	Corresponding sectors
1	Agriculture (agr)	Agriculture, forestry, fisheries
2	Mining (min)	Mining
3	Food processing (fdp)	Food processing, beverage, tobacco
4	Textile (tex)	Fiber, clothes, other fiber products
5	Paper (pap)	Pulp, paper, processed paper, printing, bookbinding, publication
6	Chemistry (chm)	Chemical products, synthetic, pharmaceuticals
7	Oil (oil)	Oil and coal products, plastic products, rubber products
8	Ceramic (cra)	Ceramic
9	Refining (rfn)	Steel products, non-ferrous metal products
10	Metal processing (mtp)	Metal products
11	Machinery (mch)	General machinery, office/service machinery
12	Electrical appliance (ele)	Consumer electrical machinery, electronic machinery
13	Vehicles (veh)	Automobile, other transportation machinery
14	Precision machinery (prc)	Precision machinery
15	Other manufacturing (omn)	Lumber products, furniture equipment, other manufacturing products
16	Construction (cns)	Construction, public utilities
17	Power, gas & water (pgw)	Electric power, gas/heat supply, water supply/waste treatment
18	Wholesale & retail (sal)	Commerce
19	Finance, insurance & real estate (fir)	Finance, insurance, real estate
20	Transportation & communication (trc)	Transportation, communication
21	Other services (osr)	Education/research, medical/nursing care, personal services, business services, public services, other services

Classification aggregates the 53 sectors used in the interregional input–output table

where y_{ir} is the value of sectoral output in Input–Output table where import is subtracted, and $\left(\widetilde{y_{ir}^t}, \widetilde{x_{ir,js}^t}\right)$ is the quantity of sectoral output and input in Distribution Census where export is included.

- Service industries

$$p_{ir}^t = CPI_{ir}^t, p_{js}^t = CPI_{js}^t$$

Although theoretically not incorporated, consumer prices include transportation margins. Indices such as minimum required time are available for calculating interregional and intraregional transportation margins,[6] but the present study ignores transportation costs to prioritize consistency with the theoretical framework of the network linkage model.

4.3 Estimated parameters

This study obtains estimates for each industry and region; thus, $N \times R$ parameters are to be estimated. For Eq. (10), a least square fixed effects estimator controlling for nonmarket regional factors and time trends is standard. This study employs a fixed effects model

[6] Ishikura and Ikeda (2018) employ this index.

to control for the heterogenous effect of different inputs from different regions, with the $N \times R$ dataset for each output sector as the number of input sectors as a panel. The frequency of observations is every 5 years in the period 1970–2015 (i.e., 10 observations in time). However, the least square estimator is highly likely to be biased due to the price generated by aforementioned formula. Although the value as numerator is evaluated in producer price, the quantity as denominator is distributed amount; [7] thus, the price includes demand shocks that cause an endogeneity problem. To remediate this problem, let the input and output prices instrumented with three instrumental variables: the Corporate Goods Price Index (CGPI) and Service Producer Price Index (SPPI)[8] for input j and for output i and macro-TFP for region r. The idea behind these instruments is that since the CGPI and SPPI are evaluated at production shipment stage, they should be correlated with the generated prices as explanatory variables but should not in any other way affect the demand for jth intermediate input by ith producer. In addition, macro-TFP[9] for region r should be uncorrelated with any regional demand trend regardless of industry. Theoretically, these instruments affect the expenditure shares as dependent variable only through the generated price.

Estimates of θ are shown in Table 4 (extract of Hokkaido. For full table, see Appendix Table 8). The choice of a fixed effects estimator with instrumental variables (FE IV) over a least square fixed effect estimator (LS FE) depends on the results of post-estimation tests. F statistics at the first stage (1st F) are large enough except for the service sectors from id 16 to 21. If IVs are weakly correlated with explanatory variables in these sectors, it should be attributed to employing CPI which is the only available proxy as sectoral price. Overidentification tests (Overidentification) are often rejected in some sectors even though IV are excluded when one of them are proved to be unlikely exogenous. The model selection is, however, based on Davidson–MacKinnon's J test comparing fitted values from the two models (Endogeneity). For sectors id 6, 12, 17, 18, 20, 21 in hok; 3, 13 in toh; 11 in kan; 3, 11 in chb; 8, 11, 18, 19 in kin; 8 in chg; 3, 11, 17 in sik; 3 in kyu; and 1, 3, 14, 17 in oki, the test is rejected, and therefore a LS FE estimator is applied for later study. For the rest of sectors, a FE IV estimator is employed. In most sectors, the estimated θ value by FE IV is larger than that by LS IV. Consequently, the expenditure share of intermediate inputs tends to react elastically to relative price changes and productivity shocks including 'Agriculture' and 'Food processing' sectors. This suggests that a positive productivity shock arising in those industries will propagate downstream where input demand for agricultural or food products increases elastically. Another trend observed in the results is that the estimates of θ vary more across regions among the same sectors.

Koike et al. (2012) and Koike and Naka (2014) are reliable studies to employ for comparison and validation of the estimates. However, their results are limited to

[7] For nonservice industries. Since CPI is employed for service industries, the price is purely demand oriented for sectors id 16 to 21.

[8] Both price indices are provided by Bank of Japan. CGPI is available in 1970–2015 with 2015 price as standard. SPPI is available in 1985–2015 with 2015 price as standard, so the samples between 1970 and 1980 are removed.

[9] Macro-TFP as well as sectoral TFP is available in 1970–2015 provided by RIETI.

Table 4 Estimates of elasticity of substitution (Hokkaido)

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
hok	1	0.903	0.075	0.032	0.419	5	1.8 (0.408)	3 (0.077)
	2	1.159	0.074	1.709	0.197	200	2.8 (0.244)	15 (0.000)
	3	1.161	0.101	2.587	0.668	2	5.4 (0.069)	13 (0.000)
	4	0.908	0.021	0.878	0.025	589	38.1 (0.000)	4 (0.037)
	5	1.044	0.036	0.495	0.214	18	7.2 (0.007)	10 (0.001)
	6	1.039	0.024	1.110	0.067	142	2.4 (0.305)	2 (0.205)
	7	0.990	0.016	1.132	0.054	325	3.6 (0.060)	8 (0.004)
	8	0.996	0.038	1.398	0.190	35	1.7 (0.187)	8 (0.005)
	9	1.030	0.023	1.256	0.092	29	6.2 (0.044)	8 (0.006)
	10	1.015	0.021	1.057	0.032	179	0.9 (0.646)	3 (0.076)
	11	1.119	0.058	1.578	0.203	90	8.8 (0.012)	6 (0.013)
	12	1.102	0.033	1.118	0.045	1176	0.8 (0.678)	0 (0.550)
	13	0.909	0.026	1.122	0.075	21	1.0 (0.593)	8 (0.006)
	14	0.954	0.019	0.919	0.018	229	3.7 (0.157)	4 (0.047)
	15	1.373	0.028	3.339	0.111	185	42.9 (0.000)	1514 (0.000)
	16	0.943	0.026	1.543	0.484	1	18.3 (0.000)	3 (0.074)
	17	1.058	0.060	0.779	0.309	4	2.8 (0.245)	0 (0.546)
	18	1.055	0.034	0.842	0.165	3	2.9 (0.089)	1 (0.227)
	19	0.945	0.052	0.215	0.203	21	32.1 (0.000)	9 (0.003)
	20	1.025	0.034	1.311	0.258	9	2.3 (0.322)	2 (0.185)
	21	1.031	0.037	1.573	0.471	3	0.1 (0.741)	2 (0.144)

(1) For sector classification (id), see Tables 2 and 3. Final demand sector (id = 0) is omitted

(2) All variables are taken first difference of log-transformed values in the period 1970–2015 (9 observations every 5 years after 1975 for Okinawa, 10 observations every 5 years after 1970 for the rest)

(3) LS FE is a least square fixed effect estimator with panels of input sectors. Standard error is cluster-robust assuming heteroskedasticity over input sectors

(4) FE IV is a fixed effect estimator with the instrumental variables: macro-TFP in output region, CGPI of output sector and input sectors. Standard error is cluster-robust assuming heteroskedasticity over input sectors. 1st F is the result of F test under null hypothesis that coefficients of instrumental variables equal zero (explanatory variables are weakly correlated with instruments). Overidentification is the result of Sargan–Hansen test under null hypothesis that all instruments are correlated with residuals. Endogeneity is the result of Davidson–MacKinnon's J test under null hypothesis that an ordinary least squares estimator of the same equation (i.e., LS FE) yields consistent estimates

manufacturing industries, and the models are somewhat different[10]; their estimates are generally between 0.7 and 1. The largest figure observed is 'Printing (0.96)' and 'Transport Machines (0.96)', while the smallest is 'Textile (0.61)'. Their estimate for 'Food and Beverage', equivalent to food processing in this study, is relatively small and elastic at 0.85.[11] Considering that their dataset and process for generating price vectors are generally the same as those employed in this study, the difference could be attributed to the type of model employed, whether it is nested CES or nonnested CES, or the treatment of transportation margins in consumer prices. Note that this framework poses some problems, such as oversimplification by applying a nonnested production function for the

[10] Koike et al. (2012) present an analysis nearly identical to this study except that they do not control for heterogenous effects of different inputs. Koike and Naka (2014) validate the stability of estimates over time by repeating cross-sectional estimation for each year of data.

[11] However, the estimates obtained by Koike and Naka (2014) are generally elastic, similar to those in this study.

sake of theoretical consistency with the network linkage model or ignoring the transportation margin. As another reference, Nakano and Nishimura (2023) and Atalay (2017) estimate sectoral elasticities of substitution in the United States under the two models. Where relevant to this study, the former study's estimates are 1.12 by LS IV and 3.54 by FE IV for 'Agriculture' and 0.55 by LS IV and 1.38 by FE IV for 'Miscellaneous foods and related products'. Despite the similarity of estimates, they target the United States and assume the multi-factor CES economy, whereas this study assumes a reduced form where an aggregated factor is employed under a nonnested production function.

5 Discussion of the results

The network effect ν_{ir} is scaled by the elasticity of the input–output multiplier ξ. The input–output multiplier represents the intensity of the usage of intermediate inputs; in other words, it is the complexity and length of the supply chain of the entire economy. Therefore, in a sector that relies heavily on regional markets for its procurement of production factors and intermediate inputs, network effects caused by productivity shocks in that sector should propagate differently within and across regions. This can be examined by redefining the input–output multiplier scaled by the regional economy and comparing it to the national counterpart. If there are any significant gaps between them, then the intensity of propagation toward the local economy is greater or less than that of the national economy.

This section, following the concept mentioned above, calculates network effect coefficients in two different ways and compares them to examine the superiority of intraregional network effects among agricultural and food processing industries. Then, if any characteristic trends are observed in the distribution of coefficients across industries or regions, it provides possible explanations referring to relevant studies and in-depth analysis.

