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Abstract

Using commodity-level transaction data, we estimate aggregate demand and supply shocks. When using this for continuing goods, i.e., those that exist in both the current and the base periods, the demand shock preceding a change in the consumption tax rate in Japan on April 1, 2014 is negligible. This contradicts the conventional viewpoint on stockpiling behavior before a tax rate increase. However, when considering new goods appearing within a year, the estimated demand shock becomes positive, which suggests that product turnover is critical when estimating demand shocks. Following the sharp and temporary fall associated with the Great East Japan Earthquake in 2011, the estimated supply shocks were virtually zero until the end of 2013. The supply shocks then became negative and remained at a very low level until the change in the consumption tax rate, which suggests that the increases in the prices during this period reflect, at least in parts, an inward shift of the supply curves.

Keywords: Demand shocks, Supply shocks, Elasticity, Scanner data

JEL Classification: D40, D12, D22, E30, E32

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1. Introduction

When transaction prices or quantities change, the demand and/or supply curves shift. To identify the precise nature of any change, we therefore need to know the shape of demand and supply curves along with the factors that move these curves. Consequently, the identification of demand and supply curves has been a central concern in the history of econometrics. Since the analysis by Working (1927), a number of studies have proposed a variety of identification procedures. For example, microeconomic researchers use microdata and instrumental variables or full structural models of production and demand to identify the shapes of the demand and supply curves.[1] Alternatively, macroeconomic researchers tend to focus on demand and supply shocks rather than the shape of the demand and supply curves, with vector autoregressive models including macroeconomic variables, such as gross domestic product and aggregate price indexes, being standard tools for analysis.[2] Accordingly, a micro and macro dichotomy prevails when estimating demand and supply shocks. This lies in sharp contrast to many other macroeconomic fields, such as consumption, unemployment, and investment, in which an increasing number of researchers employ micro, but not macro, data instead to identify macroeconomic structure.

The purpose of this paper is to bridge the divide between these micro and macro approaches. More specifically, we estimate aggregate demand and supply shocks using micro data. A large commodity transaction dataset enables us to estimate category-level demand and supply curves. Based on the estimated demand and supply curves, we then identify demand and supply shocks that shift either or both curves and then aggregate the demand and supply shocks to obtain the macroeconomic demand and supply shocks. Our weekly frequency dataset covers the period between 2007 and 2015 in Japan. During this period, a number of significant shocks took place, including the Global Financial Crisis (GFC) in September 2008, the Great East Japan Earthquake (GEJE) in March 2011, and a change in the rate of consumption tax in April 2014. We quantify the impact of these shocks on demand and supply.

When estimating the curves, we employ two types of estimation strategies, one based on commodity code (barcode) level information and another based on the producer-level information, which we are of the opinion are complementary approaches. When using the barcode-level micro dataset, we treat commodities with different

[1] For instance see Berry et al. (1995) for an instrumental variable approach and Byrne et al. (2015) for a structural approach.
[2] See, e.g., Blanchard and Quah (1989) and Uhlig (2005).

commodity codes as different goods. Thus, empirical complexities do not arise, such as the quality adjustment that frequently appears when constructing price indexes. However, because we require yearly differences in both prices and quantities to control for seasonal movements in our estimation, we have to restrict our dataset to goods that are present in both the base and the current periods. This implies the removal of about 30% of the goods that appear between the base and current periods. Alternatively, if we use producer-level information, we need to aggregate different goods produced by the same manufacturers. Because it is practically impossible for us to conduct detailed quality adjustment, such as hedonic regressions based on detailed barcode-level characteristics for the more than a billion commodities, we need to adopt a simplified approach using unit value prices and volumes.

More specifically, we first convert the prices and quantities of all goods belonging to the same commodity category to the same unit value, such as price per gram, and then conduct aggregation over the same producers and categories. The advantage of this method is that we can include new goods that appear between the base and current periods. As Bernard et al. (2010) argue, if product turnover plays a significant role in business cycles, ignoring it when estimating demand and supply shocks could account for serious bias.[3] We consider these estimates of aggregate demand and supply shocks—one based on barcode-level data but ignoring new goods and the other based on producer-level aggregate unit value but assuming that all products have the same qualities save volume—as extremes, trusting the actual aggregate demand and supply shocks lie somewhere between.

The differences in the estimated aggregate demand shocks between each approach are large for two of the sample periods, namely, the period before the GFC in 2008 and that preceding the change in the consumption tax in April 2014. The demand shocks based on the barcode-level information are large and positive before the GFC, whereas before the consumption tax increase, the shocks are virtually zero. Conversely, the estimates of the aggregate demand shocks based on the producer-level information are small before the GFC and positive before the change in the consumption tax. Both estimates are negative following the GFC. These differences suggest that product turnover plays a significant role in Japanese business cycles. However, compared with the aggregate demand shocks, the estimates of the aggregate supply shocks do not exhibit large discrepancies between the two sets of estimates, with one based on the barcode-level

[3] Feenstra (1994) shows that under some circumstances, we can capture the effects of product turnover on economic welfare through the changes in the product variety. While there is an emphasis on variety-expansion in the macroeconomic growth literature, it is a blue bus/red bus problem, so we do not take this approach. See Nevo (2010) for details.

information and the other on the producer-level information. Both estimates of the aggregate supply shocks are positive after the GEJE. The demand shocks also exhibit temporary increases before the change in the rate of consumption tax in April 2014. During other periods, the supply shocks are basically negative. The magnitude of negative supply shocks increased after the change in the consumption tax rate. Along with the positive aggregated demand shocks, the negative supply shocks contribute to an increase in the price index after 2014.

