Substitution elasticity of Japan's meat imports: estimation with and without instruments

Jiyoung Kim[a], Kazuhiko Nishimura[b]

Abstract

This paper is concerned with the measurement of the elasticity of substitution between goods from different countries. The commodities of our interest are bovine, swine, and poultry meat imports by Japan. To remedy potential endogeneity problems in regression estimations, we use the instrumental variables (IV) approach, and the Feenstra method that does not require the use of instruments. We find that the two approaches yield very similar results. Further, upon extracting the implicit IVs of the Feenstra method, we find them as useful as the external IVs for measuring the aggregate of foreign commodities with a fixed effects regression and for estimating the foreign-domestic substitution elasticity, possibly for each commodity. The elasticities are then utilized for examining the effect of tariff elimination.

Keywords: Two-stage CES aggregator, Instrumental variables approach, Feenstra method, Implicit instrumental variable

1. Introduction

Japan has been the world's largest meat importer (see, Figure 1). According to the 2015 input-output tables, Japan's household sector yearly consumed 635 BJPY (Billion Japanese Yens) of bovine meat, 528 BJPY of swine meat, and 273 BJPY of poultry meat. As known, these commodities are subject to trade negotiations such as the TPP, the RCEP, and numerous bilateral FTAs. To study the welfare implications of the trade liberalization regimes, general equilibrium models have been the standard device. For these models, the import demand module is typically comprised of constant elasticity of substitution (CES) aggregator functions, where the elasticity of substitution between products from different countries, called the Armington elasticity, plays an essential role. Our main purpose is thus to carefully estimate the Armington elasticities of the aforementioned commodities for Japan.

Previous empirical studies on the measurement of Armington elasticities include Corado and De Melo (1986); Reinert and Roland-Holst (1992); Gallaway et al. (2003). These studies, nevertheless, do not take into account the potential endogeneity of the explanatory variable (which typically is the international price) arising from reverse causality vis-a-vis the response variable (which typically is the demanded quantity in the home country). In contrast, the method developed by Feenstra (1994) and its extensions by Broda and Weinstein (2006), Soderbery (2015) and Feenstra et al. (2018) enable us to account for potential reverse causality without having to find instrumental variables. As we verify in the following section, the Feenstra method has the potential to provide consistent estimates in a panel setting under mild assumptions.

Our recourse to the Feenstra method stems from the difficulty of finding valid instruments. Above all, panel data analysis techniques, such as fixed effects, do not allow lagged explanatory variables as instruments. Alternatively, we could consider other indicators, such as the average prices of other exporters, as explanatory variables (as in Kee et al., 2008) under the assumption that the demand shocks for different items are independent. However, these variables have to be ruled out when the expenditure share is our response variable. We hence explore potentially relevant instruments for the components of the explanatory variable

[a] Graduate School of Humanities and Social Science, Okayama University, Okayama Japan, 700-8530. (Email: jiyoung@okayama-u.ac.jp)
[b] School of Global Studies, Chukyo University, Aichi Japan, 466-8666.

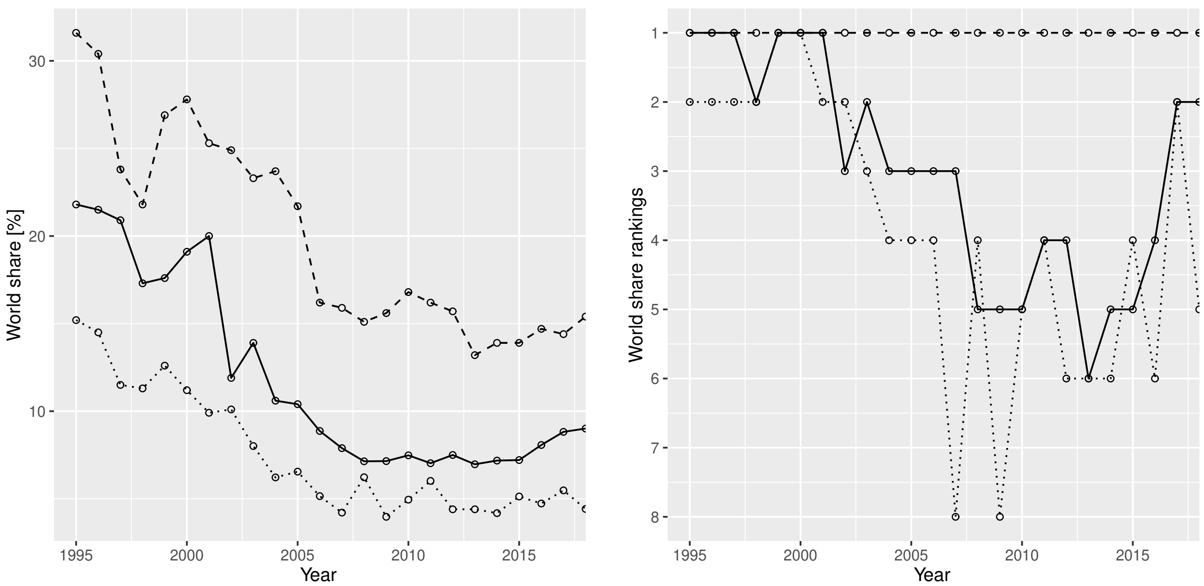

Figure 1: Japan's world share of imports (left) and their rankings (right) from 1995 to 2018. The solid line indicates bovine meat, the dashed line indicates swine meat (as pig meat), and the dotted line indicates poultry meat. *Source:* oec.world

(i.e., the international price). Nevertheless, the main component, i.e., the transportation cost measured by the difference between cost, insurance and freight (CIF) and free on board (FOB) prices, can depend on the quantity demanded.

On the other hand, components such as bilateral distances, tariff rates, and exchange rates may be considered exogenous. [1] Naturally, distances cannot be affected by demand; tariff rates may affect demand, but not the other way around; and exchange rates may not be affected by demand for the commodity as long as we assume that the underlying market is small. While distances that are temporally constant cannot be effective in a panel setting, tariff rates, as employed in Fajgelbaum et al. (2019), may be useful as long as they vary in time series. In a panel setting, exchange rates, as employed in Erkel-Rousse and Mirza (2002), seem particularly useful in the sense that they affect the international price directly. The difficulty of using the instrumental variables (IV) approach is, however, that even after one finds an exogenous instrument, it has to be approved by tests for relevancy.

Because of its versatility and ease of implementation, we may prefer to apply the Feenstra method if the Armington elasticities estimated by this method and the IV approach are not so different. In the end, the estimators for both approaches are biased but consistent. Thus, one of our purposes in this study is to compare and assess the two standing approaches under the same framework. In accordance with Feenstra et al. (2018), we focus on the CES Armington aggregator that is comprised of two stages. The first (lower) stage aggregates goods from different countries into a foreign good, and the second (upper) stage aggregates domestic and foreign goods into the partial utility of the home country. The first-stage aggregation is governed by the microelasticity, and the second-stage aggregation is governed by the macroelasticity.[2]

Previous studies that are concerned with the measurement of the Armington elasticity (Erkel-Rousse and Mirza, 2002; Saito, 2004; Feenstra et al., 2018) apply between estimation for multi-input elasticity, a typical strategy for the two-input case. Between estimation nevertheless eliminates time-specific effects such as the first stage aggregates. Previous studies deploying two-stage models hence use auxiliary indices

[1] Japan levies various non-ad valorem tariffs (e.g., tariff quotas and gate price system) on meat imports, in addition to the baseline ad valorem tariffs. Since CIF prices affect non-ad valorem tariffs, the overall tariff rates may be endogenous. To secure exogeneity of the instruments we confine our focus to Armington aggregators based on pre-fixed ad valorem tariff rates.

[2] While Saito (2004) uses the terms intragroup and intergroup, we use micro and macro as employed in Feenstra et al. (2018).

such as the Laspeyres or Sato-Vartia index for estimating the second-stage macroelasticities.[3] In contrast, we apply within (fixed effects) estimation for the first-stage regression that allows us to retrieve the first-stage aggregates as a time-varying index, together with the microelasticity estimation, while eliminating the individual specific share parameters. The indexed first-stage aggregates can be readily utilized for the second-stage macroelasticity estimation.

In this study, we find that the Feenstra method is capable of finding first-stage microelasticities very similar to those obtained by fixed effects IV regression with valid external instruments. On the other hand, while fixed effects IV regression is capable of identifying the first-stage aggregates that can be utilized for the second-stage macroelasticity estimation, the Feenstra method (Feenstra et al., 2018), with removed first-stage panel variations, evaluates the macroelasticity in a reduced manner, such that a macroelasticity common to several kinds of commodities is measured. In this regard, we take a step forward and discover a way to estimate individual macroelasticities without external instruments. Particularly, we find that the implicit IV of the Feenstra method is just as useful as the external IV in estimating microelasticities and macroelasticities.

We organize the paper as follows. In the next section, we specify the two-stage Armington aggregator. In section 3, we show how the Feenstra method works in a panel setting to maintain consistency in the estimation of microelasticity and further find a way to extract the implicit IV. In section 4, based on the same dataset, we empirically estimate microelasticities by four different means, namely, 1) IV regression using external IV, 2) the Feenstra method, 3) the Feenstra method with extended moment conditions, and 4) IV regression using the implicit IV of the Feenstra method. Then, macroelasticities are estimated by way of 1) and 4), where the first-stage aggregates are derivable. In section 5, tariff elimination is examined by further estimating the tariff elasticity of demand quantity. Finally, section 6 concludes.