5.1 Network effects

In Sect. 3.3, the coefficient of the network effect ν_{ir} is defined as propagation to the national economy, where the input–output multiplier ξ is the sum of the Domar weights λ_{ir} scaled by GDP. In brief, this can be interpreted as an average intensity of propagation of intraregional and interregional terms. To capture the intraregional term alone, first, Hulten's term for GRP is defined as:

$$\frac{d\log Y_r}{d\log A_{ir}} = \hat{\lambda}_{ir} \textit{ where } \hat{\lambda}_{ir} \equiv \frac{p_{ir}y_{ir}}{y_r^0} \tag{1'}$$

where y_r^0 is GRP, and thus $\widehat{\lambda}_{ir}$ is the Domar weight scaled by the size of the regional economy. With these Domar weights, the input–output multiplier for regional economies and the intraregional term of network effects can be defined as:

$$\xi_r \equiv \sum_{i=1}^{N} \frac{d\log Y_r}{d\log A_i} = \sum_{i=1}^{N} \hat{\lambda}_{ir} \tag{4'}$$

$$\hat{\nu}_{ir} \equiv \frac{d\log \xi_r}{d\log A_{ir}} \tag{8'}$$

Table 5 Estimates of network effect coefficients

id	hok		toh		kan		chb		kin		chg		sik		kyu		oki	
	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$	ν	$\hat{\nu}$
1	0.0214	0.0517	0.0008	0.0016	0.0019	0.0048	0.0011	0.0035	0.0015	0.0049	0.0013	0.0042	0.0007	0.0020	0.0007	0.0020	0.0004	0.0010
	(0.001)		(0.141)		(0.000)		(0.002)		(0.003)		(0.003)		(0.005)		(0.019)		(0.024)	
2	0.0077	0.0137	0.0112	0.0166	0.0064	-0.0001	-0.0033	-0.0043	0.0032	0.0053	0.0010	0.0023	0.0122	0.0203	0.0120	0.0217	-0.0012	-0.0022
	(0.941)		(0.177)		(0.361)		(0.516)		(0.093)		(0.671)		(0.038)		(0.200)		(0.275)	
3	-0.0144	-0.0549	0.0007	0.0011	0.0021	0.0015	0.0000	-0.0002	0.0007	0.0013	0.0004	0.0008	0.0001	0.0000	0.0001	0.0000	0.0000	-0.0002
	(0.001)		(0.403)		(0.246)		(0.441)		(0.158)		(0.011)		(0.415)		(0.476)		(0.020)	
4	-0.0004	-0.0020	0.0003	0.0003	0.0005	0.0006	0.0005	0.0004	0.0005	0.0006	0.0003	0.0002	0.0002	0.0002	0.0002	0.0002	0.0000	0.0000
	(0.232)		(0.827)		(0.784)		(0.661)		(0.850)		(0.582)		(0.082)		(0.054)		(0.672)	
5	0.0482	0.0767	0.0015	0.0021	0.0026	0.0026	0.0006	0.0007	0.0009	0.0012	0.0003	0.0005	0.0004	0.0008	0.0003	0.0003	0.0000	0.0000
	(0.029)		(0.266)		(0.917)		(0.440)		(0.351)		(0.199)		(0.061)		(0.577)		(0.894)	
6	0.1008	0.1796	0.0050	0.0080	0.0040	0.0098	0.0031	0.0047	0.0031	0.0060	0.0065	0.0107	0.0016	0.0026	0.0013	0.0021	0.0002	0.0003
	(0.006)		(0.015)		(0.157)		(0.189)		(0.032)		(0.022)		(0.056)		(0.266)		(0.408)	
7	0.0901	-0.0121	0.0015	0.0017	-0.0221	-0.0282	-0.0089	-0.0114	0.0044	0.0093	-0.0029	-0.0030	0.0026	0.0086	0.0016	0.0067	-0.0012	-0.0022
	(0.656)		(0.942)		(0.543)		(0.500)		(0.233)		(0.980)		(0.257)		(0.477)		(0.313)	
8	-0.1060	-0.2090	-0.0047	-0.0110	-0.0122	-0.0198	0.0012	0.0008	-0.0146	-0.0162	-0.0032	-0.0037	-0.0006	-0.0010	-0.0031	-0.0056	-0.0055	-0.0094
	(0.381)		(0.205)		(0.171)		(0.701)		(0.340)		(0.821)		(0.585)		(0.325)		(0.381)	
9	3.1435	5.0133	0.0983	0.1510	0.1411	0.2415	0.0630	0.0990	0.1157	0.1573	0.0833	0.1257	0.0329	0.0547	0.0534	0.0888	0.0100	0.0140
	(0.000)		(0.005)		(0.000)		(0.002)		(0.000)		(0.000)		(0.002)		(0.004)		(0.364)	
10	-0.0048	-0.0078	-0.0005	-0.0008	-0.0013	-0.0025	-0.0012	-0.0022	-0.0012	-0.0019	0.0002	0.0002	0.0000	0.0001	-0.0001	-0.0001	-0.0001	-0.0002
	(0.084)		(0.175)		(0.282)		(0.239)		(0.359)		(0.957)		(0.283)		(0.628)		(0.357)	
11	0.0071	0.0103	0.0000	-0.0001	-0.0007	-0.0011	0.0000	0.0000	0.0002	0.0004	0.0010	0.0014	0.0002	0.0003	0.0001	0.0002	0.0000	0.0000
	(0.305)		(0.828)		(0.257)		(0.930)		(0.683)		(0.222)		(0.120)		(0.395)		(0.937)	
12	-0.0041	-0.0055	-0.0009	-0.0014	-0.0024	-0.0041	-0.0005	-0.0006	-0.0003	-0.0007	-0.0005	-0.0007	0.0001	0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.591)		(0.239)		(0.113)		(0.481)		(0.132)		(0.318)		(0.216)		(0.696)		(0.193)	
13	0.0004	-0.0004	0.0001	0.0003	-0.0009	-0.0018	0.0001	0.0001	0.0003	0.0005	0.0000	0.0002	0.0006	0.0011	0.0002	0.0004	-0.0001	-0.0003
	(0.718)		(0.677)		(0.113)		(0.962)		(0.026)		(0.441)		(0.125)		(0.292)		(0.304)	
14	-0.0005	-0.0008	-0.0001	-0.0001	-0.0002	-0.0003	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	0.0000	-0.0001	0.0000	0.0000	0.0000
	(0.346)		(0.624)		(0.457)		(0.541)		(0.871)		(0.748)		(0.223)		(0.178)		(0.443)	
15	0.0286	0.0224	0.0010	0.0016	0.0168	0.0228	0.0003	0.0008	0.0011	0.0018	-0.0006	-0.0004	-0.0002	-0.0002	0.0000	0.0001	-0.0001	-0.0002
	(0.271)		(0.412)		(0.060)		(0.343)		(0.230)		(0.441)		(0.967)		(0.862)		(0.250)	
16	-0.1151	-0.1939	-0.0049	-0.0091	-0.0070	-0.0103	-0.0008	-0.0010	-0.0021	-0.0022	-0.0014	-0.0019	0.0000	-0.0002	-0.0007	-0.0009	-0.0034	-0.0058
	(0.063)		(0.222)		(0.152)		(0.473)		(0.950)		(0.159)		(0.547)		(0.456)		(0.345)	
17	-1.3107	-1.9181	-0.1119	-0.1550	-0.0689	-0.1028	-0.0229	-0.0339	-0.0119	-0.0206	-0.0281	-0.0415	-0.0029	-0.0054	-0.0069	-0.0097	-0.0010	-0.0016
	(0.003)		(0.055)		(0.140)		(0.116)		(0.134)		(0.045)		(0.106)		(0.223)		(0.188)	
18	0.0330	0.0480	0.0029	0.0043	0.0170	0.0253	0.0050	0.0071	0.0072	0.0106	0.0025	0.0038	0.0014	0.0023	0.0023	0.0038	-0.0001	-0.0002
	(0.019)		(0.054)		(0.013)		(0.034)		(0.003)		(0.001)		(0.003)		(0.004)		(0.642)	
19	0.0009	0.0006	-0.0015	-0.0019	0.0063	0.0079	0.0007	0.0010	0.0028	0.0040	0.0008	0.0014	0.0018	0.0030	0.0019	0.0034	-0.0004	-0.0007
	(0.942)		(0.595)		(0.389)		(0.406)		(0.017)		(0.098)		(0.014)		(0.042)		(0.422)	
20	0.0290	0.0290	0.0003	0.0004	-0.0003	-0.0002	0.0018	0.0025	0.0027	0.0037	0.0017	0.0026	0.0014	0.0025	0.0018	0.0030	-0.0003	-0.0006
	(0.996)		(0.953)		(0.965)		(0.232)		(0.151)		(0.070)		(0.002)		(0.044)		(0.489)	
21	-0.0264	-0.0369	-0.0038	-0.0051	-0.0016	0.0008	0.0007	0.0013	0.0034	0.0054	0.0003	0.0009	0.0017	0.0029	0.0021	0.0041	-0.0001	-0.0003
	(0.420)		(0.351)		(0.529)		(0.519)		(0.019)		(0.433)		(0.013)		(0.114)		(0.703)	

The intersection of a row (industries) and column (region) indicates the origin of a unitary productivity shock. The left subcolumn represents the total network effect, while the right subcolumn presents the intraregional term. Each figure is a 10-year average in the period 1970–2015. Figures in parentheses are p values of paired t tests between the left group and right group (10 observations, 9 for Okinawa)

Table 5 shows coefficients ν_{ir} and $\widehat{\nu}_{ir}$ calculated by Eqs. (8) and (8)′, respectively. Each cross section by row and column is the combination of an industry and region struck by a unitary change in Hicks-neutral productivity, and subcolumns adjacent to each other represent the direction of propagation, namely, ν_{ir} on the left and $\widehat{\nu}_{ir}$ on the right. Both coefficients are averages of 10 observations over the period 1970–2015. The values in parentheses are p values of paired t tests for the significance of differences. The results show that the $\widehat{\nu}_{ir}$ coefficients are significantly larger than ν_{ir} at the 5% level widely among regions for id 1, 9, 18; namely, 'Agriculture', 'Refining' and 'Wholesale and retail'. Another feature observed in the table is that those coefficients are smaller in agro-food industries than those in the others (i.e., the scale of network effects are smaller); however, the coefficient size for the industries varies across regions. Consequently, the intraregional term of network effects is greater in agro-food sectors; therefore, productivity shocks propagate more intensively toward the regional economy.

Possible explanations for this are primarily that these industries procure their intermediate goods mostly from suppliers located in the same region (this is to be confirmed by the visualization of network structure in Sect. 5.3). For a typical application of this hypothesis, 'Food processing' industries might demand local agricultural products for as intermediates to reduce transportation cost or as a part of location strategy. Similarly, downstream producers of 'Refining' might input iron and non-ferrous metal products in the geographically agglomerated heavy industry area. On the contrarily, any shocks in 'Wholesale and retail' sector should propagate upstream, and for those regions where distribution channels come locally, network effects should be intraregional. From another perspective, Ishikura and Ikeda (2018), who employ Dixit–Stiglitz functions to formulate diversified preferences, contend that higher

elasticities can be observed under monopolistic competition. In this sense, diversified preferences across regions might encourage processed food products to be distributed more in the local market.

Network effects are one of the secondary impacts of endogenous changes in industrial structures. Given a positive productivity shock in a sector, some industries downstream adopt its technology to use the product more intensively;[12] as a result, the sector's Domar weight in the regional economy will increase. In contrast, assuming a negative productivity shock in the same sector, its customers will switch suppliers to those in other regions, which decreases the sector's Domar weight.

5.2 Sensitivity analysis

The elasticity of substitution is a crucial parameter, as mentioned above. If it is too close to 1, the scale of network effects is suppressed such that no significant difference between $\widehat{\nu}_{ir}$ and ν_{ir} can be detected in some instances (although variations in other subparameters might offset it). As an extreme case where θ converges to one, the production function becomes Cobb–Douglas, and the impact of second-order terms is strictly zero regardless of the other subparameters. In fact, not all θ estimates used to calculate the outcome of Eq. (7) are significantly different from 1. In this section, for the sectors where the difference is observed in Table 5, a sensitivity analysis is conducted on the network effects while varying the elasticity of substitution.

Appendix Figs. 6, 7, 8, 9, 10, 11, 12, and 13 plot the difference between the two types of network effects, allowing θ to vary under interval estimation: one in the 68% CI and the other in the 98% CI. The results show that if θ is included in the 68% CI, the order of magnitude of the estimates will be preserved, and there is a difference between them in every sector. Even when the estimate varies across the 98% CI, it is certain that the difference is still recognizable if the estimates do not take extreme values. Therefore, it is reasonable to say that the superiority of intraregional network effects among agricultural sectors is robust.

5.3 Comparison to industrial structures

Let us interpret the estimated coefficients above by comparison with the industrial structure in this section. First, as mentioned in Sect. 5.1, the scale of network effects in agricultural and food processing industries differ across regions. Since the coefficients are determined by three subparameters introduced in Sect. 3.3, at least one of these is generating such differences. As shown in Table 6, the regional Domar weights (sectoral outputs divided by regional domestic products) in Hokkaido, Tohoku and Kyusyu are significantly high; indeed, the ν_{ir} and $\widehat{\nu}_{ir}$ coefficients in these regions are 2–8 times as large as those in the others. Thus, the Domar weight might be the most crucial factor that causes the regional gaps.