The remainder of the paper is organized as follows. Section 2 describes the model. Section 3 details the identification strategy and Section 4 describes the dataset used. Section 5 discusses the estimation results. Section 6 provides a brief summary and identifies some prospects for future research.

2. Model

The representative consumer has the following separable utility function at time *t*,

$$U_t = U\left(C_t^1, C_t^2, \ldots, C_t^J\right),$$

$$C_t^j = \left(\sum_{i \in \Theta_t^j} a_t^i \, x_t^{i\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \qquad a_t^i \geq 0, \qquad , \sigma > 0$$

where x_t^i is consumption of commodity *i* at time *t*. Θ_t^j is the commodity space of category *j* at time t. C_t^j is the aggregate consumption of category *j* at time *t*. a_t^i is the time-varying weight for commodity *i* at time *t*. σ is a constant parameter. U is a twice-continuously differentiable utility function that satisfies standard utility function assumptions. Because the utility function is separable across categories, and given constant elasticity of substitution (CES) for the category-level utility function, the optimal consumption for commodity *i* given the aggregate categorical aggregate, is given by the following simple compensated demand function:

$$x_t^i = \mathrm{C}_\mathrm{t}^j \left(\sum_{k \in \Theta_t^j} a_t^{k\,\sigma} p_t^{k\,1-\sigma} \right)^{\frac{\sigma}{1-\sigma}} a_t^{i\,\sigma} p_t^{i\,-\sigma}$$

Denoting,

$$P_t^j = \left(\sum_{k \in \Theta_t^j} a_t^{k\,\sigma} p_t^{k\,1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

and taking logged time differences, we obtain

$$\Delta\ln(x_t^i) = \Delta\ln\left(\mathrm{C}_\mathrm{t}^j\right) - \sigma\Delta\ln\left(p_t^i\right) + \sigma\Delta\ln\left(P_t^j\right) + \varepsilon_t^i, \tag{1}$$

where $\varepsilon_t^i = \sigma\Delta\ln\left(a_t^i\right)$.

The first term on the right-hand side of (1), $\Delta\ln\left(\mathrm{C}_\mathrm{t}^j\right)$, represents the income effect, the second and third terms reflect the effects of the relative prices, and the final term, ε_t^i, captures the commodity-specific demand shocks. Note that the category-specific demand shocks, $\Delta\ln\left(\mathrm{C}_\mathrm{t}^j\right)$ and $\Delta\ln\left(P_t^j\right)$, do not include subscript *i*, which implies that these shocks are common to all commodities belonging to the same category. Given category-specific demand shocks are likely relate to the supply shocks, we need to eliminate these components from (1) when estimating the demand elasticity, σ. For this, Feenstra (1994) proposed taking the difference from a reference country to control for the shocks. Following this procedure, it is possible to take the difference from a reference good, such as the commodity with the largest market share.

However, we do not do this approach because of two main reasons. The first is the high rate of commodity turnover. As described in Section 4, our dataset contains a number of processed foods and daily necessities, cosmetics, and drugs. In these categories, it is very difficult to find a commodity that is a market leader for more than eight years (corresponding to the subsample period). The second reason is that by taking the difference from a reference good, we will remove observations of the reference good itself, representing a large loss of information. Instead, we take the differences between the quantity of commodity *i* from the categorical average quantity without commodity *i*, within the same store, *s*. More specifically, we use the following double difference,

$$\Delta\ln(x_t^i) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k\in\Theta_t^{j,s},k\neq i} \Delta\ln(x_t^k)$$

$$= -\sigma\left(\Delta\ln\left(p_t^i\right) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k\in\Theta_t^{j,s},k\neq i} \Delta\ln(p_t^k)\right) + \tilde{\varepsilon}_t^i$$

$$\tilde{\varepsilon}_t^i = \sigma\,\Delta\ln\left(a_t^i\right) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k\in\Theta_t^{j,s},k\neq i} \sigma\,\Delta\ln\left(a_t^k\right)$$

where $\#\left(\Theta_t^{j,s}\right)$ is the number of products included in the product set at store s, $\Theta_t^{j,s}$.

For simplification, denote

$$\tilde{x}_t^i = \Delta\ln(x_t^i) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k\in\Theta_t^{j,s},k\neq i} \Delta\ln(x_t^k),$$

$$\tilde{p}_t^i = \Delta\ln\left(p_t^i\right) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k\in\Theta_t^{j,s},k\neq i} \Delta\ln(p_t^k).$$