2. Two-stage Armington aggregator

2.1. Two-stage CES specification

Consider, for each kind of commodity g (index omitted), a two-stage Armington aggregator of the following type:

$$u = \left(\beta^{\frac{1}{\rho}} z^{\frac{\rho-1}{\rho}} + (1-\beta)^{\frac{1}{\rho}} y^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}} \qquad\qquad y = \left(\sum_{i=1}^{N} (\alpha_i)^{\frac{1}{\sigma}} (x_i)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}$$

where x_i denotes the quantity (of commodity g) imported from country i, y denotes the utility of aggregated imports, z denotes the quantity produced and consumed in the home country, and u denotes the representative utility in the home country. For the parameters, σ denotes the elasticity of substitution among imports from different countries (or microelasticity), ρ denotes the elasticity of substitution between domestic and aggregate imports (or macroelasticity), and $\alpha_i \geq 0$ and $\beta \geq 0$ are the preference parameters with $\sum_{i=1}^{N} \alpha_i = 1$ and $\beta \leq 1$. The first function (on the right) is called the first-stage aggregator, and the second (on the left) is called the second-stage aggregator.

The dual function of this two-stage Armington aggregator is as follows:

$$v = \left(\beta r^{1-\rho} + (1-\beta) q^{1-\rho}\right)^{\frac{1}{1-\rho}} \qquad\qquad q = \left(\sum_{i=1}^{N} \alpha_i (p_i)^{1-\sigma}\right)^{\frac{1}{1-\sigma}} \tag{1}$$

where p_i denotes the import commodity price from country i in the home country. Note that the price of the commodity from the ith country p_i (LCU/kg) in terms of the home country's LCU (local currency unit), domestic price r (LCU/kg), import physical quantity x_i (kg), and domestic physical quantity z (kg) are all

[3] Note that the Sato-Vartia index is an exact index for a two-input CES aggregator but is not for multi-input versions of CES like the ones that we are considering for a micro-aggregator function (see Lau, 1979).

observable, but the aggregated values, namely, y (utility), q (LCU/utility), u (utility) and v (LCU/utility), are not. As per duality, however, we know that the following identities must hold.

$$vu = rz + qy \qquad\qquad qy = \sum_{i=1}^{N} p_i x_i \tag{2}$$

Applying Shephard's lemma for the first-stage aggregator gives the following:

$$s_i = \frac{p_i x_i}{qy} = \frac{\partial q}{\partial p_i}\frac{p_i}{q} = \alpha_i \left(\frac{p_i}{q}\right)^{1-\sigma}$$

Here, s_i denotes the value share of imports of the commodity from the ith country. As we label observations by $t = 1, \cdots, T$, we have the following regression equation:

$$\ln s_{it} = \ln \frac{p_{it} x_{it}}{\sum_{i=1}^{N} p_{it} x_{it}} = -(1-\sigma)\ln q_t + (1-\sigma)\ln p_{it} + \ln \alpha_i + \epsilon_{it} \tag{3}$$

where the error terms ϵ_{it} are assumed to be iid normally distributed with mean zero. The regression equation (3) can be estimated (for σ and q_t from p_{it} and s_{it}) by fixed effects (FE) panel regression.[4] More specifically, we measure q_t by the coefficients on time dummy variables (see section 4) through FE panel regression. Alternatively, we could instead measure α_i by the coefficients on item (country) dummy variables through between panel regression. In this case, the first-stage aggregates q_t must be evaluated by the proxies, as done in previous studies, or by applying the estimates $\hat{\alpha}_i$ and $\hat{\sigma}$ to (1). In the latter case, however, the criteria that $\sum_{i=1}^{N} \hat{\alpha}_i = 1$ can hardly be met. We shall hence remain with FE panel regression for the first-stage microelasticity estimation.

Below are the first-order conditions (Shephard's lemma) for the second-stage aggregator:

$$\frac{r}{v}\frac{\partial v}{\partial r} = \frac{rz}{vu} = \beta \left(\frac{r}{v}\right)^{1-\rho} \qquad\qquad \frac{q}{v}\frac{\partial v}{\partial q} = \frac{qy}{vu} = (1-\beta)\left(\frac{q}{v}\right)^{1-\rho}$$

In this case, we shall fully utilize the time series variation since the cross-sectional variation is minimal. By combining the above two identities, we obtain the following simple regression equation:

$$\ln \frac{r_t z_t}{q_t y_t} = \ln \frac{r_t z_t}{\sum_{i=1}^{N} p_{it} x_{it}} = \ln \frac{\beta}{1-\beta} + (1-\rho)\ln \frac{r_t}{q_t} + \nu_t \tag{4}$$

where the error terms ν_t are assumed to be iid normally distributed with mean zero. Regression equation (4) can be estimated (for ρ and β from z_t, y_t, r_t, and q_t) by time series analysis, where we can use the first-stage aggregates ($\hat{q}_t$) obtainable from (3) for the explanatory variable in (4).

2.2. External instruments

Regression equation (3) for the first-stage suffers from an endogeneity problem because the demand shock ϵ_{it} enters the explanatory variable $\ln p_{it}$ through the reverse causality between $\ln s_{it}$ and $\ln p_{it}$ so that the error term ϵ_{it} and the explanatory variable $\ln p_{it}$ become correlated with each other. To obtain a consistent estimation, we must apply instrumental variables onto the endogenous explanatory variable. As we assume independence of the error terms, we may consider lagged explanatory variables such as $\ln p_{it-1}$ and ϵ_{it} to be uncorrelated even when $\ln p_{it-1}$ and ϵ_{it-1} are correlated and $\ln p_{it}$ and ϵ_{it} are correlated. However, a lagged explanatory variable cannot be used if we estimate (3) by FE or first-difference (FD) regression. This

[4] In contrast, Saito (2004) estimate σ via between regression, which eliminates q_t. The Feenstra method (as well as Romalis (2007)) uses double differences (within-between) estimation, eliminating both α_i and q_t. The first-stage aggregates q_t are hence proxied by auxiliary indices such as the Laspeyres (Saito, 2004), Stone (Blonigen and Wilson, 1999; Huchet-Bourdon and Pishbahar, 2009), and Sato-Vartia (Feenstra et al., 2018) indices.

is because $\Delta \ln p_{it-1} = \ln p_{it-1} - \ln p_{it-2}$ and $\Delta\epsilon_{it} = \epsilon_{it} - \epsilon_{it-1}$ are correlated when $\ln p_{it-1}$ and ϵ_{it-1} are correlated. From another point of view, one might consider using $\ln p_{kt}$, where $k \neq i$, to instrument for $\ln p_{it}$. This idea fails, however, because $\ln p_{kt}$ affects the response variable $\ln s_{it}$ directly.

We shall thus search for external IVs. The usual practice in this case is to look at the components of the explanatory variable, since the relevancy of the instrument is imperative. The price of a commodity imported from country i faced by consumers in the home country can be decomposed as follows:

$$p_{it} = e_{01t}(1 + r_{it})c_{it} \qquad\qquad c_{it} = (1 + m_{it})f_{it}/e_{i1t}$$

where f_{it} (LCU/kg) denotes the FOB price in terms of country i's LCU at time t, c_{it} (USD/kg) denotes the CIF price of i's product in terms of US dollars (USD) at t, $r_{it} > 0$ denotes the tariff rate on i's commodities at t, $m_{it} > 0$ denotes the transportation cost (including freight and insurance) for the commodity shipped from i at t, and e_{01t} (LCU/USD) and e_{i1t} (LCU/USD) denote the home currency exchange rate against USD and i's local currency exchange rate against USD, respectively.

Here, we note that f_{it} and m_{it} (and thus c_{it}) depend on the quantity demanded and therefore must be endogenous with respect to taste shocks ϵ_{it} in the home country. On the other hand, tariff rates r_{it} and exchange rates e_{1it} can be considered exogenous.[5] Hence, we prepare them for further examination with respect to their relevance. A similar strategy (to utilize an exogenous component of the explanatory variable) can be sought for the second-stage regression (4). Note that the first-stage aggregate q_t in (3) is uncorrelated with ϵ_{it} because ϵ_{it} does not enter q_t, even if there were reverse causation between s_{it} and p_{it}. That given, the error term ν_t in (4), which represents the difference between domestic and (aggregated) foreign taste shocks, where both are uncorrelated with q_t, must also be uncorrelated with q_t. We can therefore use q_t to instrument the explanatory variable in (4).

3. Feenstra method and extensions

3.1. Microelasticity

Below, we briefly review the framework of the Feenstra method. By timely differencing (3), we have the following:

$$\Delta \ln s_{it} = -(1 - \sigma)\Delta \ln q_t + (1 - \sigma)\Delta \ln p_{it} + \Delta\epsilon_{it} \tag{5}$$

By subtracting the item average values, such that $\Delta\ln s_t = \sum_{i=1}^{N} \Delta \ln s_{it}/N$, from (5), we have the following:[6]

$$(\Delta \ln s_{it} - \Delta\ln s_t) = (1 - \sigma)\left(\Delta \ln p_{it} - \Delta\ln p_t\right) + (\Delta\epsilon_{it} - \Delta\epsilon_t)$$

Below, we rewrite this demand function (left) along with the supply function (right), which is supposed to give rise to the endogeneity problem:

$$S_{it} = \gamma P_{it} + \varepsilon_{it} \qquad\qquad P_{it} = \kappa S_{it} + \delta_{it} \tag{6}$$

where $\gamma = 1 - \sigma$, $P_{it} = \Delta \ln p_{it} - \Delta \ln p_t$, $S_{it} = \Delta \ln s_{it} - \Delta \ln s_t$, and $\varepsilon_{it} = \Delta\epsilon_{it} - \epsilon_t$. Note that taste shocks ε_{it} and innovations δ_{it} are not observable to the econometrician, and we assert that they are independent.

While it is obvious that P_{it} is endogenous in the demand (left) equation of (6), consistent estimation is possible by instrumenting P_{it} with δ_{it}. In the Feenstra method, the corresponding moment condition is considered by means of the following linear regression equation:

$$Y_{it} = \theta_1 X_{1it} + \theta_2 X_{2it} + u_{it} \tag{7}$$

[5] Although exogenous, e_{01t} has no cross-sectional variation; thus, we exclude it from the candidates.