Among the subparameters, the input–output covariance's role is also important since it captures the substitutive/complementarity relation in an arbitrary pair of

[12] It is the consequence of second-order term as Eq. (7) implies. The more substitutable the product is to the other inputs, the greater input–output covariance between these inputs will be since downstream industries change technology over time. In contrast, if the product is rather complementary to the other inputs, input–output covariance will have a limited impact for this sake. Besides, elasticity of substitution and Domar weight decide the scale of this impact as well.

Table 6 Domar weights in steady state (2005)

id	hok	toh	kan	chb	kin	chg	sik	kyu	oki
1	0.079	0.047	0.013	0.014	0.008	0.021	0.045	0.048	0.029
2	0.005	0.003	0.002	0.001	0.000	0.001	0.003	0.002	0.002
3	0.114	0.064	0.063	0.050	0.064	0.055	0.062	0.090	0.053
4	0.002	0.006	0.004	0.014	0.014	0.017	0.018	0.005	0.001
5	0.021	0.015	0.011	0.012	0.011	0.012	0.053	0.007	0.001
6	0.011	0.026	0.056	0.052	0.069	0.107	0.079	0.032	0.003
7	0.068	0.019	0.025	0.025	0.032	0.101	0.097	0.016	0.065
8	0.009	0.015	0.009	0.021	0.014	0.018	0.013	0.017	0.013
9	0.029	0.035	0.035	0.066	0.061	0.117	0.075	0.049	0.006
10	0.012	0.019	0.021	0.040	0.035	0.023	0.018	0.018	0.010
11	0.009	0.047	0.063	0.098	0.088	0.074	0.055	0.037	0.001
12	0.007	0.055	0.054	0.053	0.061	0.033	0.031	0.028	0.001
13	0.018	0.046	0.077	0.316	0.046	0.134	0.045	0.089	0.000
14	0.010	0.044	0.017	0.045	0.023	0.037	0.007	0.037	0.000
15	0.024	0.045	0.051	0.080	0.062	0.067	0.035	0.039	0.009
16	0.136	0.172	0.106	0.092	0.097	0.097	0.103	0.110	0.163
17	0.060	0.063	0.059	0.063	0.063	0.067	0.062	0.059	0.069
18	0.213	0.155	0.247	0.167	0.212	0.163	0.162	0.180	0.163
19	0.195	0.178	0.262	0.168	0.218	0.176	0.186	0.175	0.205
20	0.180	0.121	0.222	0.135	0.171	0.138	0.137	0.164	0.234
21	0.511	0.428	0.450	0.336	0.413	0.397	0.430	0.444	0.611

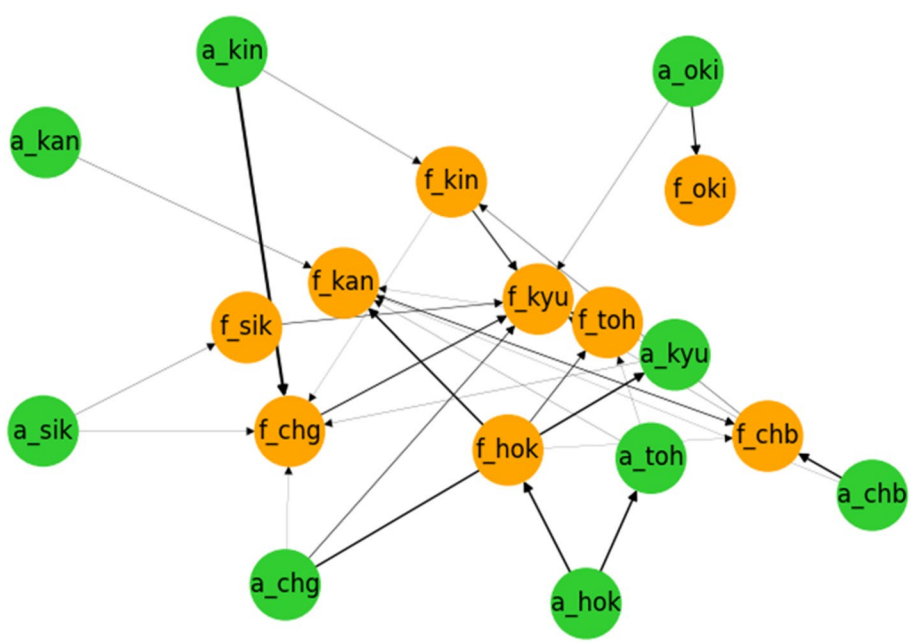

Fig. 3 Interregional network in agriculture and food processing (in Steady State, 2005). Visualization based on the input coefficients matrix of the Interregional Input–Output table 2005. The thickness of edges corresponds to the scale of input coefficients (thick if $\omega \geq 0.05$; moderate if $0.03 \leq \omega < 0.05$; thin if $0.01 \leq \omega < 0.03$; or omitted if $\omega < 0.01$). Green nodes denote agriculture (a_), yellow nodes represent food processing (f_)

sectors, in other words, directions of propagation. Figure 3 visualizes input–output networks between agriculture and food processing across different regions. With nodes corresponding to each sector and edges that indicate the scale and direction of input coefficients in Input–Output tables, the industrial position in the network is unique to each sector. Agricultural sectors (indicated by a_) supply their products mainly to their own region's food processing industry (f_); however, Tohoku (toh), Chugoku (chb) and Kyusyu (kyu) have relations with food processing industries in other regions. In the network, the food processing industries in Kanto (kan) and Kyusyu (kyu) are centered, which suggests being supplied by the most sectors. Since such sectors in input–output relations with multiple sectors can be stimulated by multiple shocks, the scale of network effects tends to be maximized (but the scale of intraregional networks depends on the complexity and length of the shocked sector's supply chain within the region).

By introducing a detailed industrial classification, it will be possible to conduct an in-depth study of the substitutive/complementary relations between industries and regions. Figure 4 visualizes a detailed input–output network with 7 agricultural and 10 food-processing subsectors in the Hokkaido region, 2005. Among the network described in the figure, there are 9 edges with intensities of $\omega \geq 1$ (as thick lines indicate) and $0.05 \leq \omega < 0.1$ (as indicated by moderately thick lines): 'rice to rice milling', 'wheat and barley to flour milling', 'flour milling to noodles, bread and confectionary',

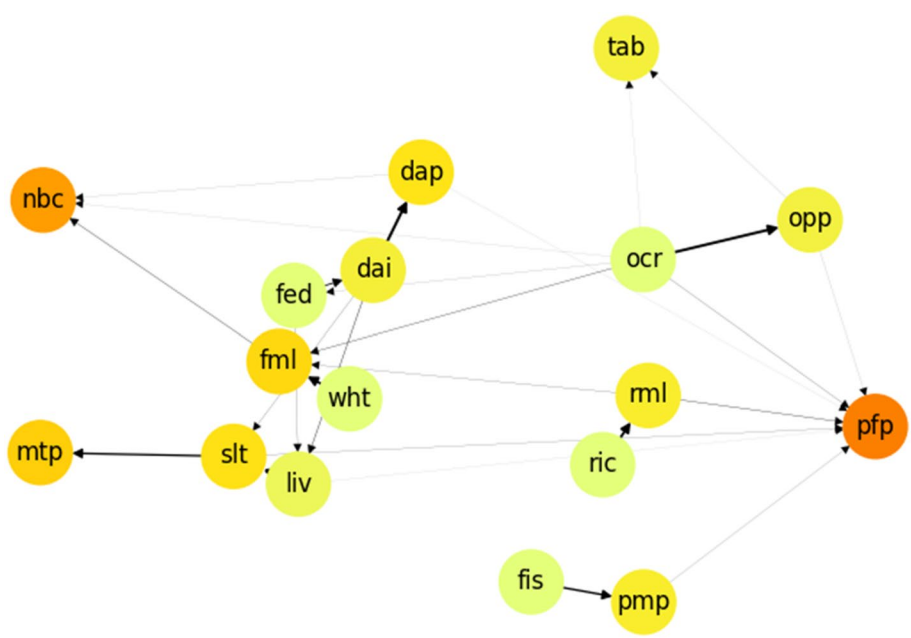

Fig. 4 Detailed network in agriculture and food processing (in Steady State, Hokkaido, 2005). Visualization based on the input coefficients matrix of the Interregional Input–Output Table 2005. The thickness of edges corresponds to the scale of input coefficients (thick if $\omega \geq 0.05$; moderate if $0.03 \leq \omega < 0.05$; thin if $0.01 \leq \omega < 0.03$; or omitted if $\omega < 0.01$). Darker color of nodes indicates higher intensity of self-input. Agriculture is classified as rice (ric), wheat and barley (wht), other crops (ocr), feeding crops (fed), dairy farming (dai), livestock (liv), and fisheries (fis). Food processing is classified as follows: slaughter (slt), meat products (mtp), dairy products (dap), processed marine products (pmp), rice milling (rml), flour milling (fml), noodles bread confectionary (nbc), other processed products (opp), prepared food products (pfp), and tobacco alcohol tea (tab)

'feeding crops to dairy farming', 'dairy farming to dairy products', 'feeding crops to livestock', 'livestock to slaughter', 'slaughter to meat products' and 'fishery to prepared marine products'. Supplementarily, Appendix Figs. 14, 15, 16, 17, 18, 19, 20, and 21 describe each edge in interregional networks. Each trade in the sector pairs above is most significant within the same region; however, some goods are traded interregionally at a considerable value. For example, in 'rice to rice milling (Appendix Fig. 14)', rice farming in Tohoku and Kanto supplies a few other regions' rice milling industries, which is why they occupy the central positions in the network. In addition, self-centered regions include Hokkaido in 'wheat and barley to flour milling (Appendix Fig. 15)', Kanto in 'flour milling to noodles, bread and confectionary (Appendix Fig. 16)' and Kyusyu in dairy- and livestock-related industries (Appendix Figs. 17, 18, 19 and 20). Although traded values partly determine the scale of network effects, it is confirmed that wider input–output networks across regions enhance the region's network effect.

How can the superiority of the intraregional network be explained in this context? As noted in Sect. 5.1, the primary reason is a greater share of intermediate goods and factor from the own region within and between agricultural and food processing industries. This can be verified with the detailed industrial classification. Table 7 shows the rates of input values into the own region divided by the total input and output values of the 9 trades introduced above. The rate weighted by total input values describes how much of the products are allocated to the own region's intermediate market, while the other weighted by total output values are the self-sufficiency

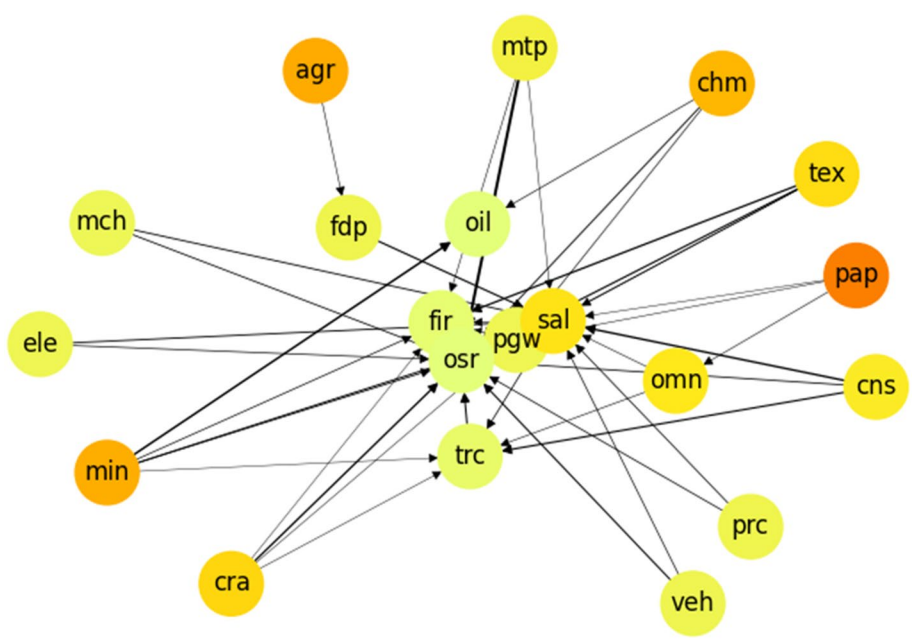

Fig. 5 Entire Regional Input–Output Network (in Steady State, Hokkaido, 2005). Visualization based on the input coefficients matrix of the interregional Input–Output Table 2005. The thickness of edges corresponds to the scale of input coefficients (thick if $\omega \geq 0.05$; moderate if $0.03 \leq \omega < 0.05$; thin if $0.01 \leq \omega < 0.03$; or omitted if $\omega < 0.01$). Darker color of nodes indicates higher intensity of self-input. Industries are described in abbreviation in Table 3

