Product Cycle and Consumer Price Index *

- Very Preliminary -

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Abstract

This paper shows that the official Consumer Price Index (CPI) is quantitatively well affected by product entry and exit, i.e., the number of product in the entire market. We make use of an unique environment where the Nikkei point of sale (POS) scanner data has larger samples than the official CPI for food products and daily necessities in Japanese supermarkets. We first estimate the representative product entry model in Bilbiie, Ghironi, and Melitz (2007) for the Nikkei data and confirm that the model fits to the data well and a free entry shock related to a product entry explains about 49 percent of price variations. Then, we evaluate whether the official CPI holds the same features as the Nikkei data or not. When we estimate the product entry model for variants of the official CPIs, estimated parameters are the almost same as the cases for the Nikkei data and a free entry shock explains about 19 percent of price variations in the official CPI including all items. Sampling for the official CPI is sufficiently precise to reflects Japanese product market features and an effect of the number of products on prices through an intensive margin effect though the official CPI assume a constant basket.

Our result provides several implications for economic analyses. A product entry makes quantitatively significant effects on prices and decreases a standard deviation of the official CPI inflation rates by about 41 percent. Moreover, a product entry contributes to make a secular deflation in the last several decades and a large inflation rise in the last few years in Japan. It implies that a model discarding an endogenous product entry and product number data can not evaluate these and suffers from under and over-evaluation in estimations, variance decompositions, and impulse responses.

Keywords: product entry; consumer price index; economic analysis

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1 Introduction

Bilbiie, Ghironi, and Melitz (2007, 2012) show that a new product entry changes price setting behaviors in a product market by a variety effect which is described by the number of products. Moreover, it is conventional idea in economics that a firm's price setting is affected by other firms' price settings across the entire market. A price setting behavior changes by a degree of competition under monopoly, oligopoly, monopolistic competition, or perfect competition. Therefore, the number of products in a market is an important element to change individual prices.

Recently, we can precisely observe a product cycle, i.e., a new product entry into a market and an old product exit from a market, everyday using product-level micro data. The number of products frequently changes in a market.[1] On the other hand, the official Consumer Price Index (CPI) excludes such frequent product entry and exit and assumes a constant basket of products. Therefore, the index seems to ignore product entry and exit. It, however, is not necessarily discarding effects of product entry and exit.

The index naturally excludes a price effect by a change in the number of products in the basket, i.e., an extensive margin effect. However, the index can include a price effect by a variable number of products in the entire market on an individual price in the basket, i.e., an intensive margin effect. Here, we have two "if(s)" to conclude that the official CPI is affected by the number of products. The official CPI is affected by the number of products if prices in the population data are affected by the number of products, and if the official CPI well represents the population data.

For Japan, we can evaluate these two "if(s)". We take advantage of an unique Japanese data environment where the Nikkei point of sale (POS) scanner data has larger samples than the official CPI as shown in Imai and Watanabe (2015) and Watanabe and

[1] Several empirical studies find that a frequent product entry and exit in a product market. Broda and Weinstein (2010) show, when using product-level micro data, that the product turnover rate in the US is about 25 percent annually. Ueda, Watanabe, and Watanabe (2019) confirm the same facts for Japan using matched samples of Nikkei point of sale scanner data and show that product turnover is 30 percent annually in Japan.

Watanabe (2014). The official CPI can be interpreted as a sub-sample of the Nikkei POS scanner data. The Nikkei data is a private data and corrects sales prices and quantities for all food products and daily necessities from Japanese supermarkets for long years from April 1988 to present. In the end of 2022 year, the items included in data is about 170 out of the 588 items in the official CPI in Japan. However, when we restrict a sample to these 170 items, corrected samples are much larger in Nikkei data than the official CPI. Imai and Watanabe (2015) show that the number of products in the Nikkei data from 2000 to 2010 year is $462,906$. Among these samples, only $70,966$ products meet the Statistic Bureau of Japan specifications that can be sampled in the official CPI. This is because the Nikkei data basically includes all products in supermarkets and the official price indexes arbitrary pick up some representative products that samplers think in each category.

For the first "if", we evaluate product entry effect on prices using the Nikkei data. In evaluation, we focus on a mechanism behind an intensive margin effect on prices since an extensive margin effect is a simple calculation in aggregating individual prices in data. To see an intensive margin effect, we use the representative endogenous product entry model in Bilbiie, Ghironi, and Melitz (2007). This model is well known and commonly used to business cycle and price analyses for a product entry. In the model, a variable number of products in the entire market changes prices through a variety effect. For data, based on individual prices in the Nikkei data, we construct the sales-weighted average price across all products including temporary sales and all shops for each quarter. This is the Supermarket Basket Price Index (SBPI) as shown in Dong, Shoji, and Teranishi (2024). This price index allows the number of products to change over time by product entry and exit. Here, we know the real sales amount, the number of product, and SBPI, where these are consistent each others.