[6] To this end, Feenstra (1994) uses a reference source k that supplies in every year, whereas Feenstra et al. (2018) use the Sato-Vartia aggregate of N sources. Here, we use the arithmetic mean for simplicity.

where $Y_{it} = (P_{it})^2$, $X_{1it} = (S_{it})^2$, $X_{2it} = P_{it}S_{it}$, $\theta_1 = -\kappa/\gamma$, $\theta_2 = (1+\gamma\kappa)/\gamma$, and $u_{it} = -\varepsilon_{it}\delta_{it}/\gamma$. Since we know by (6) that

$$X_{1it} = \frac{(\varepsilon_{it})^2 + 2\gamma\varepsilon_{it}\delta_{it} + \gamma^2(\delta_{it})^2}{(1+\gamma\kappa)^2} \qquad X_{2it} = \frac{\kappa(\varepsilon_{it})^2 + (1+\gamma)\varepsilon_{it}\delta_{it} + \gamma(\delta_{it})^2}{(1+\gamma\kappa)^2}$$

it is obvious that u_{it} and both X_{1it} and X_{2it} in (7) are correlated.

In the Feenstra method, we take the temporal average of (7), i.e.,

$$Y_i = \theta_1 X_{1i} + \theta_2 X_{2i} + u_i \tag{8}$$

where, for example, $u_i = \sum_{t=1}^{T} u_{it}/T_i$, and assume that

$$\operatorname{plim} u_i = \operatorname*{plim}_{T\to\infty} \sum_{t=1}^{T} u_{it}/T_i = 0 \qquad i = 1, \cdots, N \tag{9}$$

Notice that, in this case, the following must be true:

$$\operatorname{plim} X_i u_i = (\operatorname{plim} X_i)(\operatorname{plim} u_i) = 0 \qquad i = 1, \cdots, N \tag{10}$$

Then, by (9) and (10), we can assert that the least squares estimator of (8) is consistent with the following exposition:

$$\operatorname{plim} \widehat{\operatorname{cov}}\,(X, u) = \operatorname{plim} \frac{\sum_{i=1}^{N} X_i u_i - \bar{X} \sum_{i=1}^{N} u_i}{N-1} = 0$$

In the Feenstra method, equation (8) is estimated by weighted least squares (WLS) regression, with the weights being the number of years T_i that country i appears as a source during the observation period T. Moreover, (8) is weighted further to improve efficiency. That is, the variance of the residuals from (7) is utilized to weight regression equation (8). This procedure, which is equivalent to the optimal weighting in generalized method of moments (GMM) estimation, can be iterated to obtain more efficient estimates. Below, we note σ (the microelasticity) and κ in terms of the parameters estimated by the Feenstra method:

$$1 - \sigma = \gamma = \frac{-\theta_2 \pm \sqrt{(\theta_2)^2 + 4\theta_1}}{2\theta_1} \qquad \kappa = \frac{\theta_2 \mp \sqrt{(\theta_2)^2 + 4\theta_1}}{2} \tag{11}$$

For later convenience, we label these solutions as (γ_1, γ_2) and (κ_1, κ_2), respectively.

3.2. Empirical strategy

For the sake of convenience, instead of manually performing WLS regression of (8) using T_i and T_i/V_i as weights, we take an alternative approach. Let $a_{kt}^{(i)}$ for $k = 1, \cdots N$ denote N dummy variables (of dimension $N \times T$) that indicate source country $i = k$ at period t of the panel data. More specifically,

$$a_{kt}^{(i)} = \begin{cases} 1 & (\text{if } i = k \text{ and } Y_{it} \neq 0) \\ 0 & (\text{otherwise}) \end{cases}$$

If we use all N dummy variables to instrument the two explanatory variables for (7), the N moment conditions for $i = 1, \ldots, N$ is reduced as follows:

$$\sum_{k=1}^{N} \sum_{t=1}^{T} (Y_{kt} - \theta_1 X_{1kt} - \theta_2 X_{2kt}) a_{kt}^{(i)} = (Y_i - \theta_1 X_{1i} - \theta_2 X_{2i}) T_i = 0$$

where $\sum_{t=1}^{T}\sum_{k=1}^{N} Y_{kt}a_{kt}^{(i)} = \sum_{t=1}^{T} Y_{it} = Y_i T_i$, $T_i = \sum_{t=1}^{T}\sum_{k=1}^{N} a_{kt}^{(i)}$ and so on. That is, a pooled two-stage least squares (2SLS) regression for (7) using all N dummy variables as instruments would yield the same result as that derived from performing WLS regression for (8) using T_i as weights. Moreover, a pooled GMM using all these instruments would yield the same result as that derived from performing WLS regression using T_i/V_i as weights. Thus, by means of the Feenstra method, we use the latter scheme (by way of GMM) to estimate the parameters θ_1 and θ_2.

Furthermore, we might be tempted to consider an alternative version of the Feenstra method that takes the cross-section average of (7), i.e.,

$$Y_t = \theta_1 X_{1t} + \theta_2 X_{2t} + u_t \tag{12}$$

where, for example, $u_t = \sum_{i=1}^{N} u_{it}/N_t$, and assume that

$$\operatorname{plim} u_t = \operatorname*{plim}_{N\to\infty} \sum_{i=1}^{N} u_{it}/N_t = 0 \qquad\qquad t = 1,\cdots,T \tag{13}$$

The same logic as that behind the the original time-averaged version can be applied to show the consistency of the least squares estimate of (12). Moreover, by using the following T dummy variables of dimension $N \times T$, WLS regression is possible given the panel structure of the data.

$$b_{ik}^{(t)} = \begin{cases} 1 & (\text{if } k = t \text{ and } Y_{it} \neq 0) \\ 0 & (\text{otherwise}) \end{cases}$$

If we use all these variables to instrument the two regressors in pooled regression (7), we obtain the following T moment conditions for $t = 1, \ldots, T$:

$$\sum_{k=1}^{T}\sum_{i=1}^{N} (Y_{ik} - \theta_1 X_{1ik} - \theta_2 X_{2ik}) b_{ik}^{(t)} = (Y_t - \theta_1 X_{1t} - \theta_2 X_{2t}) N_t = 0$$

where $\sum_{k=1}^{T}\sum_{i=1}^{N} Y_{ik} b_{ik}^{(t)} = \sum_{i=1}^{N} Y_{it} = Y_t N_t$, $N_t = \sum_{k=1}^{T}\sum_{i=1}^{N} b_{ik}^{(t)}$ and so on. In the following sections, in addition to our scheme to perform the Feenstra method by way of N dummy variables $a^{(1)}, a^{(2)}, \cdots, a^{(N)}$, we examine the *two-way Feenstra method* by way of $N+T$ dummy variables $a^{(1)}, a^{(2)}, \cdots, a^{(N)}, b^{(1)}, b^{(2)}, \cdots, b^{(T)}$ to impose the two moment conditions (9) and (13) at the same time.

3.3. Implicit IV and macroelasticity

As we assert that ε_{it} and δ_{it} of (6) are independent (and thus uncorrelated), and since δ_{it} is correlated with P_{it} through the supply function, δ_{it} must be a valid IV for the explanatory variable (P_{it}) of the demand function $S_{it} = \gamma P_{it} + \varepsilon_{it}$. We therefore call δ_{it} the *implicit IV* of the Feenstra method. Empirically, an implicit IV (δ_{it}^{*}, defined below) can be extracted from the supply function parallel to (3) as follows:

$$\ln p_{it} = \pi_t + \kappa \ln s_{it} + \omega_i + \xi_{it} = \hat{\kappa} \ln s_{it} + \delta_{it}^{*} \tag{14}$$

Since ϵ_{it} does not enter π_t or ω_i while it directly enters $\ln s_{it}$ through (3), δ_{it}^{*} must be uncorrelated with ϵ_{it}. The implicit IV approach is beneficial when we consider the measurement of macroelasticity. The Feenstra method heavily depends on the panel structure of the data, so estimation of the second-stage macroelasticity when the cross-sectional dimension is two may be ineffective. Consequently, Feenstra et al. (2018) consider a common macroelasticity over several commodities and not for each commodity.[7] In contrast, just like the standard IV approach, the IV approach using the implicit IV is capable of estimating the macroelasticity for each commodity, and external instruments are not needed.

[7] For the macroelasticity estimation, Feenstra et al. (2018) make use of the macro version of (7) with the variation of gt instead of that of it simultaneously with the micro-macro combined moment conditions.

4. Data and estimation

4.1. Main variables

Our empirical analysis is aimed at measuring the micro- and macroelasticities for three kinds of commodities, namely, bovine ($g = 1$), swine ($g = 2$), and poultry ($g = 3$) meat exported to Japan. For these cases, we were able to find valid external instruments to estimate the microelasticities. We set the period of our analysis from 1994 to 2018 (i.e., $t = 1, \cdots, 25$). As illustrated in Figure 1, Japan was long the world's largest meat importer: during this period, it imported all three kinds of meat from as many as $N = 88$ countries.We draw our main data from UN Comtrade (2020). The HS product codes for bovine meat correspond to HS0201, HS0202, HS020610, and HS020629; swine meat corresponds to HS0203, HS020630, and HS020649; and poultry meat corresponds to HS0207. We draw the yearly import transactions in terms of the CIF trade value (USD) and net weight (kg) of the home country (Japan) from all partner countries by setting Japan as the reporter, All as partners, and Import as trade flows. For each commodity g, the CIF price c_{it} (USD/kg) is evaluated by means of the corresponding total CIF trade values divided by the corresponding total net weight x_{it} of the HS products from all partner countries for all periods concerned.