Then, the equation becomes

$$\tilde{x}_t^i = -\sigma\tilde{p}_t^i + \tilde{\varepsilon}_t^i. \tag{2}$$

Following Feenstra (1994) and Broda and Weinstein (2010), we assume the following simple supply function,

$$\Delta\ln\left(x_t^i\right) = \omega\Delta\ln\left(p_t^i\right) + S_t^j + \delta_t^i, \tag{3}$$

where ω is a constant parameter, δ_t^i is a supply shock that shifts the supply curve, and S_t^j is a category-specific shock that is common across commodities in category j that could be correlated with the demand shocks. Taking additional differences within the same category as in demand curve, we obtain,

$$\Delta \ln(x_t^i) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k \in \Theta_t^{j,s}, k \neq i} \Delta \ln(x_t^k)$$

$$= \omega \left(\Delta \ln\left(p_t^i\right) - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k \in \Theta_t^{j,s}, k \neq i} \Delta \ln(p_t^k) \right) + \tilde{\delta}_t^i$$

$$\tilde{\delta}_t^i = \delta_{\mathrm{t}}^i - \frac{1}{\#\left(\Theta_t^{j,s}\right) - 1} \sum_{k \in \Theta_t^{j,s}, k \neq i} \delta_t^k.$$

By using the same notation as (2), we obtain the following supply curve,

$$\tilde{x}_t^i = \omega \tilde{p}_t^i + \tilde{\delta}_t^i \ . \qquad (4)$$

3. Identification

Our main identification assumption for estimating the elasticities, σ and ω, is the orthogonality between the shocks for supply and demand, $\tilde{\delta}_t^i$ and $\tilde{\varepsilon}_t^i$. Note that these are error terms after controlling for the category-specific time-varying shocks, such as natural disasters and large macroeconomic shocks, which could shift both the demand and supply curves at the same time. As we have two unknown parameters, σ and ω, we require two or more moment conditions to identify them. In this analysis, we use the following three moment conditions,[4]

$$E\left[\tilde{\delta}_t^i \tilde{\varepsilon}_t^i\right] = 0,$$

$$\mathrm{E}\left[\tilde{\delta}_t^{i\,2} \tilde{\varepsilon}_t^i\right] = 0 \ ,$$

$$\mathrm{E}\left[\tilde{\delta}_t^i \tilde{\varepsilon}_t^{i\,2}\right] = 0 \ ,$$

which implies that the model is overidentified.[5] As pointed out by Leamer (1981),

[4] Note that the obvious moment conditions, $E\left[\tilde{\delta}_t^i\right] = 0$ or $E\left[\tilde{\varepsilon}_t^i\right] = 0$, cannot be used for identification because, by construction, the sample moments of $\tilde{\delta}_t^i$ and $\tilde{\varepsilon}_t^i$ are always zero for all *j* and *t*, i.e., $\sum_{i \in \Theta_t^{j,s}} \tilde{\delta}_t^i = 0$ and $\sum_{i \in \Theta_t^{j,s}} \tilde{\varepsilon}_t^i = 0$.

[5] Instead of three moment conditions, Feenstra (1994) and others, including Broda and Weinstein (2010), used only a single condition, $E\left[\tilde{\delta}_t^i \tilde{\varepsilon}_t^i\right]$ =0. To identify two parameters, Feenstra (1994) used

identification based on orthogonality between the residuals cannot yield the unique estimates of the parameters. The reason is simple. Suppose a set of parameters $(\hat{\sigma}, \widehat{\omega}) = (\alpha, \beta)$ satisfies the above moment conditions. Then, another set, $(\hat{\sigma}, \widehat{\omega}) = (\beta, \alpha)$, also satisfies the moment conditions because the system is symmetric for demand and supply. In our analysis, we consider an estimate with a negative slope as the elasticity of the demand curve, while the one with a positive slope as for the elasticity of supply curve. If the estimated pair of elasticities indicates that both slopes have the same sign, we remove the category.[6]

After obtaining the estimates of the elasticities, $(\hat{\sigma}, \widehat{\omega})$, we plug them into (1) and (3), which gives us the following two sets of shocks,

$$\hat{\varepsilon}_t^i \equiv \Delta \ln(x_t^i) + \hat{\sigma} \Delta \ln\left(p_t^i\right), \text{ and}$$
$$\hat{\delta}_t^i \equiv \Delta \ln\left(x_t^i\right) - \widehat{\omega} \Delta \ln\left(p_t^i\right),$$

where $\hat{\varepsilon}_t^i$ and $\hat{\delta}_t^i$ contain both commodity- and category-specific shocks that shift the category-level demand and supply curves, respectively.

The final step of the estimation is aggregation over commodities and categories. We use Törnqvist weights of sales for both aggregations. It is also possible that given we assume a CES function for the category-level aggregation formula, a Sato–Vartia-type aggregation formula could be more appropriate for aggregating the demand shocks.[7] We employ the Törnqvist weights for two reasons. First, the Törnqvist index is a superlative index considered a good approximation for a large class of expenditure/cost functions.[8] Because of these characteristics, we do not need to specify the functional form of the utility or cost function. Second, aggregation with Törnqvist weights creates very similar results to those using the Sato–Vartia formulation.

One drawback of this above approach is the restriction imposed on the product space.

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the relationship, $\tilde{\delta}_t^i \tilde{\varepsilon}_t^i = {\tilde{x}_t^i}^2 + (\sigma - \omega)\tilde{x}_t^i \tilde{p}_t^i - \omega\sigma {\tilde{p}_t^i}^2$, and regressed ${\tilde{p}_t^i}^2$ on ${\tilde{x}_t^i}^2$ and $\tilde{x}_t^i \tilde{p}_t^i$ with the product indicators as instruments. Although this approach is frequently used in the literature, including Broda and Weinstein (2010) and Soderbery (2015), to implement this procedure $\tilde{\delta}_t^i \tilde{\varepsilon}_t^i$ needs to be uncorrelated with $\tilde{x}_t^i \tilde{p}_t^i$ and ${\tilde{x}_t^i}^2$, which requires additional assumptions on both the demand and supply shocks. Rather than adding these assumptions, we use additional moment conditions.