Table 7 Rates for interregional transactions (2005)

id	ric—rml		wht—fml		fml—nbc		fis—pmp			
	Input	Output	Input	Output	Input	Output	Input	Output		
hok	0.495	0.556	0.122	0.941	0.809	0.816	0.852	0.865		
toh	0.452	0.817	0.717	0.691	0.675	0.172	0.771	0.646		
kan	0.802	0.733	0.975	0.658	0.822	0.937	0.774	0.537		
chb	0.730	0.648	0.964	0.684	0.767	0.731	0.654	0.542		
kin	0.844	0.482	1.000	0.613	0.841	0.824	0.709	0.584		
chg	0.814	0.862	0.972	0.633	0.743	0.490	0.354	0.332		
sik	0.699	0.657	0.822	0.667	0.600	0.575	0.178	0.513		
kyu	0.907	0.787	0.669	0.912	0.659	0.795	0.666	0.890		
oki	1.000	0.046	1.000	0.985	1.000	0.651	0.095	0.521		
id	**fed—dai**		**dai—dap**		**fed—liv**		**liv—slt**		**slt – mtp**	
	Input	**Output**	**Input**	**Output**	**Input**	**Output**	**Input**	**Output**	**Input**	**Output**
hok	0.997	0.968	0.507	0.980	0.971	0.966	0.697	0.834	0.441	0.753
toh	0.970	0.938	0.445	0.751	0.983	0.935	0.760	0.973	0.687	0.948
kan	0.891	0.930	0.951	0.548	0.938	0.929	0.939	0.816	0.961	0.758
chb	0.786	0.945	0.917	0.646	0.829	0.942	0.834	0.745	0.880	0.697
kin	0.801	0.753	0.524	0.175	0.765	0.748	0.868	0.409	0.945	0.625
chg	0.610	0.771	0.752	0.739	0.547	0.770	0.704	0.905	0.770	0.638
sik	0.983	0.638	0.593	0.922	0.981	0.639	0.883	0.877	0.800	0.905
kyu	0.917	0.905	0.610	0.757	0.930	0.905	0.913	0.969	0.500	0.978
oki	1.000	0.546	0.980	0.982	0.997	0.546	0.895	0.997	1.000	0.889

Interregional input–output table 2005

The left subcolumn reports input values supplied to the own region weighted by total allocated value. The right subcolumn reports input values weighted by total output value (or self-sufficient rate of intermediate demand)

rates of the intermediate demands. Overall, except for a few regions, more than 60% of intermediate goods in these agro-food industries are allocated within regions. The rates in the industrial clusters related to dairy and livestock are especially high, which indicates the straight value chain within the region from feed production to raising and processing. These transactions are included in the same local industrial cluster and considering the significance of dairy and livestock sectors in Japan's agro-food economy, such a form explains much of the superiority of the intraregional network.[13] In future studies, empirical analysis is needed to examine the extent of the difference in the network effects between regional allocation and interregional trade.

Finally, let us compare the network effects in the agro-food sectors with those of the others. The coefficients in these sectors are relatively smaller than those in other manufacturing and service industries since the sectors are peripheral in the overall economy and propagations from other industries are quite limited. Figure 5 shows Hokkaido's entire input–output network in 2005. According to this, the products of 'Agriculture (agr)' are supplied exclusively to 'Food processing (fdp)' and then to

[13] Estimation with the detailed classification would provide empirical evidence of this, but the classification is only available for the I-O table in 2005. Even if available, other data corresponding to the classification would be insufficient to obtain time-invariant estimates of elasticities of substitution. Therefore, the detailed I-O data are for supplemental use in this study.

'Wholesale and retail (sal)'. In contrast, the central sectors such as 'Wholesale and retail', 'Power, gas and water (pgw)' and 'Transportation and communication (trc)' are supplied from almost all other industries directly or indirectly; therefore, productivity shocks in most industries can influence these sectors. In fact, the scales of the network effect in those sectors are significantly higher than those in the rest. Although this study focused on agro-food industries alone, shocks arising in these industries will propagate to the central sectors through the distribution and transport of fresh and processed food products, which might make considerable contributions to the region's macroeconomy. Future research should identify and numerically evaluate indirect propagation to such related industries.

6 Conclusions

This study provided asymmetric input–output network linkages in agricultural and food industries across nine domestic regions, modified the generalized network linkage model such that the interregional input–output structure is incorporated, and empirically examined the direction of the propagation of agro-food sectoral shocks in regional outcomes. The generalized network linkage model incorporates an endogenous change in industrial structure as a nonlinear approximation of Hulten's theorem; as a part of this effect, changes in intermediate demand for the entire economy generated by productivity shocks are defined as network effects. To evaluate these effects, elasticities of substitution between intermediate inputs across regions are empirically estimated. By comparing the network effects on the national economy and regional economy, the superiority of intraregional networks among agro-food sectors is empirically verified, which means that productivity shocks arising in these industries propagate more within the own region. This is due to intraregional industrial clusters and heterogeneity of products in the industry.

These findings offer the following implications. First, positive network effects in agricultural and food processing industries provide surplus value added in regional (and national) macroeconomies when positive productivity shocks arise in these industries. This means that the intermediate demand expands around the stimulated industries, and regional output grows more than the multiplier generated by Hulten's theory. The scale of network effects depends on the intensity of the input–output network upstream and downstream; especially for its interregional term, propagation is more intensive if the supply chain extends across regions. As a result, even if productivity shocks are common across regions, the intraregional term of network effects will cause deviations in each region's economic growth in the long term. Since the shock itself is unbalanced across regions in reality, it might be the source of the disparity in the performance of the agro-food economy.

7 Appendix

See Table 8 and Figs. 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21.

Table 8 Estimates of elasticity of substitution

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
hok	1	0.903	0.075	0.032	0.419	5	1.8 (0.408)	3 (0.077)
	2	1.159	0.074	1.709	0.197	200	2.8 (0.244)	15 (0.000)
	3	1.161	0.101	2.587	0.668	2	5.4 (0.069)	13 (0.000)
	4	0.908	0.021	0.878	0.025	589	38.1 (0.000)	4 (0.037)
	5	1.044	0.036	0.495	0.214	18	7.2 (0.007)	10 (0.001)
	6	1.039	0.024	1.110	0.067	142	2.4 (0.305)	2 (0.205)
	7	0.990	0.016	1.132	0.054	325	3.6 (0.060)	8 (0.004)
	8	0.996	0.038	1.398	0.190	35	1.7 (0.187)	8 (0.005)
	9	1.030	0.023	1.256	0.092	29	6.2 (0.044)	8 (0.006)
	10	1.015	0.021	1.057	0.032	179	0.9 (0.646)	3 (0.076)
	11	1.119	0.058	1.578	0.203	90	8.8 (0.012)	6 (0.013)
	12	1.102	0.033	1.118	0.045	1176	0.8 (0.678)	0 (0.550)
	13	0.909	0.026	1.122	0.075	21	1.0 (0.593)	8 (0.006)
	14	0.954	0.019	0.919	0.018	229	3.7 (0.157)	4 (0.047)
	15	1.373	0.028	3.339	0.111	185	42.9 (0.000)	1514 (0.000)
	16	0.943	0.026	1.543	0.484	1	18.3 (0.000)	3 (0.074)
	17	1.058	0.060	0.779	0.309	4	2.8 (0.245)	0 (0.546)
	18	1.055	0.034	0.842	0.165	3	2.9 (0.089)	1 (0.227)
	19	0.945	0.052	0.215	0.203	21	32.1 (0.000)	9 (0.003)
	20	1.025	0.034	1.311	0.258	9	2.3 (0.322)	2 (0.185)
	21	1.031	0.037	1.573	0.471	3	0.1 (0.741)	2 (0.144)
toh	1	0.907	0.134	3.160	3.559	1	0.2 (0.672)	3 (0.070)
	2	1.078	0.076	1.455	0.154	214	19.4 (0.000)	10 (0.002)
	3	1.312	0.135	0.961	0.176	14	17.2 (0.000)	2 (0.170)
	4	0.867	0.016	0.699	0.018	1204	31.8 (0.000)	169 (0.000)
	5	1.041	0.042	0.155	0.232	19	15.4 (0.000)	17 (0.000)
	6	0.919	0.026	0.541	0.055	114	55.0 (0.000)	74 (0.000)
	7	1.078	0.018	1.226	0.051	127	48.5 (0.000)	9 (0.003)
	8	1.154	0.027	1.503	0.064	66	88.1 (0.000)	58 (0.000)
	9	1.097	0.039	2.872	0.709	3	16.1 (0.000)	62 (0.000)
	10	1.196	0.022	1.514	0.040	74	65.7 (0.000)	136 (0.000)
	11	1.207	0.046	3.638	0.494	39	7.3 (0.026)	460 (0.000)
	12	0.831	0.037	0.584	0.052	674	6.0 (0.050)	54 (0.000)
	13	1.103	0.115	0.571	0.223	12	0.5 (0.764)	2 (0.122)
	14	0.972	0.031	0.863	0.033	222	8.7 (0.013)	20 (0.000)
	15	1.392	0.032	3.328	0.102	182	73.1 (0.000)	818 (0.000)
	16	0.958	0.042	1.618	0.314	2	43.5 (0.000)	7 (0.011)
	17	0.992	0.067	−1.857	0.994	5	3.9 (0.145)	23 (0.000)
	18	1.091	0.038	3.674	0.739	7	7.7 (0.021)	207 (0.000)
	19	0.992	0.064	5.825	2.089	4	0.3 (0.597)	94 (0.000)
	20	1.042	0.033	3.638	3.172	0	18.3 (0.000)	10 (0.002)
	21	1.023	0.046	4.198	1.314	4	0.0 (0.905)	67 (0.000)

Table 8 (continued)