To obtain the foreign commodity price in the home country p_{it} (JPY/kg), we need the exchange rates e_t (JPY/USD) against the home currency and tariff rates r_{it} applied to all partner countries for all periods concerned. The exchange rates against all currencies e_{it} were drawn from the historical rates tab at fxtop.com. The tariff rates r_{it} levied in the home country against any HS products from any partner countries from 1996 to 2018 were obtained from the tariff download facility of WTO (2020). For the 1994 and 1995 tariff rates, however, we use the rate for 1996. The home country's yearly expenditure on country i's commodity thus amounts to $p_{it}x_{it}$ (JPY), and this is used to evaluate the expenditure share s_{it} for the regression analyses.

For domestic production pertaining to bovine and swine meat, the data were drawn from the Survey of Livestock Distribution (Chikusanbutsu Ryutsu Tokei), available at e-Stat (2020). For yearly domestic meat production z_t (kg), we use the survey on carcass (Edaniku) production of adult beef cattle (Seigyu) and pigs (Buta). For domestic poultry meat, we use the yearly production (in metric tons) available in the survey of broiler slaughterhouses (Shokucho Shorijo Chosa). For unavailable years, the amount of meat produced is estimated by the ratio (60%) against the processed broilers measured in metric tons. [8] For domestic prices r_t (JPY/kg) of bovine and swine meat, we use the survey of central wholesale meat market prices (Shokuniku Chuo Oroshiuri Shijo Kakaku). For poultry meat prices, we use the 2015-based corporate goods price index (CGPI) provided by BOJ (2020) for chicken (Tori).[9]

4.2. First-stage aggregator

Let us rewrite the regression equation (3) using time dummy variables as follows:

$$Y_{it} = \mu_1 + (\mu_2 - \mu_1) D_2 + \cdots + (\mu_{25} - \mu_1) D_{25} + \mu X_{it} + \ln \alpha_i + \epsilon_{it} \tag{15}$$

where $Y_{it} = \ln s_{it}$, $X_{it} = \ln p_{it}$ and D_k, for $k = 2, \cdots, 25$, denotes a dummy variable that equals 1 if $k = t$ and 0 otherwise. The coefficients therefore denote that

$$\mu_t = -(1 - \sigma) \ln q_t \qquad\qquad \mu = 1 - \sigma \tag{16}$$

As we normalize the microaggregated prices at 1994 (i.e., $q_1 = 1$ and thus $\mu_1 = 0$), the parameters μ and μ_t for $t = 2, \ldots, 25$ can all be estimated by FE regression of (15), and hence, q_t for $t = 2, \cdots, 25$ can be resolved by the following calculation:

$$q_t = e^{\mu_t/\mu} \qquad\qquad t = 2, \cdots, 25$$

[8] The data for years in which figures for both processed broilers and poultry meat produced are available suggest that the ratio is 60%.

[9] The price index for poultry meat is identified as item PR01'PRCG15_2202050011. The 2015-based index is converted into JPY using the 2015 representative wholesale price of poultry meat, which we estimated as 395 (JPY/kg).

Table 1: Microelasticity estimation for bovine meat.

	FE (LS)		FE (IV)		Delta Method		
	coef.	s.e.	coef.	s.e.		estim.	s.e.
X	−1.710	0.272	−0.921	0.993	σ	2.710	0.272
D_{25}	0.454	0.477	0.345	0.482	q_{25}	1.304	0.364
D_{24}	0.469	0.480	0.482	0.467	q_{24}	1.315	0.374
D_{23}	0.452	0.488	0.429	0.476	q_{23}	1.303	0.375
D_{22}	0.523	0.513	0.518	0.499	q_{22}	1.358	0.413
D_{21}	−0.024	0.510	−0.182	0.531	q_{21}	0.986	0.294
D_{20}	0.377	0.544	0.390	0.529	q_{20}	1.247	0.399
D_{19}	0.263	0.589	0.421	0.604	q_{19}	1.166	0.405
D_{18}	−0.002	0.594	0.276	0.669	q_{18}	0.999	0.347
D_{17}	−0.192	0.619	0.043	0.666	q_{17}	0.894	0.322
D_{16}	−0.823	0.596	−0.508	0.694	q_{16}	0.618	0.212
D_{15}	0.628	0.549	0.660	0.535	q_{15}	1.444	0.473
D_{14}	0.685	0.549	0.735	0.537	q_{14}	1.493	0.492
D_{13}	0.856	0.537	0.827	0.523	q_{13}	1.649	0.533
D_{12}	0.512	0.551	0.380	0.558	q_{12}	1.349	0.434
D_{11}	0.081	0.572	0.028	0.560	q_{11}	1.049	0.351
D_{10}	−1.791	0.615	−1.853	0.602	q_{10}	0.351	0.141
D_9	−0.888	0.560	−0.859	0.545	q_9	0.595	0.200
D_8	−1.300	0.545	−1.168	0.553	q_8	0.468	0.155
D_7	−1.072	0.491	−0.769	0.603	q_7	0.534	0.151
D_6	−0.736	0.532	−0.556	0.561	q_6	0.650	0.202
D_5	−0.367	0.486	−0.365	0.473	q_5	0.807	0.231
D_4	−0.258	0.490	−0.186	0.484	q_4	0.860	0.246
D_3	−0.628	0.495	−0.523	0.498	q_3	0.693	0.202
D_2	−0.436	0.477	−0.487	0.468	q_2	0.775	0.220
					q_1	1.000	.
obs.	347		330				
F stat.	3.2 (0.000)		1.61 (0.036)				
— Tests for 2SLS estimation —	`tr20629, trall`						
Underidentification				Anderson LM statistic		21.255	(0.000)
Weak identification				Cragg-Donald Wald F statistic		10.446	
Overidentifying restriction				Sargan statistic		0.303	(0.582)
Endogeneity				Davidson-MacKinnon F statistic		0.701	(0.402)

Notes: The numbers in parentheses are the p-values for rejecting the null hypotheses. Excluded instruments are the sum of all rates of tariffs on bovine meat, and tariff rate for HS20629. Based on the endogeneity test results, FE (LS) is selected for delta method estimation.

The estimation results are summarized in Tables 1, 2, and 3 for bovine, swine, and poultry meat, respectively. Below, let us briefly review the diagnostics regarding the 2SLS regression. The first two tests are concerned with whether the instruments are relevant—that is, whether the instruments (e.g., Z) are relevant predictors of the endogenous regressors (e.g., X). The corresponding statistic (the LM from Anderson's canonical correlation test) is used to assess the null hypothesis that the minimal canonical correlations between X and Z are zero. The relevance of instruments is further examined by the weak identification test. The rule of thumb for rejection of the null hypothesis that X are only weakly correlated with Z is for the first-stage (Cragg-Donald Wald) F statistic to exceed 10. The third test is concerned with

Table 2: Microelasticity estimation for swine meat.

	FE (LS)		FE (IV)		Delta Method		
	coef.	s.e.	coef.	s.e.		estim.	s.e.
X	−1.656	0.433	−6.657	1.401	σ	7.657	1.401
D_{25}	0.754	0.428	0.032	0.498	q_{25}	1.005	0.075
D_{24}	0.733	0.428	0.059	0.499	q_{24}	1.009	0.076
D_{23}	0.578	0.428	−0.126	0.498	q_{23}	0.981	0.074
D_{22}	0.739	0.436	0.073	0.506	q_{22}	1.011	0.077
D_{21}	0.537	0.422	−0.215	0.495	q_{21}	0.968	0.072
D_{20}	0.228	0.429	−0.539	0.500	q_{20}	0.922	0.071
D_{19}	0.603	0.445	−0.130	0.516	q_{19}	0.981	0.076
D_{18}	0.030	0.429	−0.776	0.502	q_{18}	0.890	0.070
D_{17}	0.511	0.446	−0.224	0.517	q_{17}	0.967	0.076
D_{16}	−0.126	0.429	−0.842	0.504	q_{16}	0.881	0.072
D_{15}	0.161	0.429	−0.550	0.502	q_{15}	0.921	0.072
D_{14}	0.446	0.439	0.269	0.536	q_{14}	1.041	0.081
D_{13}	0.473	0.437	−0.239	0.509	q_{13}	0.965	0.074
D_{12}	0.282	0.436	−0.318	0.511	q_{12}	0.953	0.075
D_{11}	0.720	0.438	0.531	0.535	q_{11}	1.083	0.083
D_{10}	0.376	0.447	0.579	0.582	q_{10}	1.091	0.088
D_9	0.520	0.484	0.806	0.621	q_9	1.129	0.095
D_8	−0.117	0.441	−0.178	0.550	q_8	0.974	0.083
D_7	0.518	0.412	−0.173	0.494	q_7	0.974	0.073
D_6	0.223	0.431	−0.541	0.506	q_6	0.922	0.072
D_5	0.181	0.428	−0.654	0.508	q_5	0.906	0.072
D_4	0.694	0.432	0.614	0.550	q_4	1.097	0.085
D_3	0.296	0.432	0.541	0.595	q_3	1.085	0.089
D_2	0.050	0.440	−0.160	0.551	q_2	0.976	0.083
					q_1	1.000	.
obs.	492		464				
F stat.	1.3 (0.157)		1.55 (0.045)				
— Tests for 2SLS estimation —	`lnxrall, L.xrall`						
Underidentification					Anderson LM statistic	52.685	(0.000)
Weak identification					Cragg-Donald Wald F statistic	28.191	
Overidentifying restriction					Sargan statistic	0.005	(0.943)
Endogeneity					Davidson-MacKinnon F statistic	11.528	(0.001)

Notes: Excluded instruments are the log and first lag of exchange rates. Based on the endogeneity test results, FE (IV) is selected for delta method estimation.

the exogeneity of the instruments—that is, whether Z are uncorrelated with the error term (e.g., u). The corresponding statistic (Sargan) examines the null hypothesis that Z are uncorrelated with the residuals $\hat{u}$ given that at least one of the instruments is exogenous. The fourth test (endogeneity) is concerned with the endogeneity of the regressor—that is, whether X are correlated with u. The corresponding statistic (the Davidson-MacKinnon F) tests the endogeneity of the regressor in the fixed effects setting. A rejection of the null hypothesis indicates that the instrumental variables fixed effects estimator should be employed.