We estimate the BGM model by Bayesian inference and show that the endogenous product entry model fits to the data well. By variance decomposition, we show that a free entry shock that is related to a product entry explains about a half of SBPI variations. When we compare BGM model and a standard New Keynesian model to quantitatively evaluate a contribution of a product entry on price variations, contributions significantly change from 40.9 percent to 56.8 percent in different specifications. These results imply that a product entry quantitatively holds a clear effect on prices for food products and daily necessities in Japan. This conclusion does not change even for several SBPI variants that replicate sampling and calculation method in the official CPI. In particular, we show two cases, using a trend component of SBPI to exclude temporary sales and a matched-products version of SBPI to calculate inflation rate based on individual prices. These results are proof for the first "if".

For the second "if", supposing a relationship between the Nikkei data as a population data and the official CPI as a sub-sample of the Nikkei data, we replace SBPI by the official CPIs and estimate models. Here, we also make use of a feature of the BGM model in which an individual price is the same for all products and is determined by an aggregate demand and the number of products for whole products after applying the symmetric equilibrium assumption. Thus, if the official CPI correctly reflects the population data, we can replace SBPI by the official CPI. We suggest a new approach for price analyses by combining Japanese macro-level official CPI data with micro-level Nikkei data. In the first experiment, we replace SBPI by the limited official CPI that only includes categories of the Nikkei data. In the second experiment, we replace SBPI by the official CPI for all items including all service prices and all goods prices. Here, we need a strong assumption that the same endogenous entry effect holds for services and goods that are excluded in the Nikkei data.

Estimation results show that the model is well estimated and estimated key parameters such as elasticity of substitution across goods and intertemporal elasticity of labor substitution are the almost same as the case using Nikkei data. For a price stickiness, a price adjustment parameter is estimated larger than the case using the Nikkei data since the official CPI excludes temporary sales and its price variations are smaller than ones of the Nikkei data. For this point, we confirm that a price adjustment parameter is estimated larger when we exclude temporary sales from SBPI. As the case of the Nikkei data, a free entry shock explains non-trivial part of price variations in the official CPI.

These results show that the official CPI is affected by a product entry as the Nikkei data though the official index itself assumes a constant basket. Thus, the official CPI is a representative sample of population data of the Nikkei data. It implies that the second "if" is proved.

Then, we show several implications for macro-level economic analysis using the official CPI. First, a product entry have quantitatively non-trivial effects on prices. A standard deviation of CPI inflation rates decreases 40.9 percent by a product entry. Second, a free entry shock that is related to a product entry explains about 19 percent of price variations in the official CPI. Free entry shocks sometime decrease official CPI inflation rates more than one percent and further the shock continuously contributes to a secular deflation in Japan. Moreover, the latest inflation surge is explained by increasing number of products. Third, a model selection failure makes a serious problem when we use the official CPI and a model discarding a product entry and a variable number of the products. By misidentifications, models suffer from large over- and under-evaluations in estimation, impulse responses, and variance decompositions.

The rest of our paper is organized as follows. Section 2 describes our data and discuss advantage of the data. Section 3 introduces BGM model and estimate it using Nikkei data. We show that BGM model fits to Nikkei data well. Then, we evaluate a quantitative effect of a product entry and a variable number of product on prices in Section 4. Section 5 shows that SBPI variant data that includes sampling features of the official CPI gives the same result for estimations. In Section 6, we show that the official CPI is a good sample of Nikkei data and is affected by a product entry and a variable number of products. Section 7 discuss some implications for economic analyses. Section 8 concludes.

2 the Nikkei POS scanner data

We use a unique data set, the Nikkei POS scanner data.[2] Our data includes sales prices and quantities for each product at each retail shop on each day from April 1988 to December 2022. The retail shops consist of supermarkets in Japan, where typically food products and daily necessities are sold. The scanner data covers 170 out of the 588 items in the Japanese CPI.[3] At the start of our sample period, there are 29 supermarkets and the number of shops increases to 300 at the end of the sample. Our analysis is restricted to the 7 supermarkets that appear throughout the sample period. This sample restriction avoids any bias caused by shop entry and exit in prices. We interpret the data from the 7 supermarkets as a random sample to observe prices, the sales amount, and the number of products. The 7-supermarket sample has $900,000$ products in total, about $77,000$ products on average per year, and about $30,000$ products on average per retailer per year. We use quarterly data though the original Nikkei POS scanner data is daily.[4]

The first advantage of our data is that we can observe product cycles. An individual product's life cycle can be clearly identified through its entry into and exit from the product market. We know an exact product number in a market. The average of the number of products in our Nikkei data is 52884.32 and the standard deviation of the number of products is 15438.89, as shown in Table 1. It is in sharp contrast with the official CPI which changes the number of products and a variety of products only every five years. Entry rate and exit rate in data are 0.122 and 0.115, respectively, as shown in Table 1. These imply that all product are replaced by about nine quarters on average. The second advantage is that we can observe individual product prices over the product's life cycle. Based on individual prices, we construct the sales-weighted average price across all products including temporary sales and all shops for each quarter. We label this unique price index as the Supermarket Basket Price Index (SBPI) as in Dong,

[2]Appendix A has detailed information about the data, including product identification by Japanese Article Number (JAN) code, average price, entry rate, exit rate, and product varieties.