[6] When estimating the elasticities, we used STATA command for the generalized moment methods (GMM) with a diagonal weight matrix.

[7] Sato (1976) provides details.

[8] See Diewert (1976).

To take the first differences in price and quantity for each product, we need information on price and quantity in two different periods, i.e., the current period and the base period. In other words, we are unable to calculate first differences for new products that do not exist in any base period. Therefore, we would be obliged to ignore these observations in our estimations. As long as the appearance of new products is uncorrelated with either demand or supply shocks, exclusion of new (and even withdrawn) goods might not be a serious problem when estimating demand and supply shocks.

However, if producers with large supply shocks, or households with large demand shocks, change their product choices more often than without shocks, estimation based only on continuing goods could lead to biased estimation of the magnitude of shocks. Of course, we could consider the effects of product turnover on the cost of living index by including variety-expansion effects (and their corresponding terms) in (1) and (3).[9] Because the effects of variety expansion or contraction are common to all the commodities in the same category, these effects are included in the category-specific effects. That is, our estimates of the aggregate demand and supply shocks include effects through changes in the variety-expansion effects as long as the variety effects shift the demand or supply curves. If not, our model cannot capture these effects, which will be one of our research tasks.

In addition to the barcode-level estimation, we also employ producer-level aggregate variables. More specifically, for each category and producer, we first construct a total volume and unit value price by dividing total sales by total volume (i.e. price per gram). Then, after taking the first difference, we take additional differences from the average quantity for each category after excluding the same producer to control for category-specific demand and supply shocks. Using the unit value price enables us to include any new goods that did not exist a year before. Therefore, if producers introduce new goods with a smaller or larger portion than the incumbent goods, we can regard their introduction as a price adjustment.

The obvious disadvantage of using unit values is that we need to assume that the qualities of all the goods are identical apart from their volumes. It is often the case that producers claim improvements in quality when introducing new goods,. As long as we use barcode-level information, we do not need to consider the difference in quality among products because we treat all the goods as different commodities, even if some goods are virtually identical to the incumbent goods. Alternatively, if we consider all unit value price, we treat all goods from the same producer as having the same quality,

[9] See Feenstra (1994) for detail.

which is at the other extreme. The ideal way would be to conduct a hedonic regression including all observable characteristics, but this is impractical for large scanner datasets. Thus, we adopt two extreme strategies, one employing barcode-level information, and the other producer-level unit value.

4. Data

We use Japanese store-level weekly scanner data, known as SRI,[10] collected by INTAGE Inc. The sales records included in the dataset cover processed foods, daily necessities, as well as cosmetics and drugs with a Japanese Article Number (JAN) code.[11,12] The sample period is between January 2007 and February 2016. The dataset covers about 1,000 supermarkets located throughout Japan.

One of the noteworthy characteristics of the dataset is its detailed commodity classification, with commodities classified into 1,041 different subcategories. This is about seven times larger than the number of classifications adopted by the Japanese official statistics for similar types of goods. Table 1 presents the basic statistics for the dataset used.

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[10] SRI is the abbreviation for "Syakaichosa-kenkyujo Retail Index," translated from Japanese as Retail Index by The Institute of Social Research.

[11] The dataset provide pretax price information.

[12] Unfortunately, fresh foods are not included in the dataset because of the lack of suitable commodity codes.

Table 1: Summary of Weekly Transaction Data

	Mean	Std. Dev.	Min	Max
Total				
Sales (million yen)	5,290	348	3,916	6,408
Continuing Goods	3,609	328	2,711	4,598
New Goods	1,681	237	1,205	2,470
New Product Ratio	0.318	0.041	0.249	0.429
Number of Categories	930	5.163	917	944
Number of Stores	980	23.834	929	1042
Foods				
Sales (million yen)	4,930	345	3,617	6,049
Continuing Goods	3,410	321	2,566	4,369
New Goods	1,520	223	1,052	2,275
New Product Ratio	0.308	0.041	0.238	0.418
Number of Categories	785	4.360	773	796
Number of Stores	980	23.834	929	1042
Daily Commodities				
Sales (million yen)	360	28	273	553
Continuing Goods	199	21	145	316
New Goods	161	21	120	237
New Product Ratio	0.446	0.041	0.360	0.566
Number of Categories	145	2.302	139	151
Number of Stores	974	24.146	922	1038