According to the results obtained, the fixed effects instrumental variables (FE (IV)) estimation for all cases (bovine, swine, and poultry meat) are satisfactory with regard to the relevance and exogeneity of the instruments used. Regarding the endogeneity test, the null hypothesis is rejected for swine and poultry meat,

Table 3: Microelasticity estimation for poultry meat.

	FE (LS)		FE (IV)		Delta Method		
	coef.	s.e.	coef.	s.e.		estim.	s.e.
X	−0.321	0.166	−3.155	0.982	σ	4.155	0.982
D_{25}	0.386	0.502	0.852	0.745	q_{25}	1.310	0.307
D_{24}	0.406	0.503	1.096	0.769	q_{24}	1.415	0.334
D_{23}	0.762	0.501	0.932	0.737	q_{23}	1.344	0.330
D_{22}	0.487	0.524	1.201	0.790	q_{22}	1.463	0.358
D_{21}	0.599	0.568	1.516	0.854	q_{21}	1.617	0.421
D_{20}	0.328	0.566	0.800	0.814	q_{20}	1.288	0.331
D_{19}	0.595	0.541	0.339	0.786	q_{19}	1.114	0.285
D_{18}	−0.234	0.536	0.046	0.776	q_{18}	1.015	0.249
D_{17}	0.107	0.550	0.447	0.797	q_{17}	1.152	0.289
D_{16}	0.450	0.572	1.244	0.847	q_{16}	1.483	0.386
D_{15}	0.180	0.572	1.173	0.870	q_{15}	1.450	0.373
D_{14}	−0.057	0.536	0.492	0.791	q_{14}	1.169	0.287
D_{13}	0.486	0.515	0.813	0.758	q_{13}	1.294	0.316
D_{12}	0.642	0.488	0.673	0.727	q_{12}	1.238	0.297
D_{11}	0.577	0.464	0.318	0.717	q_{11}	1.106	0.259
D_{10}	0.152	0.474	−0.220	0.731	q_{10}	0.933	0.213
D_9	0.387	0.491	0.272	0.734	q_9	1.090	0.258
D_8	−0.197	0.477	−0.252	0.719	q_8	0.923	0.211
D_7	−0.427	0.494	−1.529	0.838	q_7	0.616	0.145
D_6	−0.014	0.495	−0.267	0.748	q_6	0.919	0.216
D_5	0.144	0.512	0.250	0.760	q_5	1.083	0.262
D_4	0.061	0.490	0.060	0.736	q_4	1.019	0.238
D_3	0.078	0.493	0.091	0.740	q_3	1.029	0.242
D_2	−0.333	0.441	−0.492	0.695	q_2	0.856	0.188
					q_1	1.000	.
obs.	480		445				
F stat.	0.68 (0.875)		0.71 (0.851)				
— Tests for 2SLS estimation —	`L.key, tr207`						
Underidentification					Anderson LM statistic	21.226	(0.000)
Weak identification					Cragg-Donald Wald F statistic	10.481	
Overidentifying restriction					Sargan statistic	1.078	(0.299)
Endogeneity					Davidson-MacKinnon F statistic	14.266	(0.000)

Notes: Excluded instruments are the first lag of the variable 'key' (which is a concatenation of the year followed by the ISO numeric country code) and tariff rate for HS207. Based on the endogeneity test results, FE (IV) is selected for delta method estimation. However, overall the model is nonsignificant, according to the F statistic.

whereas it is not rejected for bovine meat. Correspondingly, the noninstrumented (FE (LS)) estimator is used for the final assessment of $\hat{\sigma}$ and $\hat{q}_t$ via the delta method subject to (16) for bovine meat, while the FE (IV) estimator is employed for swine and poultry meat cases. Tariff rates turn out to be relevant instruments for bovine meat, and for swine meat, exchange rates are found to be relevant. These instruments, however, are not relevant for poultry meat. The instrument (named 'key') that we use for poultry meat is a concatenation of year t and ISO numeric country code i, which we accidentally discovered to be relevant in this case.

Regarding the Feenstra method estimation, the result is summarized in Table 4. The parameters θ_1 and θ_2 of equation (8) are estimated by WLS using N dummy variables ($a^{(i)}$, $i = 1, \cdots, N$) as described

Table 4: Summary of Feenstra method estimation.

	Bovine		Swine		Poultry	
	estim.	s.e.	estim.	s.e.	estim.	s.e.
γ_1	-2.373	0.137	-5.185	1.069	-2.795	0.663
κ_1	0.030	0.004	0.067	0.019	0.160	0.030
γ_2	32.922	3.822	14.876	4.217	6.262	1.167
κ_2	-0.421	0.024	-0.193	0.040	-0.358	0.085

Notes: The standard errors are obtained through the delta method via (11). In all cases, the relevant solution is γ_1 since concavity requires that $\sigma = 1 - \gamma > 0$. The slope of the supply function must therefore be κ_1.

Table 5: Summary of estimated microelasticities (σ).

	Bovine		Swine		Poultry	
	estim.	s.e.	estim.	s.e.	estim.	s.e.
External IV	2.710	0.272	7.657	1.401	4.155	0.982
Feenstra	3.373	0.137	6.185	1.069	3.795	0.663
Two-way	3.725	0.206	5.344	0.406	3.072	0.029
Implicit IV	3.297	0.265	7.481	0.544	3.020	0.203

Notes: All external IV estimates are based on FE (IV) except for the bovine estimates, which are based on FE (LS). All implicit IV estimates are based on FE (IV).

in section 3.2, and then the estimates for γ and κ by (11) are obtained by the delta method. Since γ_1 turns out to be a legitimate solution in all cases, where $\sigma = 1 - \gamma > 0$ must hold for concavity of the aggregator, the corresponding κ_1 is used to extract the implicit IV in all cases. In Table 5, we summarize the microelasticities estimated by way of all approaches considered in this study. Here, 'External IV' refers to IV estimation by the external IV (such as tariffs and exchange rates), the results of which are shown in Tables 1, 2 and 3; 'Feenstra' refers to the Feenstra method based on the estimate of γ_1, the results of which are shown in Table 4; 'Two-way' refers to the two-way Feenstra method as described in section 3.2; and 'Implicit IV' refers to IV estimation by the implicit IV extracted from (14), using $\hat{\kappa} = \kappa_1$, in all cases. Furthermore, the implicit IVs are relevant; thus, FE(IV) estimators are selected in all cases.[10] Figures 2, 3, and 4 show how the first-stage aggregates $\hat{q}_t$ (the foreign meat price index) are estimated with the implicit IVs and compared with those estimated by the external IVs.[11]

4.3. Second-stage aggregator

Let us rewrite the regression equation (4) for the macroelasticity estimation as follows:

$$Y_t = \mu_0 + \mu X_t + \nu_t \tag{17}$$

where the parameters are denoted as $\mu_0 = \ln \beta - \ln(1-\beta)$ and $\mu = 1 - \rho$. The response variable is the log ratio of cost shares for which we can use the observable data, i.e., $Y_t = \ln r_t z_t - \ln \sum_{i=1}^{N} p_{it} x_{it}$. On the other hand, the explanatory variable in (4) includes the first-stage aggregate (or foreign price) q_t, which in this case can be evaluated by the predicted value $\hat{q}_t$ obtained from the first-stage regression.[12] The explanatory variable is therefore $X_t = \ln r_t - \ln \hat{q}_t$. As noted in the previous section, we examine two sets of estimates

[10] Tables not shown for brevity. In this case, the explanatory variable X_{it} is instrumented solely by δ^*_{it}.
[11] Note that the foreign meat price indices $\hat{q}_t$ obtained by the external IV in Figures 2, 3 and 4 are taken from Tables 1, 2, and 3.
[12] We treat $\hat{q}_t$ as stochastic like any other stochastic variable such as r_t, even when we know the variances.

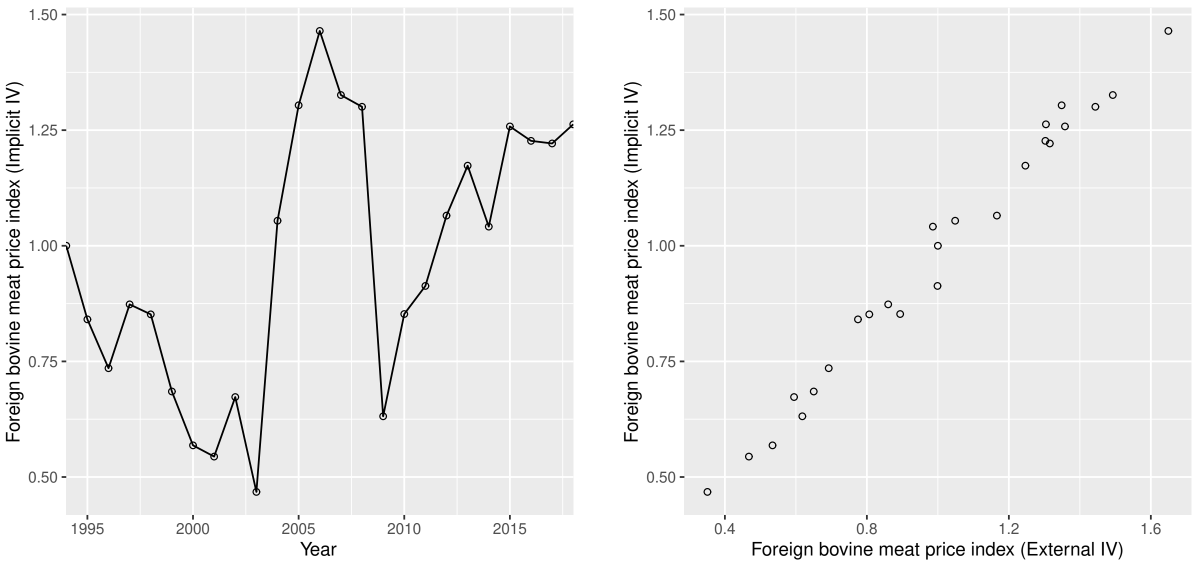

Figure 2: The foreign price index q_t estimated by means of the implicit IV (left) and its comparison with the estimate based on the external IV (right) for Japan's bovine meat imports.