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
kan	1	1.070	0.108	0.426	0.194	13	14.8 (0.001)	12 (0.001)
	2	1.253	0.063	1.583	0.110	336	2.6 (0.269)	31 (0.000)
	3	1.233	0.071	0.475	0.313	4	11.9 (0.003)	8 (0.005)
	4	0.783	0.019	0.705	0.016	1338	53.1 (0.000)	68 (0.000)
	5	0.965	0.025	0.748	0.085	11	41.0 (0.000)	5 (0.033)
	6	0.990	0.027	0.359	0.118	33	72.2 (0.000)	78 (0.000)
	7	0.946	0.019	1.364	0.076	58	32.2 (0.000)	29 (0.000)
	8	1.031	0.019	1.152	0.084	30	1.1 (0.302)	3 (0.069)
	9	1.024	0.021	0.637	0.091	14	134.0 (0.000)	18 (0.000)
	10	1.009	0.024	1.068	0.029	56	3.7 (0.053)	4 (0.055)
	11	1.128	0.026	1.325	0.153	10	5.8 (0.056)	2 (0.193)
	12	0.982	0.031	0.551	0.077	205	3.3 (0.191)	78 (0.000)
	13	0.985	0.051	0.845	0.061	86	1.7 (0.431)	9 (0.003)
	14	1.004	0.010	1.390	0.073	158	3.9 (0.048)	43 (0.000)
	15	1.396	0.025	3.294	0.086	249	63.5 (0.000)	1500 (0.000)
	16	1.015	0.039	1.527	0.198	5	44.6 (0.000)	14 (0.000)
	17	1.005	0.053	0.135	0.456	4	33.8 (0.000)	11 (0.001)
	18	1.065	0.036	2.247	0.430	5	25.0 (0.000)	53 (0.000)
	19	0.990	0.045	−0.697	0.599	5	57.3 (0.000)	45 (0.000)
	20	1.046	0.038	2.027	0.464	4	12.5 (0.002)	16 (0.000)
	21	1.024	0.032	1.302	0.178	14	15.7 (0.000)	6 (0.018)
chb	1	1.386	0.112	4.568	1.638	2	1.3 (0.533)	21 (0.000)
	2	1.202	0.049	1.552	0.088	292	2.4 (0.308)	46 (0.000)
	3	1.346	0.129	0.286	0.511	3	11.0 (0.004)	2 (0.157)
	4	0.750	0.024	0.630	0.019	728	19.3 (0.000)	76 (0.000)
	5	1.019	0.024	1.314	0.077	13	10.2 (0.006)	15 (0.000)
	6	1.001	0.018	0.788	0.052	65	18.5 (0.000)	20 (0.000)
	7	1.120	0.027	1.202	0.026	116	69.9 (0.000)	13 (0.000)
	8	1.063	0.022	1.361	0.071	17	10.0 (0.007)	32 (0.000)
	9	1.194	0.040	2.307	0.241	15	2.0 (0.374)	181 (0.000)
	10	1.049	0.022	1.269	0.042	30	5.6 (0.060)	32 (0.000)
	11	1.091	0.028	1.155	0.297	2	39.4 (0.000)	0 (0.809)
	12	0.986	0.025	0.836	0.052	652	29.8 (0.000)	23 (0.000)
	13	0.992	0.034	1.484	0.280	19	6.8 (0.009)	4 (0.058)
	14	0.953	0.009	0.980	0.026	411	8.5 (0.014)	3 (0.076)
	15	1.352	0.029	3.120	0.079	297	19.0 (0.000)	3465 (0.000)
	16	1.062	0.036	2.187	0.451	3	32.6 (0.000)	35 (0.000)
	17	1.105	0.069	2.667	0.494	7	6.4 (0.042)	18 (0.000)
	18	1.039	0.039	0.687	0.142	5	26.3 (0.000)	5 (0.032)
	19	0.998	0.040	0.345	0.237	9	21.8 (0.000)	11 (0.001)
	20	0.963	0.046	−2.265	1.089	5	0.8 (0.373)	115 (0.000)
	21	1.032	0.042	2.291	0.384	10	18.2 (0.000)	30 (0.000)

Table 8 (continued)

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
kin	1	1.271	0.085	2.345	0.432	3	9.2 (0.010)	8 (0.006)
	2	1.269	0.054	1.455	0.092	348	5.4 (0.068)	11 (0.001)
	3	1.375	0.133	0.127	0.573	4	3.6 (0.059)	3 (0.066)
	4	0.831	0.033	0.747	0.029	642	35.3 (0.000)	16 (0.000)
	5	1.052	0.021	1.186	0.054	21	22.1 (0.000)	5 (0.021)
	6	1.008	0.022	0.619	0.079	31	13.0 (0.002)	51 (0.000)
	7	1.055	0.023	1.131	0.018	208	73.0 (0.000)	22 (0.000)
	8	0.978	0.026	0.928	0.127	8	0.9 (0.641)	0 (0.690)
	9	0.795	0.027	0.234	0.112	28	74.1 (0.000)	61 (0.000)
	10	0.945	0.022	0.788	0.040	43	23.1 (0.000)	23 (0.000)
	11	1.071	0.021	1.101	0.110	42	0.6 (0.732)	0 (0.818)
	12	1.027	0.028	0.736	0.069	266	8.0 (0.019)	33 (0.000)
	13	0.970	0.068	0.814	0.054	64	4.0 (0.139)	12 (0.001)
	14	1.015	0.011	0.964	0.024	201	9.9 (0.007)	12 (0.001)
	15	1.379	0.023	3.000	0.081	211	173.8 (0.000)	1174 (0.000)
	16	1.003	0.021	1.611	0.382	2	5.8 (0.016)	12 (0.001)
	17	1.056	0.060	2.344	0.373	8	15.9 (0.000)	15 (0.000)
	18	1.054	0.038	1.334	0.265	5	19.0 (0.000)	1 (0.277)
	19	0.983	0.045	0.701	1.488	1	19.3 (0.000)	0 (0.796)
	20	1.034	0.040	−0.460	0.481	6	16.1 (0.000)	59 (0.000)
	21	1.004	0.048	1.546	0.277	8	52.8 (0.000)	5 (0.027)
chg	1	1.296	0.137	6.802	2.161	5	2.5 (0.284)	94 (0.000)
	2	1.116	0.047	1.426	0.079	279	3.5 (0.174)	17 (0.000)
	3	1.466	0.145	3.577	1.236	2	0.1 (0.808)	5 (0.024)
	4	0.878	0.019	0.712	0.019	867	39.9 (0.000)	167 (0.000)
	5	0.913	0.020	0.811	0.030	111	21.2 (0.000)	30 (0.000)
	6	0.942	0.030	0.583	0.128	19	58.8 (0.000)	14 (0.000)
	7	1.064	0.018	1.099	0.026	210	12.3 (0.002)	4 (0.050)
	8	1.050	0.031	0.890	0.120	61	26.1 (0.000)	2 (0.145)
	9	0.991	0.021	0.745	0.047	41	114.9 (0.000)	20 (0.000)
	10	0.959	0.027	0.873	0.039	58	6.9 (0.009)	4 (0.036)
	11	0.973	0.028	0.612	0.151	30	32.9 (0.000)	5 (0.022)
	12	1.044	0.028	0.946	0.046	730	42.4 (0.000)	10 (0.002)
	13	1.017	0.045	0.932	0.071	188	23.2 (0.000)	3 (0.084)
	14	1.033	0.012	1.081	0.030	292	4.1 (0.126)	6 (0.019)
	15	1.411	0.033	1.741	0.046	176	182.8 (0.000)	63 (0.000)
	16	0.980	0.031	−0.048	0.552	2	11.3 (0.001)	19 (0.000)
	17	1.046	0.087	−0.121	0.459	8	1.9 (0.396)	9 (0.003)
	18	1.020	0.049	−0.349	1.086	1	0.1 (0.754)	6 (0.017)
	19	0.934	0.047	0.197	0.363	9	0.3 (0.616)	10 (0.002)
	20	0.989	0.037	−0.058	0.428	6	0.1 (0.814)	18 (0.000)
	21	1.002	0.034	2.756	1.317	1	4.4 (0.037)	9 (0.003)

Table 8 (continued)

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
sik	1	1.175	0.106	2.866	0.636	15	4.3 (0.115)	21 (0.000)
	2	1.010	0.058	2.295	0.593	6	3.7 (0.054)	11 (0.001)
	3	1.428	0.167	2.138	0.460	6	1.2 (0.272)	2 (0.128)
	4	0.784	0.022	0.588	0.020	642	54.7 (0.000)	332 (0.000)
	5	1.010	0.038	0.518	0.179	10	24.6 (0.000)	8 (0.006)
	6	0.852	0.032	0.584	0.046	155	5.8 (0.056)	47 (0.000)
	7	0.974	0.015	1.639	0.208	51	1.2 (0.271)	14 (0.000)
	8	1.064	0.016	1.232	0.059	148	2.3 (0.320)	14 (0.000)
	9	0.789	0.042	0.543	0.052	504	58.0 (0.000)	38 (0.000)
	10	0.664	0.050	0.256	0.100	85	6.0 (0.049)	28 (0.000)
	11	0.987	0.025	1.136	0.123	86	37.0 (0.000)	1 (0.338)
	12	0.546	0.053	0.224	0.053	1197	101.0 (0.000)	48 (0.000)
	13	0.823	0.036	0.377	0.312	7	9.5 (0.002)	2 (0.181)
	14	0.912	0.020	1.242	0.042	229	19.2 (0.000)	121 (0.000)
	15	1.333	0.022	3.255	0.104	186	84.1 (0.000)	1649 (0.000)
	16	0.975	0.047	3.425	2.155	1	2.9 (0.234)	24 (0.000)
	17	1.290	0.109	2.422	0.696	8	1.5 (0.218)	2 (0.131)
	18	1.035	0.047	−0.873	0.380	13	2.5 (0.288)	61 (0.000)
	19	0.946	0.046	−2.403	0.867	15	0.6 (0.725)	144 (0.000)
	20	1.014	0.037	0.033	0.267	8	98.5 (0.000)	16 (0.000)
	21	1.049	0.048	2.434	0.670	4	0.0 (0.954)	10 (0.001)
kyu	1	1.160	0.120	1.799	0.374	4	31.1 (0.000)	3 (0.080)
	2	0.891	0.057	0.563	0.140	137	6.6 (0.037)	11 (0.001)
	3	1.232	0.138	0.604	0.291	3	6.4 (0.042)	2 (0.166)
	4	0.877	0.014	0.841	0.014	1883	69.0 (0.000)	26 (0.000)
	5	0.967	0.019	1.196	0.084	35	16.9 (0.000)	6 (0.019)
	6	1.007	0.021	0.008	0.209	15	2.4 (0.125)	49 (0.000)
	7	0.954	0.025	1.491	0.082	51	37.7 (0.000)	46 (0.000)
	8	1.162	0.031	1.814	0.132	21	103.4 (0.000)	59 (0.000)
	9	1.363	0.030	2.054	0.090	59	42.5 (0.000)	268 (0.000)
	10	1.215	0.033	1.890	0.078	49	62.1 (0.000)	321 (0.000)
	11	1.067	0.021	1.842	0.174	43	9.5 (0.009)	124 (0.000)
	12	0.647	0.045	−0.088	0.082	290	7.3 (0.026)	233 (0.000)
	13	1.069	0.042	0.009	0.378	27	5.1 (0.024)	17 (0.000)
	14	0.947	0.016	0.898	0.036	152	2.5 (0.285)	3 (0.072)
	15	1.306	0.025	2.812	0.075	223	131.8 (0.000)	493 (0.000)
	16	0.995	0.024	2.047	0.653	2	0.7 (0.401)	23 (0.000)
	17	1.015	0.103	−3.975	1.446	5	0.9 (0.646)	52 (0.000)
	18	1.031	0.039	0.403	0.269	3	1.1 (0.285)	12 (0.001)
	19	0.974	0.043	−2.389	1.184	4	0.0 (0.994)	76 (0.000)
	20	1.020	0.033	−0.206	0.443	4	0.1 (0.775)	22 (0.000)
	21	1.033	0.053	2.043	0.391	19	4.3 (0.038)	17 (0.000)

Table 8 (continued)

id		LS FE		IV FE				
		θ	$\theta - 1$s.e	θ	$\theta - 1$s.e	1st F	Overidentification	Endogeneity
oki	1	1.124	0.109	1.822	0.471	7	8.8 (0.003)	2 (0.169)
	2	1.474	0.149	3.898	0.807	19	0.2 (0.926)	36 (0.000)
	3	0.447	0.167	0.512	1.399	11	1.4 (0.494)	0 (0.955)
	4	0.617	0.025	0.566	0.019	878	3.9 (0.141)	35 (0.000)
	5	0.855	0.135	0.008	0.456	17	6.7 (0.034)	8 (0.005)
	6	0.859	0.020	0.908	0.037	183	6.8 (0.033)	4 (0.056)
	7	1.087	0.012	1.034	0.015	1339	0.1 (0.943)	37 (0.000)
	8	1.192	0.042	1.063	0.070	54	3.9 (0.139)	7 (0.008)
	9	1.087	0.075	0.141	0.346	6	5.6 (0.062)	21 (0.000)
	10	1.154	0.020	1.331	0.046	60	1.7 (0.190)	11 (0.001)
	11	0.897	0.063	0.619	0.081	295	24.6 (0.000)	24 (0.000)
	12	1.182	0.076	1.356	0.068	159	14.3 (0.001)	11 (0.001)
	13	0.923	0.104	0.642	0.137	81	1.7 (0.191)	3 (0.096)
	14	1.085	0.086	1.089	0.085	3874	2.5 (0.111)	0 (0.503)
	15	1.388	0.030	1.826	0.064	109	49.6 (0.000)	50 (0.000)
	16	1.029	0.048	5.028	3.527	1	2.3 (0.318)	38 (0.000)
	17	1.088	0.166	0.925	0.666	3	39.0 (0.000)	0 (0.808)
	18	1.135	0.051	3.574	0.854	9	46.6 (0.000)	58 (0.000)
	19	1.031	0.110	−0.949	0.891	6	50.6 (0.000)	7 (0.009)
	20	1.022	0.038	0.005	0.311	9	104.3 (0.000)	27 (0.000)
	21	1.195	0.069	2.591	0.368	10	45.1 (0.000)	20 (0.000)