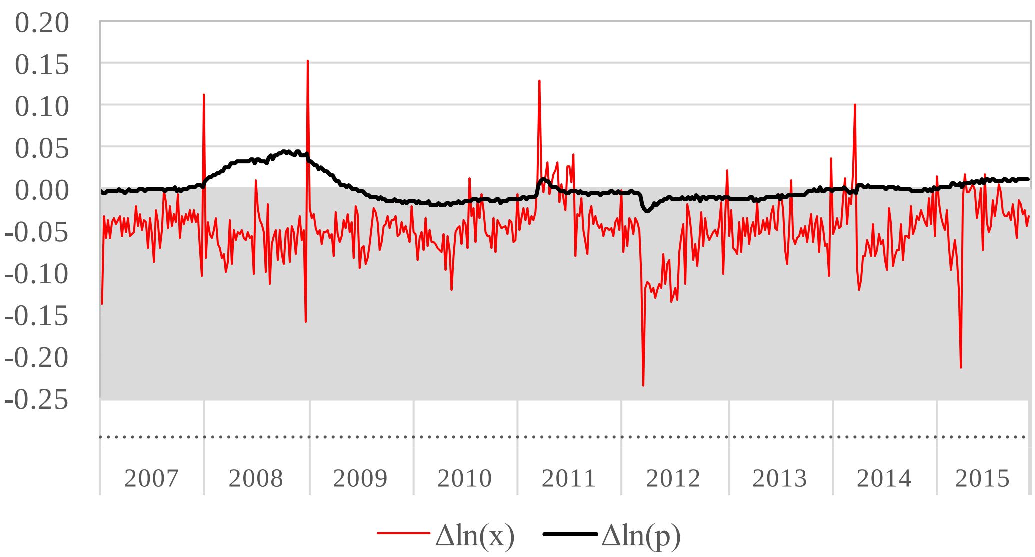
Note: Weekly point of sale data for supermarkets, from January 2007 to February, 2016. Tobacco is not included. "Foods" include processed food such as milk, bottled water, canned or frozen foods, pasta, sugar, and salt. "Daily Commodities" includes various items available in supermarkets, such as detergent, shampoo, and toilet papers.

Figure 1 plots the movements of the aggregate first-difference series of prices and quantities.[13] We treat commodities with the same JAN code sold at different stores as different commodities when constructing the series. As shown, the aggregate price is much smoother than the aggregate quantity. The effect of the GFC is clear in the second half of 2009. Likewise, the sudden increase in both price and quantity in early 2011 reflects the GEJE. We can also observe an increase in quantity in early 2014, likely

[13] These shocks are the weighted average of the categorical-level first differences using the Törnqvist sales weights.

reflecting the change in the consumption tax rate from 5% to 8% on April 1, 2014.

Figure 1: Barcode-level Price and Quantity (Continuing Goods)



Continuing goods are commodities that exist in both the current week and the same week in a year before. In other words, continuing goods are commodities for which we can calculate yearly differences in their prices and quantities. New goods are commodities without a sales record in the same week in a year before. According to Table 1, a significant amount of new goods is present in the dataset, which represents about 30% of all goods included.

Figure 2: Unit Value Price and Volume×Quantity (All Goods)

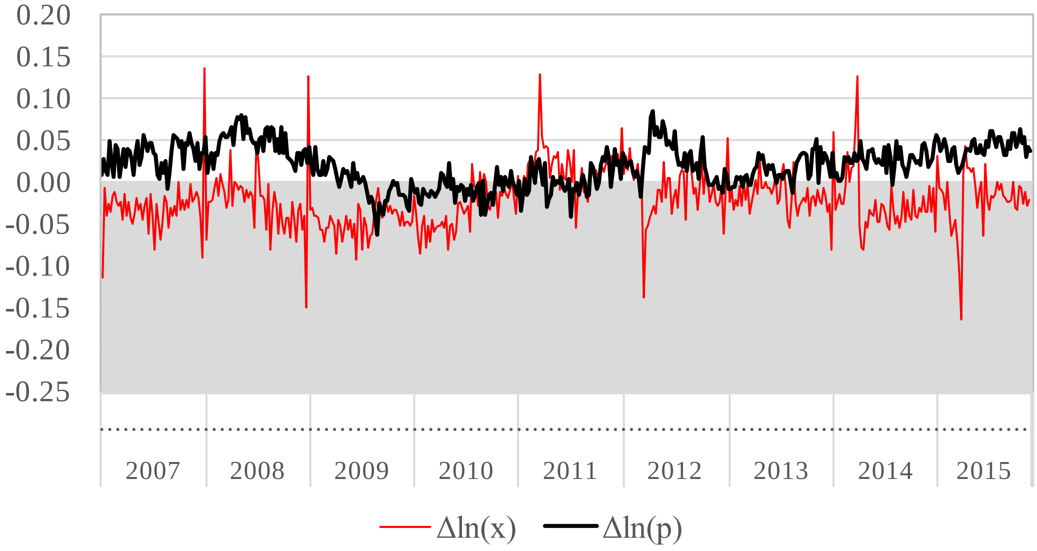
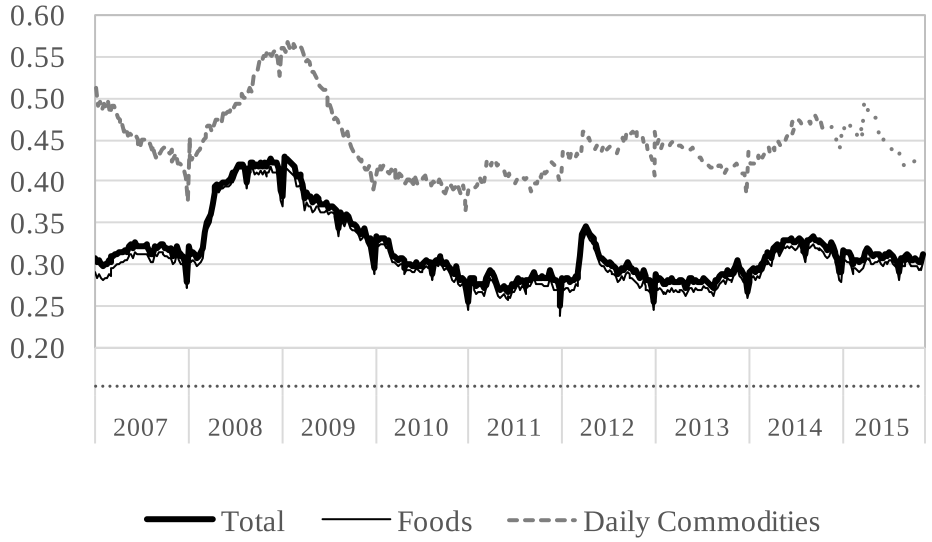