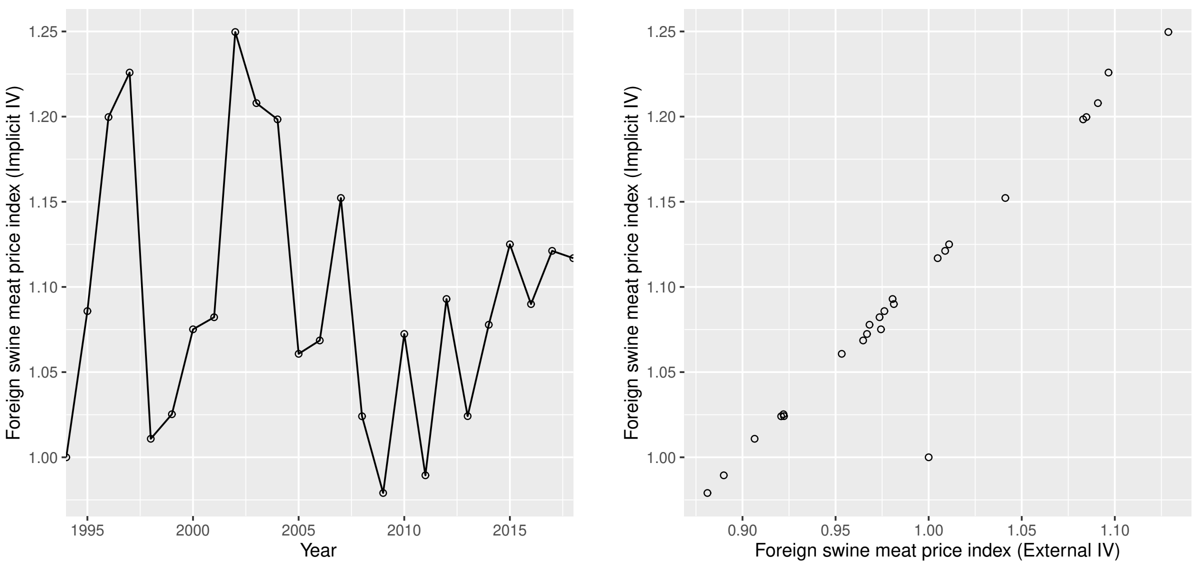

Figure 3: The foreign price index q_t estimated by means of the implicit IV (left) and its comparison with the estimate based on the external IV (right) for Japan's swine meat imports.

of first-stage aggregators ($\hat{q}_t$, $t = 1, \cdots, T$), where one is obtained by the external IV and the other by the implicit IV of the Feenstra method.

In regard to the time-series nature of regression equation (17), we first examine the stationarity of all variables. We perform a unit root test on all variables in levels (X_t and Y_t) and first differences (ΔX_t and ΔY_t) based on augmented Dickey-Fuller statistics. The results (not shown for brevity) suggest that the variables are nonstationary in levels but stationary in first differences in all cases. We therefore estimate (17) with first differences. Regarding the endogeneity problem, we use $\hat{q}_t$ to instrument for X_t, as we describe

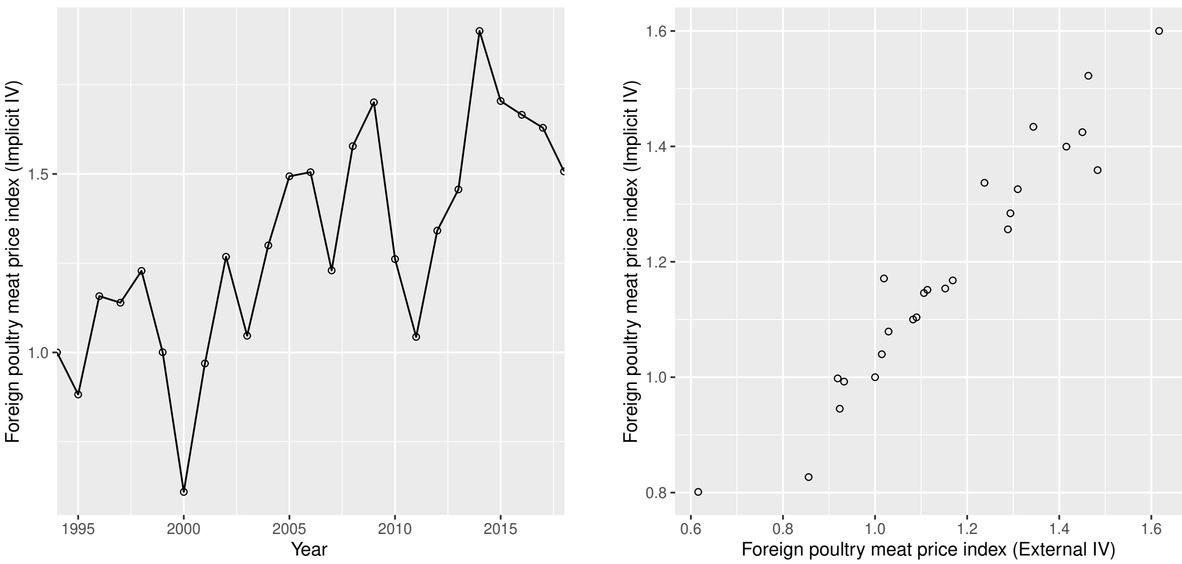

Figure 4: The foreign price index q_t estimated by means of the implicit IV (left) and its comparison with the estimate based on the external IV (right) for Japan's poultry meat imports.

Table 6: Macroelasticity estimation for bovine meat (first-stage instrument: external IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	−0.225	0.129	−0.223	0.132	1.225	0.129
const.	−0.006	0.030	−0.006	0.029		
DW stat.	2.460		2.462			
— Tests for 2SLS estimation —	`D.lnqib, L.lnqip`					
Underidentification			Anderson LM statistic		5.688	(0.058)
Weak identification			Cragg-Donald Wald F statistic		165.798	
Overidentifying restriction			Sargan statistic		0.031	(0.861)
Endogeneity			Davidson-MacKinnon F statistic		0.003	(0.956)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the first lag of the first-stage aggregate for poultry meat. Based on the endogeneity test results, OLS is selected for delta method estimation.

earlier (in section 2.2). Tables 6, 7, and 8 show the estimation results using the first-stage aggregates estimated by the external IV for bovine, swine, and poultry meat, respectively. Similarly, Tables 9, 10, and 11 show the estimation results using the first-stage aggregates estimated by the implicit IV for bovine, swine, and poultry meat, respectively. As we coordinate the estimates (in Table 12) with the first-stage instruments used, we find that the two approaches yield similar results.

Our macroelasticity estimates are significantly smaller (less elastic) than those employed in the GTAP database, which we also display in Table 12. The micro- and macroelasticity estimates for bovine meat (where the noninstrumented estimates are selected) indicate that the 'rule of two,' i.e., an assumption (made following Corado and De Melo (1986)) that the macroelasticity should be roughly half the microelasticity, may be in effect. However, this rule does not seem to be operative for the other cases (swine and poultry meat), for which the instrumented estimates are selected. Finally, we find that for swine meat (of which Japan was the world's largest importer in the sample period), the microelasticity is large (with the most

Table 7: Macroelasticity estimation for swine meat (first-stage instrument: external IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	0.402	0.131	0.656	0.165	0.344	0.165
const.	−0.024	0.024	−0.025	0.023		
DW stat.	1.821		2.077			
— Tests for 2SLS estimation —	`D.lnqis, D.lnqib`					
Underidentification				Anderson LM statistic	9.111	(0.011)
Weak identification				Cragg-Donald Wald F statistic	11.9	
Overidentifying restriction				Sargan statistic	0.897	(0.344)
Endogeneity				Davidson-MacKinnon F statistic	4.056	(0.044)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the difference of the log of the first-stage aggregate for bovine meat. Based on the endogeneity test results, 2SLS is selected for delta method estimation.

Table 8: Macroelasticity estimation for poultry meat (first-stage instrument: external IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	−0.118	0.217	0.190	0.194	0.810	0.194
const.	0.014	0.035	0.015	0.036		
DW stat.	2.559		2.770			
— Tests for 2SLS estimation —	`D.lnqip, D.lnxrjpy`					
Underidentification				Anderson LM statistic	6.827	(0.033)
Weak identification				Cragg-Donald Wald F statistic	38.477	
Overidentifying restriction				Sargan statistic	0.028	(0.867)
Endogeneity				Davidson-MacKinnon F statistic	5.9	(0.015)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the difference of the log of the exchange rate (JPY/USD). Based on the endogeneity test results, 2SLS is selected for delta method estimation.