(1) For sector classification (id), see Tables 2 and 3. Final demand sector (id = 0) is omitted

(2) All variables are taken first difference of log-transformed values in the period 1970–2015 (9 observations every 5 years after 1975 for Okinawa, 10 observations every 5 years after 1970 for the rest)

(2) LS FE is a least square fixed effect estimator with panels of input sectors. Standard error is cluster-robust assuming heteroskedasticity over input sectors

(3) FE IV is a fixed effect estimator with the instrumental variables: macro-TFP in output region, CGPI of output sector and input sectors. Standard error is cluster-robust assuming heteroskedasticity over input sectors. 1st F is the result of F test under null hypothesis that explanatory variables are weakly correlated with instruments. Overidentification is the result of Sargan–Hansen test under null hypothesis that all instruments are correlated with residuals. Endogeneity is the result of Davidson–MacKinnon's J test under null hypothesis that an ordinary least squares estimator of the same equation (i.e., LS FE) yields consistent estimates

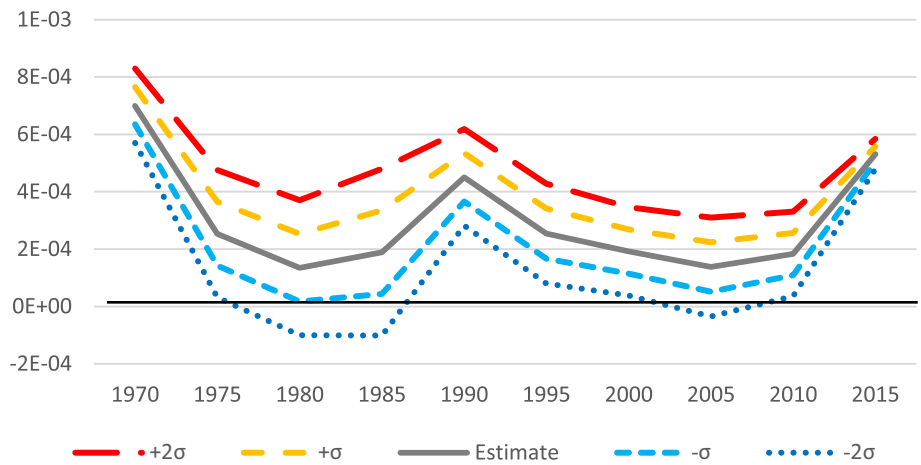

Fig. 6 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Hokkaido). Plots the difference between two types of network effects in Table 5, allowing $\boldsymbol{\theta}$ to vary under interval estimation: one in the 68% CI and the other in the 98% CI. If they are above zero under variation, the result shown in Table 5 is robust

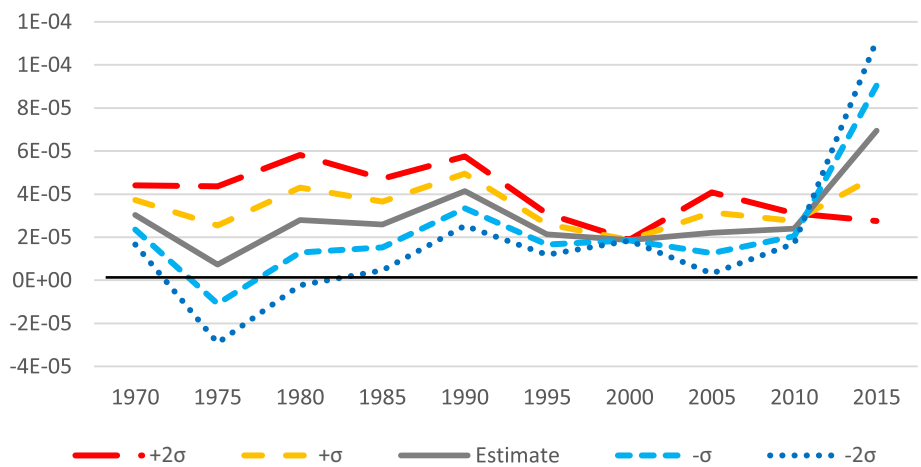

Fig. 7 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Kanto)

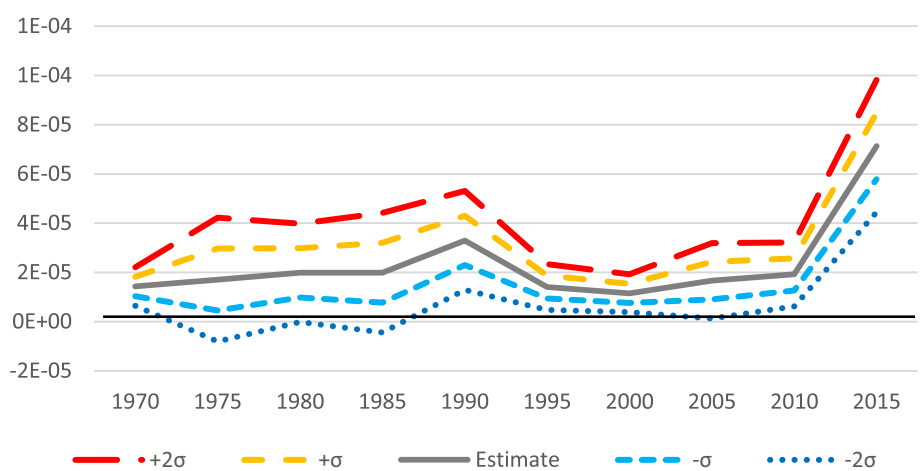

Fig. 8 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Chubu)

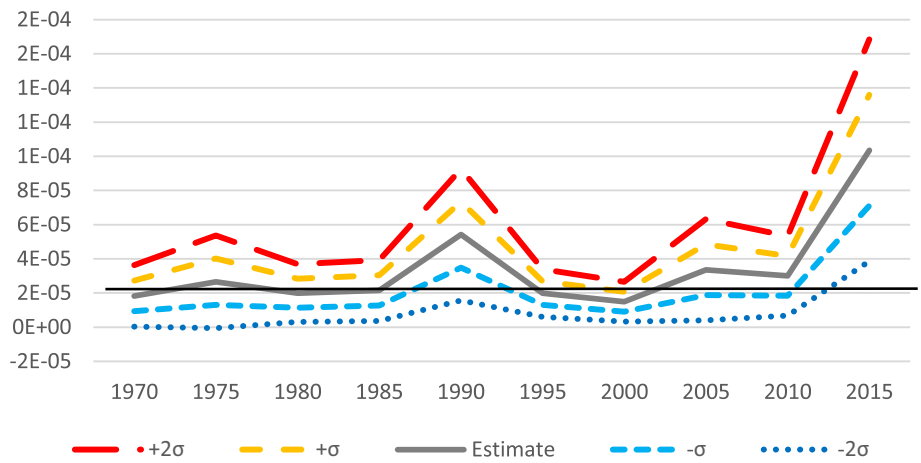

Fig. 9 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Kinki)

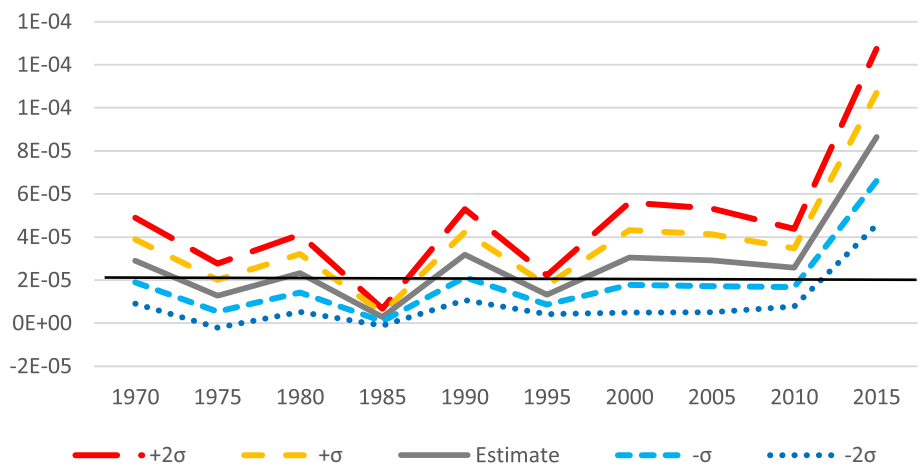

Fig. 10 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Chugoku)

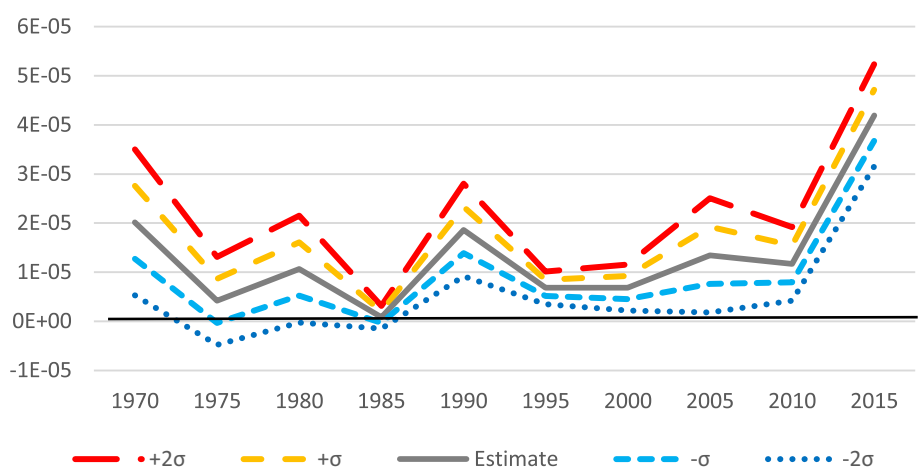

Fig. 11 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Shikoku)

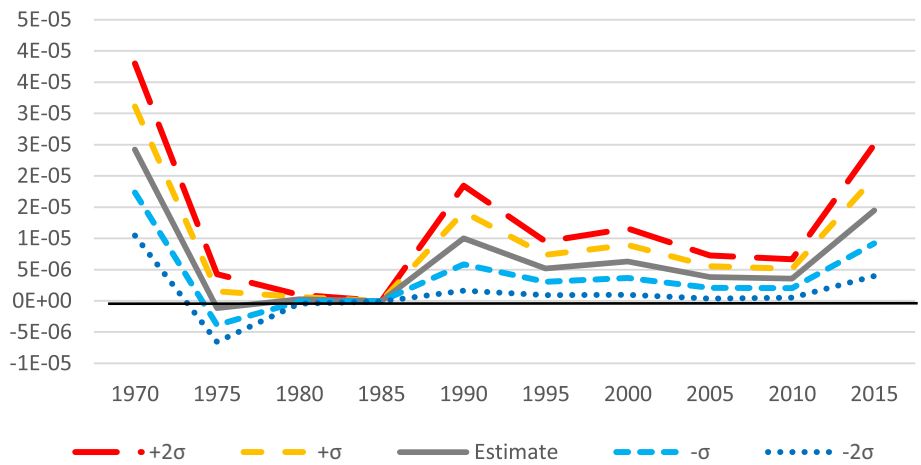

Fig. 12 Sensitivity of difference between $\boldsymbol{\nu}$ **and** $\widehat{\boldsymbol{\nu}}$ (Agriculture, Okinawa)