Figure 2 depicts the movements of price and quantity when we use the producer-level unit value price and total volume that includes both new goods as well as incumbent goods. Compared with the previous figure, we can observe higher price increases since mid-2013, which suggests the significant effects of the introduction of relatively more expensive goods during that period. These differences between Figures 1 and 2 suggest a relation between macroeconomic conditions and the introduction and removal of goods. Figure 3 illustrates the changes in the sales of new goods to total goods, we readily can observe a sharp increase and a sharp decrease before and after the GFC in 2008-2009, respectively. The surge in the new product ratio in 2012 reflects the shortage immediately following the GEJE in March 2011. In early 2014, the new product ratio began again to increase, which is consistent with the difference between Figures 1 and 2 over the same period.

Figure 3: New Product Ratio



5. Estimation Results

Table 2 provides the estimation results for the demand and supply shocks. The demand elasticity estimates employ barcode-level information similar to previous estimates by Broda and Weinstein (2010), in which the median elasticity is 11.5 and ours is 11.86. The supply elasticities are generally smaller than those for demand, suggesting a relatively flatter supply curve than demand curve, which we consider a reasonable response for changes in the one year.

The producer-level elasticities are much smaller than the barcode-level elasticities, implying a smaller level of substitution between producers than between commodities. In this paper, we use the nationwide category-and producer-level aggregate unit value price and volume for each producer, and the store- and barcode-level data for the barcode-level estimation. Thus, if one store conducts bargain sales for one commodity, we would observe large increases and decreases in quantity, which can make the estimates of the demand elasticities very large. We expect the nationwide category- and producer-level aggregates to be largely unaffected by store-level bargain sales.[14]

[14] Note that the sample size is large when estimating the model, which leads to very strong power in the overidentification test.

Table 2: Estimation Results of Demand and Supply Elasticities

	Barcode Level (continuing goods only)		Producer Level (including new goods)	
Number of Categories				
Achieved Convergence	790		830	
The sign of σ and ω are consistent with the model	701		806	
Passing Overidentifying Restrictions (p_value(J-stat) >0.1)	474		550	
Basic Statistics for σ and ω	Demand Elasticity σ	Supply Elasticity ω	Demand Elasticity σ	Supply Elasticity ω
Mean	13.21	10.16	2.46	1.42
Min	0.62	0.03	0.00	0.01
Max	115.80	1248.37	39.51	55.86
Std. Dev.	8.70	47.65	2.65	2.97
Skew	4.64	25.11	5.74	11.30
Kurt	41.17	652.38	61.87	176.89
p10	6.11	1.53	0.67	0.23
p20	8.33	3.27	0.97	0.34
p30	9.97	4.75	1.20	0.49
p40	10.88	5.74	1.46	0.66
p50	11.86	6.70	1.75	0.84
p60	12.76	7.78	2.10	1.03
p70	13.82	9.06	2.62	1.29
p80	15.82	10.90	3.50	1.69
p90	20.92	14.75	4.88	2.54

Note: Using GMM with three moment conditions over 1,041 categories. Only estimates whose signs are consistent with theory (negative slope for demand, positive slope for supply) were included in the basic statistics.

Figure 4 depicts the movement of the estimated demand and supply shocks based on the barcode-level information. Supply shocks were negative during 2008, likely reflecting the increase in the prices of materials and oil before the GFC. For the remaining periods, there are no notable supply shocks, except for negative supply shocks after late 2013. Compared with the supply shocks, the demand shocks are more frequent and exhibit larger fluctuations. Before the GFC in 2008, very large positive demand shocks took place. According to Figure 1, during that period, prices increased while quantities did not, which suggests upward shifts in the demand curve and downward shifts in the supply curve. After the GEJE, there was another large positive demand shock. However, before the change in the consumption tax rate in April 1, 2014, the demand shock is negligible, which is somewhat perplexing. According to Figure 1, prices declined during that period, while quantity surged. In our model, given the supply shocks, positive demand shocks arise when the demand curve shifts up, which lets the equilibrium price increase. However, before the tax increase, and as shown in Figure 1, prices did not increase, which results in very small estimates for the demand shocks.