Table 9: Macroelasticity estimation for bovine meat (first-stage instrument: implicit IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	−0.263	0.180	−0.267	0.190	1.263	0.180
const.	−0.006	0.031	−0.006	0.030		
DW stat.	2.499		2.493			
— Tests for 2SLS estimation —	`D.lnqib, D.lnqip`					
Underidentification				Anderson LM statistic	5.058	(0.080)
Weak identification				Cragg-Donald Wald F statistic	97.075	
Overidentifying restriction				Sargan statistic	0.006	(0.938)
Endogeneity				Davidson-MacKinnon F statistic	0.008	(0.928)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the difference of the log of the first-stage aggregate for poultry meat. Based on the endogeneity test results, OLS is selected for delta method estimation.

Table 10: Macroelasticity estimation for swine meat (first-stage instrument: implicit IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	0.451	0.135	0.717	0.185	0.283	0.185
const.	−0.023	0.023	−0.022	0.023		
DW stat.	1.971		2.293			
— Tests for 2SLS estimation —	`D.lnqis, D.lnqib`					
Underidentification				Anderson LM statistic	9.718	(0.008)
Weak identification				Cragg-Donald Wald F statistic	12.936	
Overidentifying restriction				Sargan statistic	0.272	(0.602)
Endogeneity				Davidson-MacKinnon F statistic	4.79	(0.029)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the difference of the log of the first-stage aggregate for bovine meat. Based on the endogeneity test results, 2SLS is selected for delta method estimation.

Table 11: Macroelasticity estimation for poultry meat (first-stage instrument: implicit IV).

	OLS		2SLS		Delta Method	
	coef.	s.e.	coef.	s.e.	estim.	s.e.
ΔX	−0.107	0.171	0.072	0.152	0.928	0.152
const.	0.014	0.035	0.015	0.035		
obs.	24		24			
DW stat.	2.694		2.779			
— Tests for 2SLS estimation —	`D.lnqip0, D.lnxrjpy`					
Underidentification				Anderson LM statistic	8.444	(0.015)
Weak identification				Cragg-Donald Wald F statistic	68.033	
Overidentifying restriction				Sargan statistic	0.112	(0.738)
Endogeneity				Davidson-MacKinnon F statistic	5.838	(0.016)

Notes: Excluded instruments are the difference of the log of the first-stage aggregate and the difference of the log of the exchange rate (JPY/USD). Based on the endogeneity test results, 2SLS is selected for delta method estimation.

Table 12: Summary of estimated macroelasticities (ρ).

	Bovine		Swine		Poultry	
	estim.	s.e.	estim.	s.e.	estim.	s.e.
External IV	1.225	0.129	0.344	0.165	0.810	0.194
Implicit IV	1.263	0.180	0.283	0.185	0.928	0.152
GTAP	Bovine meat products			Meat products nec.		
macro	3.85			4.40		
micro	7.70			8.80		

Notes: For both external IV and implicit IV cases, bovine estimates are based on OLS. All other cases are based on 2SLS. The GTAP elasticities are taken from Hertel et al. (2007), where the microelasticities are evaluated by doubling the estimates of the macroelasticities, following the 'rule of two.'

elastic response among the three kinds of meat), whereas the macroelasticity is small (with the least elastic response among the three kinds of meat).

5. Application

5.1. Tariff elimination

Below, let us consider tariff elimination as a counterfactual scenario. Our purpose here is to evaluate the potential shifts in foreign and domestic expenditures to assess the shifts in total expenditures for each commodity over the course of the counterfactual scenario. Tariff elimination reduces prices by the rate of the tariff levied, i.e.,

$$\ln p'_{it} = \ln p_{it} - \ln (1 + r_{it})$$

All counterfactual variables are hereafter indicated by a prime. We then can evaluate the counterfactual foreign aggregate price $\hat{q}'_t$ as follows:

$$\ln \hat{q}'_t = \ln \hat{q}_t - \ln (1 + \bar{r}_t) = \ln \hat{q}_t - \ln \left(\frac{\sum_{i=1}^N p_{it} x_{it}}{\sum_{i=1}^N p'_{it} x_{it}} \right)$$

where we call $\bar{r}_t$ the effective tariff rate.[13]

Now, let us consider foreign utility shifts concerning foreign commodities. To do so, however, we need the price elasticity of demand η so that we can evaluate the counterfactual shifts in foreign commodity demand (y) by means of the shifts in the foreign commodity price (q). The elasticity can be estimated by the following simple regression equation, with λ_t (the demand shock for the foreign commodity) being the error term, which must be uncorrelated with the explanatory variable; we treat $\hat{q}_t$ as exogenous with respect to the demand shock.

$$\ln \hat{y}_t = \eta_0 + \eta \ln \hat{q}_t + \lambda_t \tag{18}$$

Here, the response variable is obtained with the following identity, in regard to (2):

$$\ln \hat{q}_t + \ln \hat{y}_t = \ln \sum_{i=1}^N p_{it} x_{it}$$

We can use the estimates of parameters (i.e., $\hat{\eta}_0$ and $\hat{\eta}$) to evaluate $\hat{y}'_t$ from $\hat{q}'_t$. However, since (18) is likely to be estimated by the differences of variables, in which event η_0 is dropped from the estimation, we measure y'_t relatively by means of the following identity:

$$\ln \hat{y}'_t - \ln \hat{y}_t = \hat{\eta} (\ln \hat{q}'_t - \ln \hat{q}_t) = \hat{\eta} \ln (1 + \bar{r}_t)^{-1} \tag{19}$$

Next, let us consider the shifts in domestic commodity consumption z_t. We know that the domestic/foreign expenditure ratios ($\ln r_t z_t - \ln q_t y_t$) can be evaluated with the corresponding price ratios ($\ln r_t - \ln q_t$) by using the estimated parameters of regression (17). Counterfactual variables can also be evaluated with the same function.

$$\ln \frac{r_t \hat{z}_t}{\hat{q}_t \hat{y}_t} = \hat{\mu}_0 + \hat{\mu} \ln \frac{r_t}{\hat{q}_t} \qquad \ln \frac{r_t \hat{z}'_t}{\hat{q}'_t \hat{y}'_t} = \hat{\mu}_0 + \hat{\mu} \ln \frac{r_t}{\hat{q}'_t} \tag{20}$$

Note that the price of domestic commodity r_t is assumed to be unaffected in the course of the counterfactual scenario. We may then use the parameters (i.e., $\hat{\mu}_0$ and $\hat{\mu}$) to evaluate $\hat{z}'_t$ from $\hat{q}'_t$ and $\hat{y}'_t$. However, since (17)

[13] Since the share parameters α_i are dropped from the fixed effects regression, we opt to evaluate $\hat{q}'_t$ with the total recorded amount of the tariff levied.

Table 13: Tariff elasticity of expenditure for domestic and foreign commodities.

	Bovine		Swine		Poultry	
	coef.	s.e.	coef.	s.e.	coef.	s.e.
$\Delta \ln \hat{q}$	-1.116	0.131	-0.474	0.180	-0.644	0.210
const.	0.011	0.031	0.022	0.024	0.005	0.047
$\hat{\rho}$	1.225		0.344		0.810	
$\hat{\rho}+\hat{\eta}$	0.109		-0.131		0.166	
$1+\hat{\eta}$	-0.116		0.526		0.356	
$1+\hat{\rho}+2\hat{\eta}$	-0.007		0.395		0.522	

Notes: The first row (i.e., as coefficients for $\Delta \ln \hat{q}$) shows the estimates of the tariff elasticity of demand for a foreign commodity η. The estimates of the macroelasticity (foreign-domestic substitution elasticity $\hat{\rho}$) based on the external IV are statistically significant in all cases, and they are repeated from Table 12.

is likely to be estimated by the differences of variables, in which event μ_0 is dropped from the estimation, we measure $\hat{z}'_t$ relatively by means of the following identity based on (20):

$$\ln \hat{z}'_t - \ln \hat{z}_t = (1-\hat{\mu})\,(\ln \hat{q}'_t - \ln \hat{q}_t) + (\ln \hat{y}'_t - \ln \hat{y}_t) \tag{21}$$

In regard to (19, 21) and taking the fact that $\hat{\rho} = 1 - \hat{\mu}$ into account, we have:

$$\ln \hat{z}'_t - \ln \hat{z}_t = (\hat{\eta}+\hat{\rho})\,(\ln \hat{q}'_t - \ln \hat{q}_t) = (\hat{\eta}+\hat{\rho}) \ln (1+\bar{r}_t)^{-1} \tag{22}$$

We may then evaluate the counterfactual expenditure change by using (19, 22) as follows:

$$\begin{aligned} \ln (v_t u_t)' - \ln (v_t u_t) &= \ln (r_t \hat{z}'_t) - \ln (r_t \hat{z}_t) + \ln (\hat{q}'_t \hat{y}'_t) - \ln (\hat{q}_t \hat{y}_t) \\ &= (\hat{\eta}+\hat{\rho}) \ln (1+\bar{r}_t)^{-1} + (1+\hat{\eta}) \ln (1+\bar{r}_t)^{-1} \end{aligned}$$

Correspondingly, $(\hat{\eta}+\hat{\rho})$ denotes the tariff elasticity of expenditure for a domestic commodity, whereas $(\hat{\eta}+1)$ denotes the tariff elasticity of expenditure for a foreign commodity.

5.2. Tariff elasticity and tariff elimination

In regard to the time series nature of regression equation (18), we first examine the stationarity of all variables. We perform a unit root test on all variables in levels ($\ln \hat{q}_t$ and $\ln \hat{y}_t$) and first differences ($\Delta \ln \hat{q}_t$ and $\Delta \ln \hat{y}_t$) based on augmented Dickey-Fuller statistics. The results (not shown for brevity) suggest that the variables are nonstationary in levels but stationary in first differences in all cases. We therefore estimate the parameters of the regression equation (18) with the first differences. The results are provided in Table 13. As expected, the estimates of the tariff elasticity of demand for a foreign commodity $\hat{\eta}$ are all negative and are statistically significant. Additionally, as expected, the corresponding standard errors indicate that the intercepts are essentially zero in all cases.