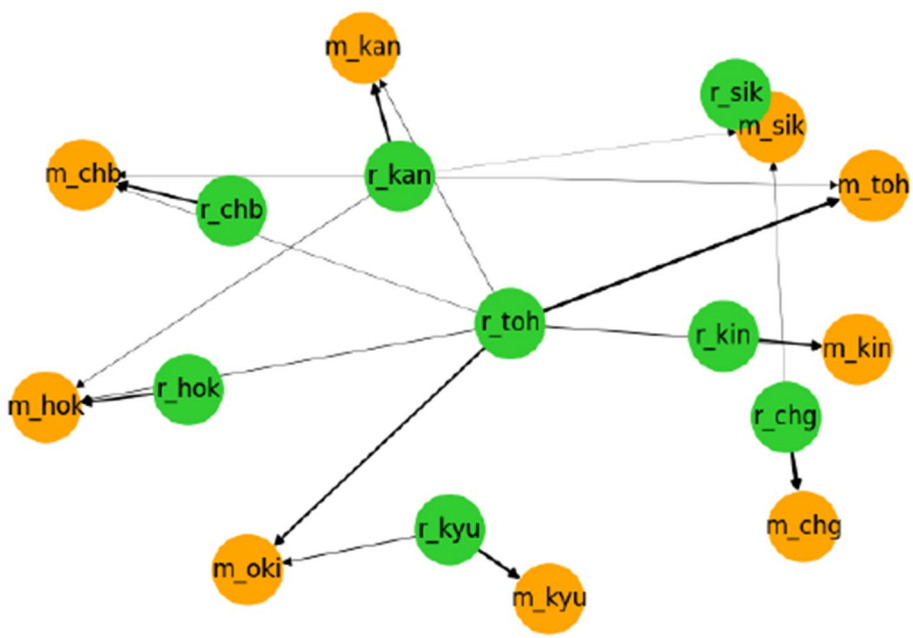

Fig. 13 Interregional Network in Rice to Rice Milling (in Steady State, 2005). Visualization based on the input coefficients matrix of the Interregional Input–Output Table 2005. The thickness of edges corresponds to the scale of input coefficients (thick if $\omega \geq 0.05$; moderate if $0.03 \leq \omega < 0.05$; thin if $0.01 \leq \omega < 0.03$; or omitted if $\omega < 0.01$). Green nodes denote rice (r_), yellow nodes represent rice milling (m_)

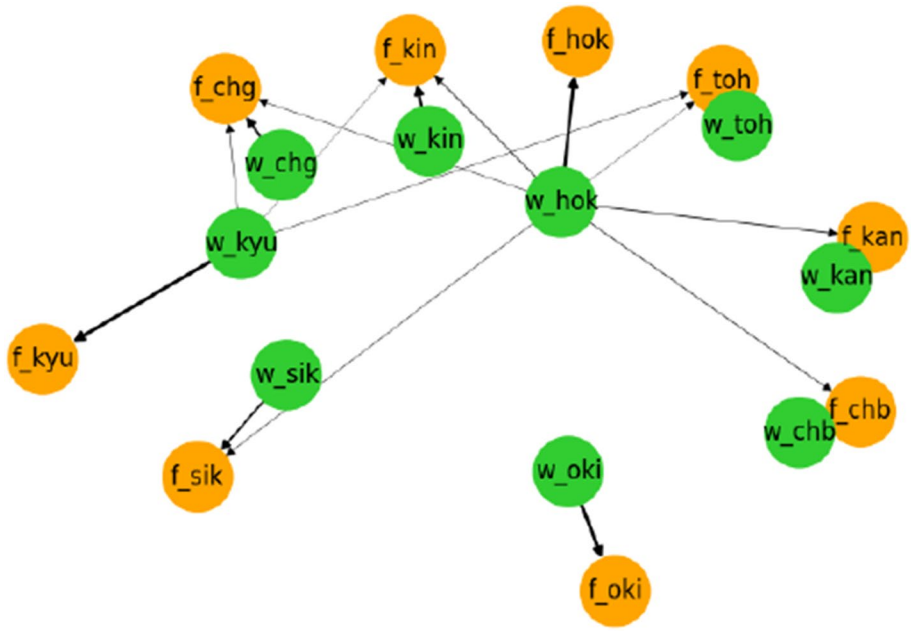

Fig. 14 Interregional Network in Wheat and Barley to Flour Milling. Green nodes denote wheat and barley (w_), and yellow nodes represent flour milling (f_)

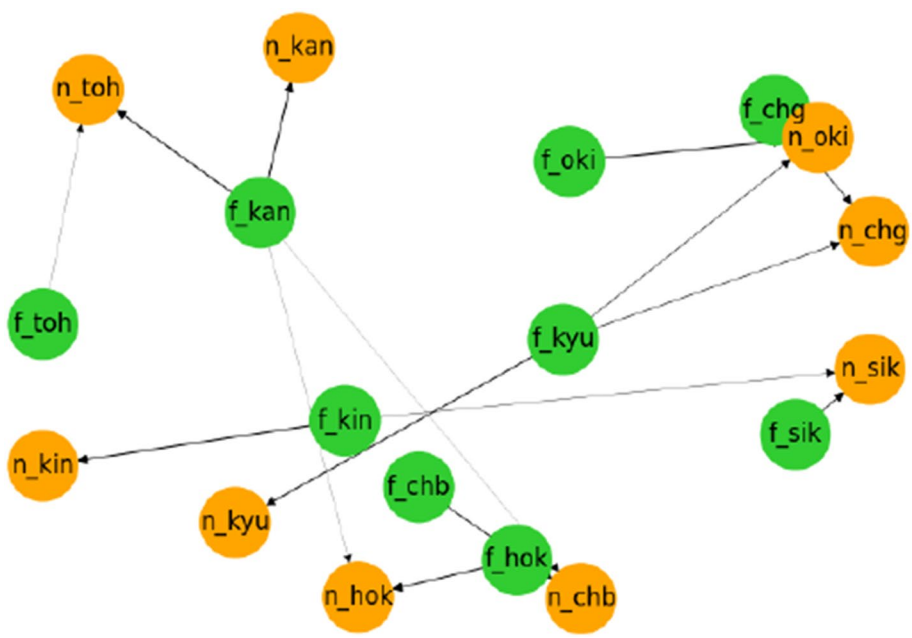

Fig. 15 Interregional Network in Flour Milling to Noodles Bread Confectionary. Green nodes denote flour milling (f_), and yellow nodes represent noodles bread confectionary (n_)

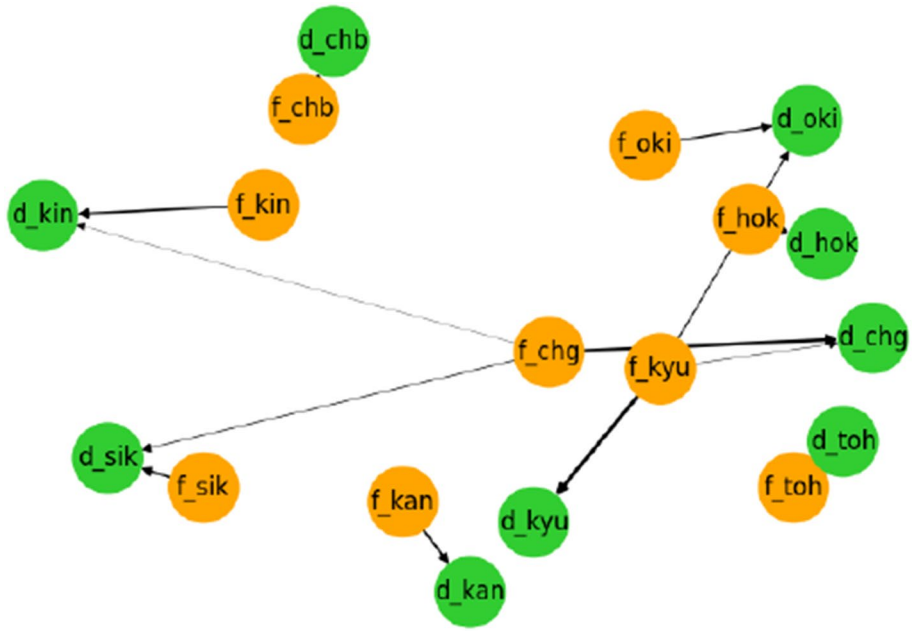

Fig. 16 Interregional Network in Feed Crops to Dairy Farming. Green nodes denote dairy farming (d_), and yellow nodes represent feed crops (f_)

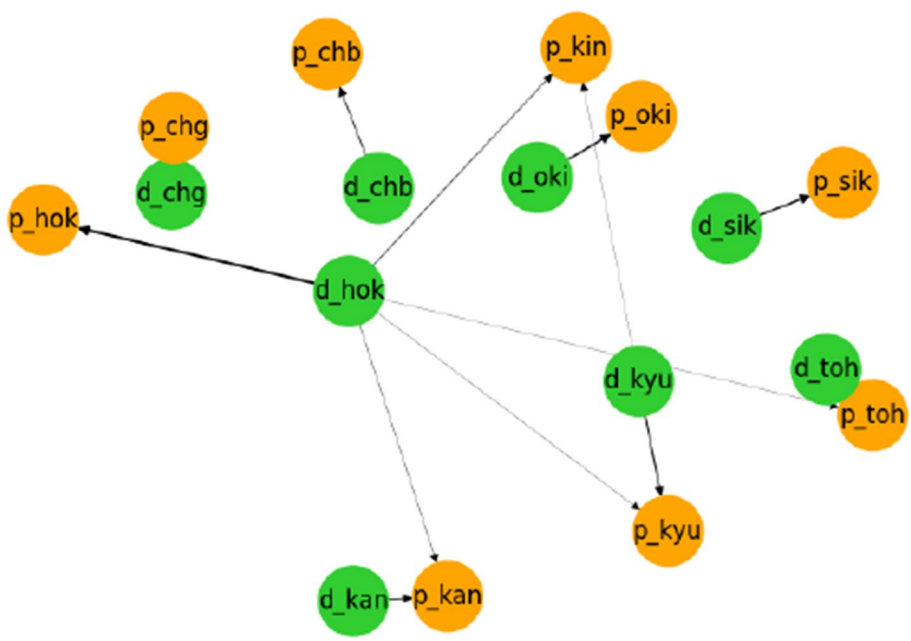

Fig. 17 Interregional Network in Dairy Farming to Dairy Products. Green nodes denote dairy farming (d_), and yellow nodes represent dairy products (p_)

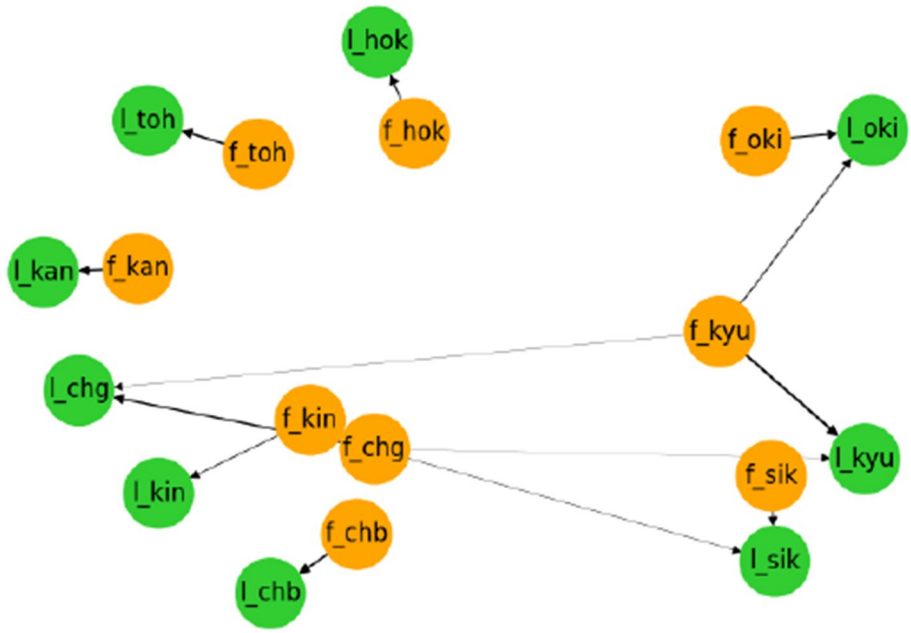

Fig. 18 Interregional Network in Feed Crops to Livestock. Green nodes denote livestock (l_), and yellow nodes represent feed crops (f_)