Figure 4: Demand and Supply Shocks Using Barcode-level Data

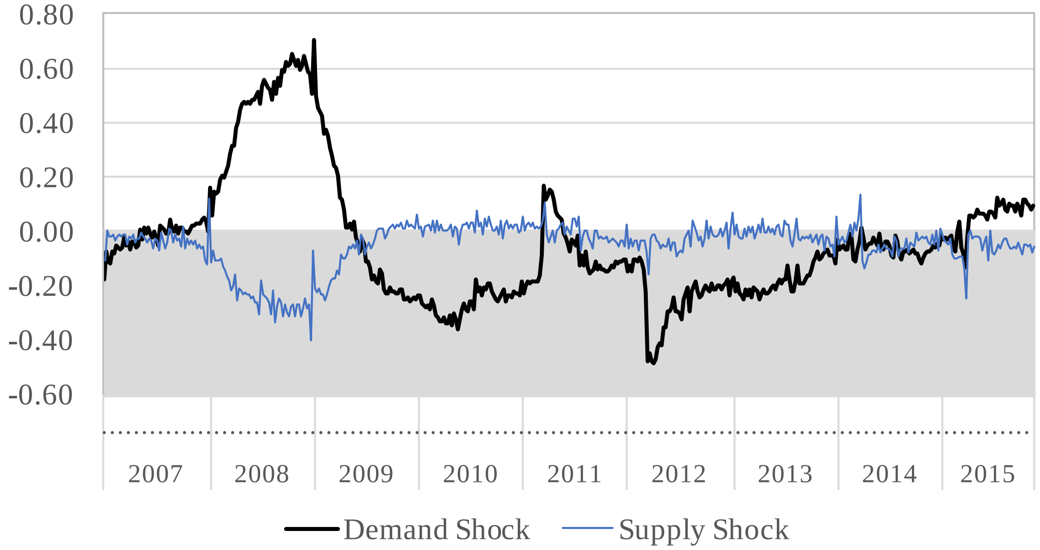
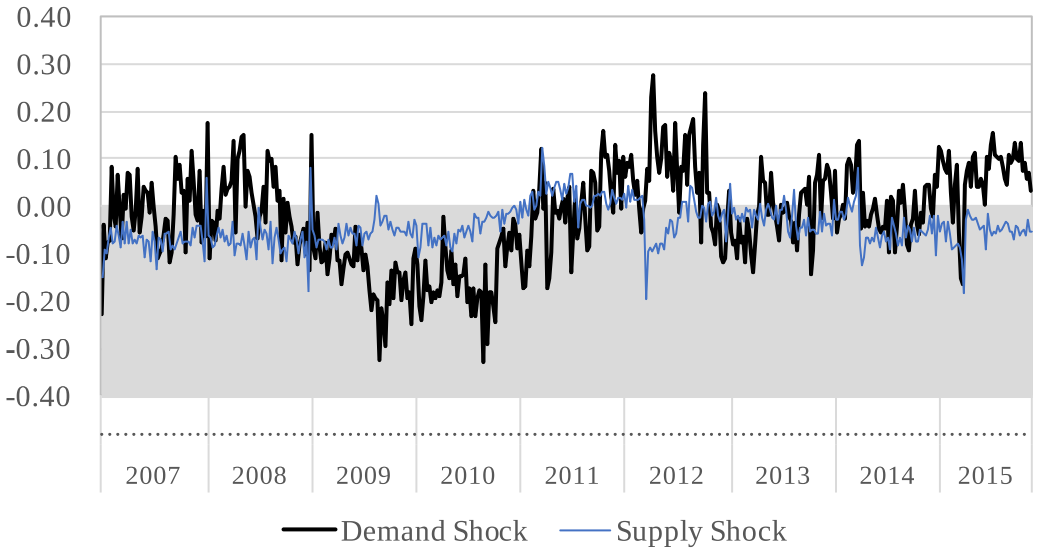


Figure 5 depicts the estimates of demand and supply shocks using the producer-level unit value prices and quantities for both new and incumbent goods. The estimated demand and supply shocks in Figure 5 are very different from those in Figure 4 with the magnitude of the demand shock becoming much smaller in Figure 5 than in Figure 4 before the GFC. This most likely reflects the increase in unit value prices before the tax change in 2014, where the demand shock before the change in the tax rate is large and positive. This is more consistent with the conventional view of stockpiling behavior preceding an increase in a tax rate than the estimates using the barcode-level continuing goods in Figure 4.

The estimated supply shocks do not exhibit a clear relationship with the GFC, which suggests that demand drove most of the shocks associated with the GFC. After the GEJE in March 2011, there were a number of temporary negative supply shocks. Large negative supply shocks arose after the change in the consumption tax rate, which reflects the increases in prices first observed in Figure 2. After mid-2013, the supply shocks remained at a very low level except for the temporary increases and decreases resulting from the change in consumption tax. In both Figures 4 and 5, the supply shocks after 2014 are negative, which indicates that price increases in this period are, at least in part, caused by inward shifts of the supply curve.

Figure 5: Demand and Supply Shocks Based on All Commodities



Figures 4 and 5 depict the results for all categories for which we can obtain estimates of the demand and supply elasticities.[15] As shown in Table 2 indicates, the numbers of categories differ across the two specifications, with the barcode-level estimates including continuing goods (701), and the producer-level estimate drawing all goods (806). Figure 6 depicts the aggregate demand and supply shocks based on the same category set between 2013 and 2015.[16] The demand shocks based on all commodities are generally larger than shocks based only on continuing goods, which suggests that some parts of the positive demand shocks are absorbed in new goods. The differences in supply shocks between the two specifications are much smaller than for the demand shocks, which suggest that supply side shocks do not coincide with the introduction of new goods nor increased product turnover.