Table 13 summarizes the various tariff elasticities of expenditure in the home country. [14] For bovine meat, a positive tariff elasticity of domestic commodity expenditure ($\hat{\rho}+\hat{\eta} > 0$) and negative tariff elasticity of foreign commodity expenditure ($1+\hat{\eta} < 0$) indicate that tariff elimination would decrease domestic and increase foreign commodity expenditure, and this is indeed reflected in Figure 5. For swine meat, a negative tariff elasticity of domestic commodity expenditure ($\hat{\rho}+\hat{\eta} < 0$) and positive tariff elasticity of

[14] To clarify, we note that if $1+\hat{\eta} > 0$, then a tariff increases (tariff elimination decreases) expenditure for a foreign commodity more; and if $1+\hat{\eta} < 0$, then a tariff decreases (tariff elimination increases) expenditure for a foreign commodity more. Similarly, if $\hat{\eta}+\hat{\rho} > 0$, then tariff increases (tariff elimination decreases) expenditure for a domestic commodity more; and if $\hat{\eta}+\hat{\rho} < 0$, then a tariff decreases (tariff elimination increases) expenditure for a domestic commodity more.

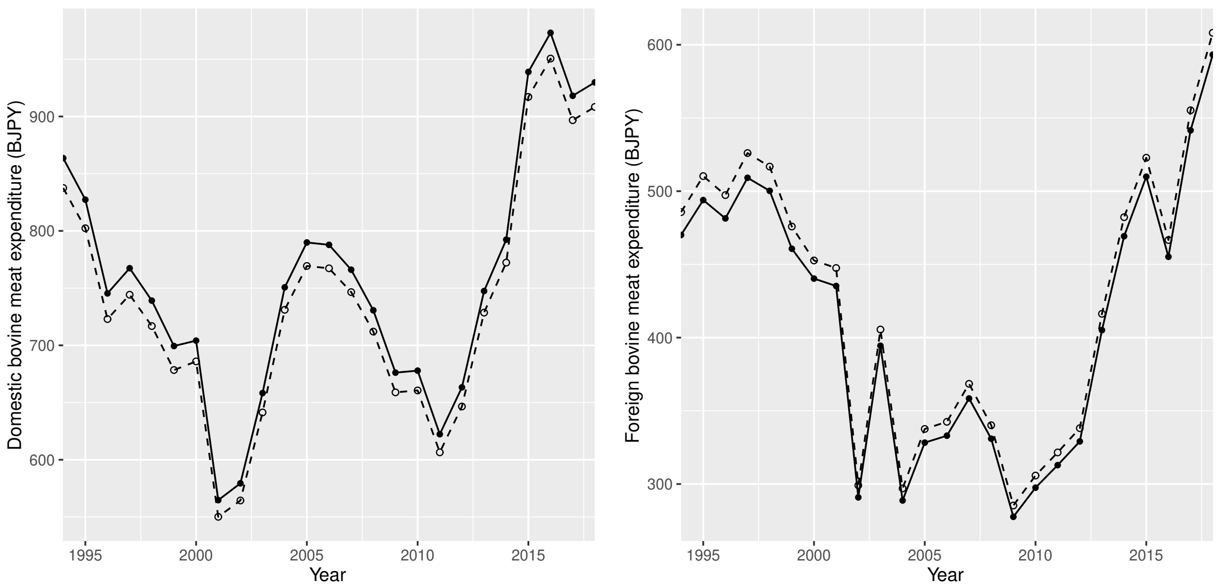

Figure 5: Factual and counterfactual expenditures for domestic (left) and foreign (right) bovine meat. Dotted lines indicate counterfactual expenditures under tariff elimination.

Figure 6: Factual and counterfactual expenditures on domestic (left) and foreign (right) swine meat. Dotted lines indicate counterfactual expenditures under tariff elimination.

foreign commodity expenditure ($1 + \hat{\eta} > 0$) indicate that tariff elimination would increase domestic and decrease foreign commodity expenditure, and this is reflected in Figure 6. For swine meat, a positive tariff elasticity of domestic commodity expenditure ($\hat{\rho} + \hat{\eta} > 0$) and positive tariff elasticity of foreign commodity expenditure ($1 + \hat{\eta} > 0$) indicate that tariff elimination would decrease domestic and foreign commodity expenditure, and this is reflected in Figure 7. Finally, by looking at the tariff elasticity of overall expenditure ($1 + \hat{\rho} + 2\hat{\eta}$), we see that tariff elimination would increase expenditure for bovine meat, whereas for swine and poultry meat, expenditure would decrease.

Figure 7: Factual and counterfactual expenditures for domestic (left) and foreign (right) poultry meat. Dotted lines indicate counterfactual expenditures under tariff elimination.

6. Concluding Remarks

Finding relevant instruments is generally an exacting task. As a matter of fact, it was only by luck that we were able to discover an external instrument that was sufficiently relevant to conduct the first-stage microelasticity estimation for poultry meat. Thus, if an alternative method exists that does not involve finding instruments and is still capable of yielding similar results to the primary ones, we would choose the alternative. The problem is that we cannot judge whether the alternative method is credible unless we find relevant instruments for use as the primary method. For its part, the Feenstra method employs an assumption so that the estimator maintains consistency. Fortunately, we were able to find relevant instruments for the three cases (the bovine, swine and poultry meat imports of Japan), and the two methods converged to similar results for the first-stage microelasticity estimation.

The similarity of the results led us to investigate the potential compatibility of the implicit IV that was effectively at work within the Feenstra method estimation with the external IV that we found sufficiently relevant. To extract the implicit IV of the Feenstra method from the data, we utilized the slope parameter of the reverse (supply) function obtainable from the Feenstra method estimation. The advantage of applying IVs (regardless of whether they are external or implicit) for the first-stage fixed effects regression is that the first-stage aggregate is not only fed into but also utilized to instrument the explanatory variable of the second-stage regression. In this sense, implicit IV extraction and utilization complement the Feenstra method's capability of evaluating macroelasticities and still help us avoid the need to find relevant external instruments.

References

Blonigen, B., Wilson, W., 1999. Explaining armington: What determines substitutability between home and foreign goods? Canadian Journal of Economics 32, 1–21.

BOJ, 2020. Corporate goods price index (CGPI) (2015 base), Bank of Japan. URL: https://www.boj.or.jp/en/statistics/pi/cgpi_2015/index.htm/.

Broda, C., Weinstein, D.E., 2006. Globalization and the Gains From Variety. The Quarterly Journal of Economics 121, 541–585. doi:10.1162/qjec.2006.121.2.541.

Corado, C., De Melo, J., 1986. An ex-ante model for estimating the impact on trade flows of a country's joining a customs union. Journal of Development Economics 24, 153 – 166. doi:10.1016/0304-3878(86)90151-3.

e-Stat, 2020. Portal site of official statistics of Japan. URL: https://www.e-stat.go.jp/en.

Erkel-Rousse, H., Mirza, D., 2002. Import price elasticities: Reconsidering the evidence. Canadian Journal of Economics 35, 282–306. doi:10.1111/1540-5982.00131.

Fajgelbaum, P.D., Goldberg, P.K., Kennedy, P.J., Khandelwal, A.K., 2019. The Return to Protectionism*. The Quarterly Journal of Economics 135, 1–55. doi:10.1093/qje/qjz036.

Feenstra, R., 1994. New product varieties and the measurement of international prices. American Economic Review 84, 157–77.

Feenstra, R.C., Luck, P., Obstfeld, M., Russ, K.N., 2018. In search of the armington elasticity. Review of Economics and Statistics 100, 135–150. doi:10.1162/REST_a_00696.

Gallaway, M.P., McDaniel, C.A., Rivera, S.A., 2003. Short-run and long-run industry-level estimates of U.S. Armington elasticities. The North American Journal of Economics and Finance 14, 49 – 68. doi:10.1016/S1062-9408(02)00101-8.

Hertel, T., Hummels, D., Ivanic, M., Keeney, R., 2007. How confident can we be of cge-based assessments of free trade agreements? Economic Modelling 24, 611 – 635. doi:10.1016/j.econmod.2006.12.002.

Huchet-Bourdon, M., Pishbahar, E., 2009. Armington elasticities and tariff regime: An application to european union rice imports. Journal of Agricultural Economics 60, 586–603. doi:10.1111/j.1477-9552.2009.00217.x.

Kee, H.L., Nicita, A., Olarreaga, M., 2008. Import demand elasticities and trade distortions. The Review of Economics and Statistics 90, 666–682. doi:10.1162/rest.90.4.666.

Lau, L.J., 1979. On exact index numbers. The Review of Economics and Statistics 61, 73–82.

Reinert, K.A., Roland-Holst, D.W., 1992. Armington elasticities for United States manufacturing sectors. Journal of Policy Modeling 14, 631 – 639. doi:10.1016/0161-8938(92)90033-9.

Romalis, J., 2007. Nafta's and cusfta's impact on international trade. The Review of Economics and Statistics 89, 416–435. doi:10.2307/40043039.

Saito, M., 2004. Armington elasticities in intermediate inputs trade: a problem in using multilateral trade data. Canadian Journal of Economics 37, 1097–1117. doi:10.1111/j.0008-4085.2004.00262.x.

Soderbery, A., 2015. Estimating import supply and demand elasticities: Analysis and implications. Journal of International Economics 96, 1 – 17. doi:10.1016/j.jinteco.2015.01.003.

UN Comtrade, 2020. UN Comtrade–International Trade Statistics Database. URL: https://comtrade.un.org.

WTO, 2020. World trade organization tariff download facility. URL: http://tariffdata.wto.org/ReportersAndProducts.aspx.