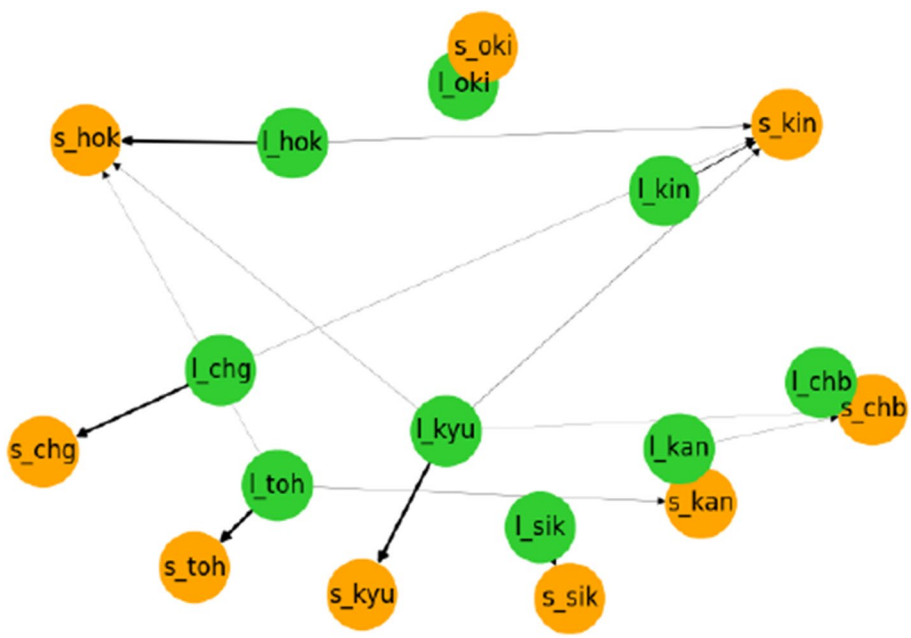

Fig. 19 Interregional Network in Livestock to Slaughter. Green nodes denote livestock (l_), and yellow nodes represent slaughter (s_)

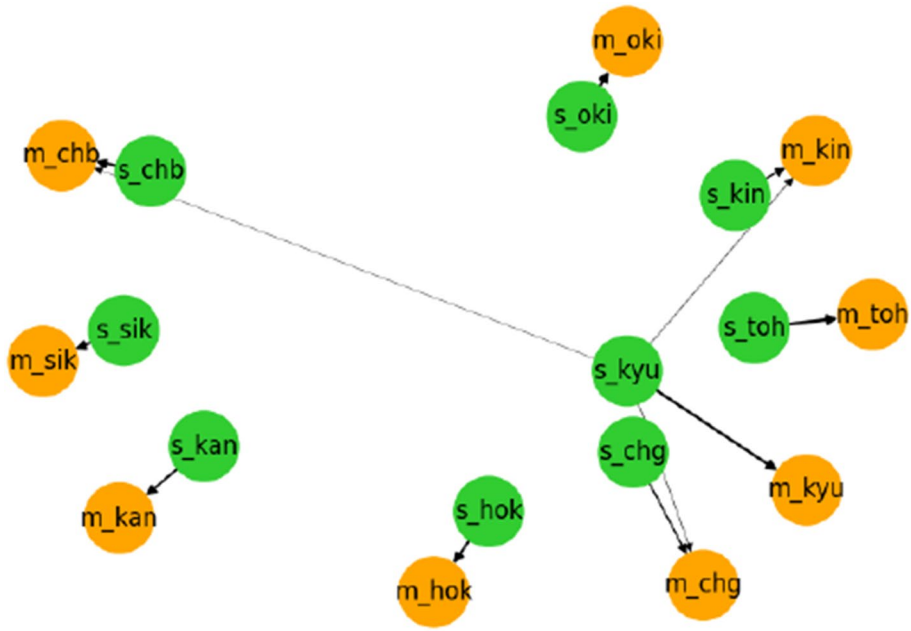

Fig. 20 Interregional Network in Slaughter to Meat Products. Green nodes denote slaughter (s_), and yellow nodes represent meat products (m_)

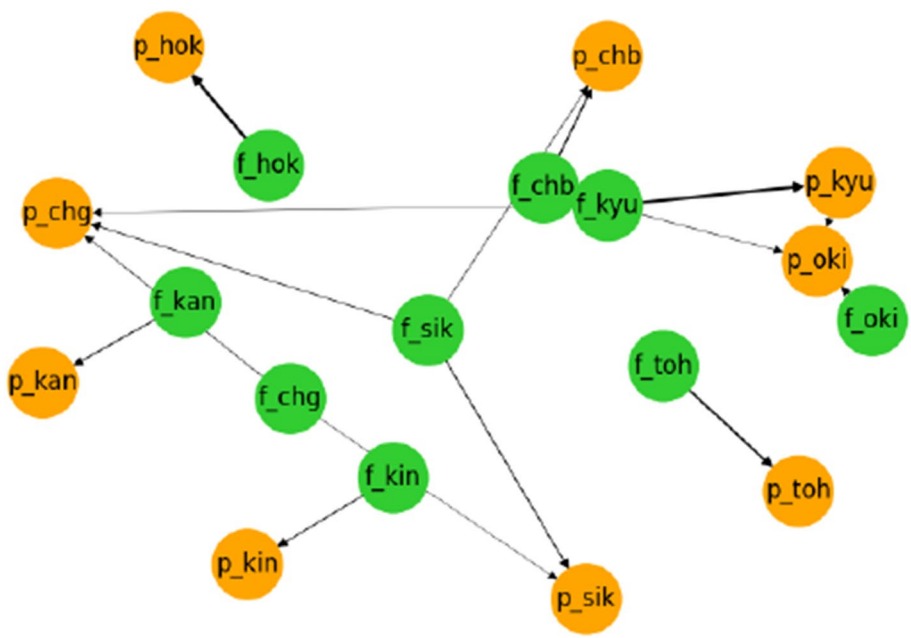

Fig. 21 Interregional Network in Fishery to Prepared Marine Products. Green nodes denote fishery (f_), and yellow nodes represent prepared marine products (p_)

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KI: conceptualizing the idea, methods, analysis and writing. The author read and approved the final manuscript.

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Availability of data and materials
All data summerized on Table 1 are available (https://github.com/ki3yo5/JES2022). Most of them are also available from Japanese government's public statistics portal (https://www.e-stat.go.jp/) and RIETI website (https://www.rieti.go.jp/jp/database/r-jip.html).

Declarations

Competing interests
The authors declare that they have no competing interests.

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References

Acemoglu D, Azar PD (2020) Endogenous production networks. Econometrica 88(1):33–82
Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A (2012) The network origins of aggregate fluctuations. Econometrica 80(5):1977–2016
Acemoglu D, Akcigit U, Kerr W (2016) Networks and the macroeconomy: an empirical exploration. NBER Macroecon Annu 30(1):273–335
Acemoglu D, Ozdaglar A, Tahbaz-Salehi A (2017) Microeconomic origins of macroeconomic tail risks. Am Econ Rev 107(1):54–108
Akune Y (2004) Empirical study on agglomeration and location selection of the food industries. Tsukuba-shobo, Tokyo, pp 74–89
Apte A (2010) Supply chain networks for perishable and essential commodities design and vulnerabilities. J Oper Supply Chain Manag 3(2):26–43
Atalay E (2017) How important are sectoral shocks? Am Econ J Macroecon 9(4):254–280
Autor DH, Dorn D, Hanson GH (2013) The China syndrome: local labor market effects of import competition in the United States. Am Econ Rev 103(6):2121–2168
Baghalian A, Rezapour S, Farahani RZ (2013) Robust supply chain network design with service level against disruptions and demand uncertainties: a real-life case. Eur J Oper Res 227(1):199–215
Baqaee D, Farhi E (2019a) The macroeconomic impact of microeconomic shocks: beyond Hulten's theorem. Econometrica 87(4):1155–1203
Baqaee D, Farhi E (2019b) Networks, barriers, and trade. National Bureau of Economic Research, Cambridge, p w26108
Barrot JN, Sauvagnat J (2016) Input specificity and the propagation of idiosyncratic shocks in production networks. Q J Econ 131(3):1543–1592
Bourlakis MA (2008) Future issues in European supply chain management. In: Bourlakis MA, Weightman PW (eds) Food supply chain management. Blackwell, Oxford, pp 297–303
Caliendo L, Parro F, Rossi-Hansberg E, Sarte PD (2018) The impact of regional and sectoral productivity changes on the US economy. Rev Econ Stud 85(4):2042–2096
Carvalho VM, Nirei M, Saito YU, Tahbaz-Salehi A (2021) Supply chain disruptions: evidence from the Great East Japan Earthquake. Q J Econ 136(2):1255–1321
Davis KF, Downs S, Gephart JA (2021) Towards food supply chain resilience to environmental shocks. Nature Food 2(1):54–65
Hobbs JE (2020) Food supply chains during the COVID-19 pandemic. Can J Agric Econ 68(2):171–176
Hobbs JE, Young LM (2000) Closer vertical co-ordination in agri-food supply chains: a conceptual framework and some preliminary evidence. Supply Chain Manag 5(3):131–143
Hsiao HI, Van der Vorst JGAJ, Omta SWF (2006) Logistics outsourcing in food supply chain networks: theory and practices. In: Bijman J, Omta SWF, Trienekens JH, Wijnands JHM, Wubben EFM (eds) International agri-food chains and networks: management and organization. Wageningen, Wageningen Academic, pp 133–150
Hulten CR (1978) Growth accounting with intermediate inputs. Rev Econ Stud 45(3):511–518
Inoue H, Todo Y (2019) Firm-level propagation of shocks through supply-chain networks. Nature Sustainability 2(9):841–847
Ishikura T, Ikeda K (2018) Estimation of elasticity of substitution for varieties in industrial sector in Japan. J Jpn Soc Civil Eng 74(5):I_37-I_42
Koike A, Naka Y (2014) Examination of time stability of Armington elasticity in Japan. J Jpn Soc Civil Eng 70(5):I_161-I_171
Koike A, Ito K, Nakao T (2012) Estimation of Armington elasticities in Japan. J Jpn Soc Civil Eng 68(6):I_55-I_61
Long JB Jr, Plosser CI (1983) Real business cycles. J Polit Econ 91(1):39–69
Mian A, Rao K, Sufi A (2013) Household balance sheets, consumption, and the economic slump. Q J Econ 128(4):1687–1726
Nagurney A (2021) Perishable food supply chain networks with labor in the COVID-19 pandemic. In: Kotsireas IS, Nagurney A, Pardalos PM, Tsokas A (eds) Dynamics of disasters: impact, risk, resilience, and solutions. Springer, Cham, pp 173–193
Nakano S, Nishimura K (2023) The elastic origins of tail asymmetry. Macroecon Dyn. https://doi.org/10.1017/S1365100523000172

Prajogo D, Olhager J (2012) Supply chain integration and performance: the effects of long-term relationships, information technology and sharing, and logistics integration. Int J Prod Econ 135(1):514–522
Renting H, Marsden TK, Banks J (2003) Understanding alternative food networks exploring the role of short food supply chains in rural development. Environ Plan Econ Space 35(3):393–411
Rong A, Akkerman R, Grunow M (2011) An optimization approach for managing fresh food quality throughout the supply chain. Int J Prod Econ 131(1):421–429
Shimowatari T (2003) Procurement of domestic raw materials under the globalization of food processing industries. J Rural Econ 75(2):47–54
Takayanagi N (2006) Spatial structure of food system: promotion of agricultural production areas under globalization. Tsukuba-shobo, Tokyo, pp 27–42
Todo Y, Nakajima K, Matous P (2015) How do supply chain networks affect the resilience of firms to natural disasters evidence from the Great East Japan Earthquake. J Reg Sci 55(2):209–229
Van Der Vorst JG (2005) Performance measurement in agrifood supply chain networks an overview. In: Wijnands JHM, Ondersteijn CJ (eds) Quantifying the agri-food supply chain: overview and new research directions. Frontis, London, pp 13–24

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