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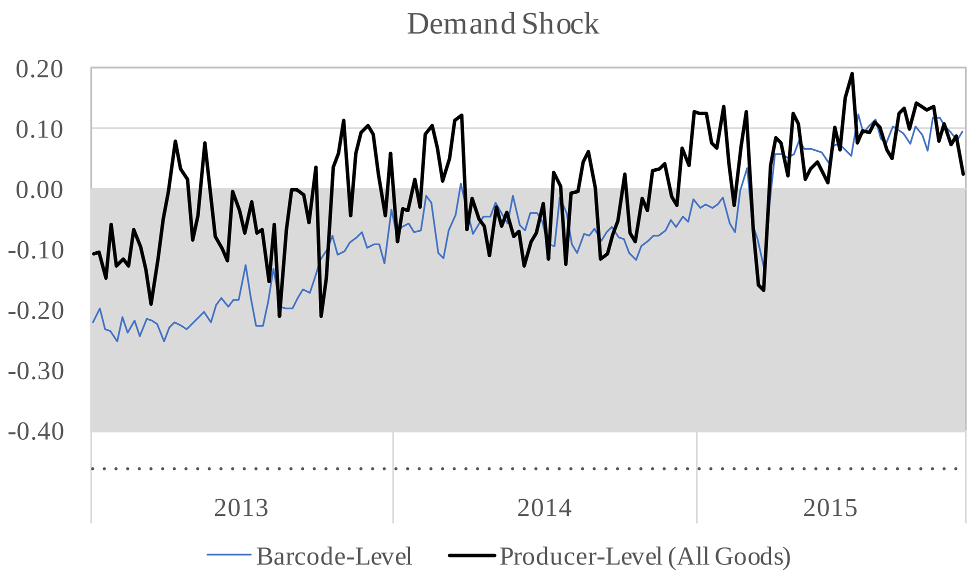
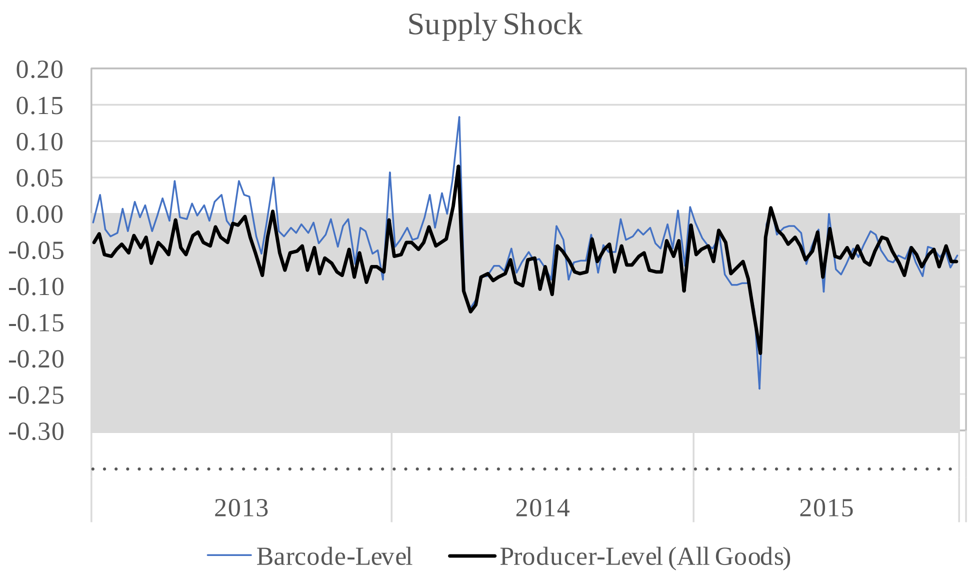
15 We dropped categories either where the GMM estimation did not converge or where the slopes of the demand and supply curves have the same sign.
16 There are 637 categories in Figures 6.

Figure 6: Comparisons of the Aggregate Demand and Supply Shocks





6. Conclusions

We used barcode-level transaction data to estimate the aggregate demand and supply shocks. The estimated demand shocks exhibit large fluctuations, while the estimated supply shocks are much smoother. When we use the barcode-level information for only continuing goods, the demand shock before the change in the rate of consumption tax is negligible, thereby contradicting the conventional view on stockpiling behavior. This somewhat perplexing result arises because of the preceding decline in the price index. When we consider goods that did not exist in the previous year, the estimated demand shock becomes positive, which suggests that significant stockpiling behavior was associated with the purchase of new goods. The supply shocks are then negative after the end of 2013, which suggests that increases in prices during that period are at least partly reflect the inward shifts of the supply curves.

There are several remaining tasks for research. First, we have not considered the source(s) of the supply and demand shocks. Macroeconomic shocks such as currency depreciation and changes in the prices of oil, grains, and materials might affect the supply, while changes in income tax, weather, monetary and fiscal policy, and stock prices could affect demand. To decompose the shocks into their several sources, we would need to use information on input-output table and category-level shocks. Investigation of regional variations of shocks is another important topic. For example, the GEJE occurred in the northeast part of Japan. While it affected the entire eastern part of Japan in March 2011, the western part of Japan was virtually intact. In addition, heavy snowfalls in northern parts of Japan or typhoons in south might create region-specific demand and/or supply shocks. Investigation of the region-specific demand and supply shocks will be our next task.

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