[3]Our data does not include fresh food, recreational durable goods, such as computers and cell phones, and services such as housing rent and utilities.

[4]See Appendix A for a description of how we convert daily data into quarterly data.

Shoji, and Teranishi (2024). Naturally, this price index allows the number of products to change over time. The third advantage is that we know the sales amount that is consistent with the number of product and SBPI. An average nominal sales amount is $4,354,313,201$ yen and its one standard deviation is $750,835,205$ yen as shown in Table 1. In real term, an average real sales amount denominated by SBPI is $6,830,135$ and its one standard deviation is $940,731$. In the official CPI, we do not know these. Figure 1 shows SBPI inflation rate, the number of products, and the real sales amount. SBPI inflation rate is given by year to year growth of SBPI. The number of products and the sales amount data are percentage deviations from trends calculated by HP filter. These numbers are not multiplied by 100. The real sales amount is deflated by SBPI and we call it as demand in following analyses. The sample covers from 1988Q2 to 2022Q4 and includes several business cycles. Therefore, we can precisely estimate models including product entry and exit.

Furthermore, our unique Nikkei POS data makes a new insight possible. As shown in Imai and Watanabe (2015) and Watanabe and Watanabe (2014), the official CPI observes the same products in Japanese supermarkets as the Nikkei data and can be interpreted as a constant sub-sample of the Nikkei data when we restrict product categories (items) as in our sample. In particular, Imai and Watanabe (2015) show that the number of products in the Nikkei data from 2000 to 2010 year is $462,906$. Among these samples, only $70,966$ products meet the Statistic Bureau of Japan specifications that can be sampled in the official CPI. This is because the Nikkei data includes all products in supermarkets and the official price indexes arbitrary pick up some representative products that samplers think in each category. These official indexes keep a constant basket size without product entry and exit and include long surviving existing products.[5] Under this unique environment in Japan, we can evaluate whether Japanese official CPI reflects a product entry effect on prices.

[5]Probably, there is forced product exit and entry by a product exit from a market and adding a new successor product to an old predecessor keeps a constant basket. We, however, can not know the details for it.

3 Product Entry Effect in SBPI

When we see Nikkei data, it is apparent that there exists a product entry and it holds a significant effect on prices. We, however, do not know a mechanism behind the data, in particular for an intensive margin effect on prices by a product entry. Thus, through lens of a representative endogenous product entry model in Bilbiie, Ghironi, and Melitz (2007), we quantitatively show an intensive margin effect on prices by a variety effect in SBPI. We estimate the model with Bayesian inferences using Dynare 5.2.

3.1 Observations using Bilbiie, Ghironi, and Melitz's Model

We use BGM model given by following five equations.

$$\begin{aligned} \mathrm{E}_t N_{t+1} &= (1+r+\psi) N_t - (r+\rho+\psi) C_t - \psi(\theta-1)\mu_t \\ &+ [(r+\rho+\psi)(\theta-1)+\rho] Z_t - \rho f_{E,t}, \end{aligned} \tag{1}$$

$$\begin{aligned} C_t &= \frac{1-\rho}{1+r}\mathrm{E}_t C_{t+1} - \left[\frac{1-\rho}{(1+r)(\theta-1)} - \frac{r+\rho}{1+r}\right]\mathrm{E}_t N_{t+1} \\ &+ \frac{1}{\theta-1}N_t - \frac{1-\rho}{1+r}\mathrm{E}_t f_{E,t+1} + f_{E,t} \\ &+ \left[\frac{1-\rho}{1+r} - \frac{r+\rho}{1+r}(\theta-1)\right]\mathrm{E}_t \mu_{t+1} - \mu_t, \end{aligned} \tag{2}$$

$$\begin{aligned} \pi_t^C &= \beta(1-\rho)\mathrm{E}_t \pi_{t+1}^C - \frac{\theta-1}{\kappa}\mu_t \\ &- \frac{1}{\theta-1}\left[N_t - N_{t-1} - \beta(1-\rho)(\mathrm{E}_t N_{t+1} - N_t)\right], \end{aligned} \tag{3}$$

$$\mathrm{E}_t C_{t+1} = C_t + i_t - \mathrm{E}_t \pi_{t+1}^C + \frac{1}{\theta-1}\mathrm{E}_t N_{t+1} - \frac{1}{\theta-1}N_t, \tag{4}$$

$$i = \phi_\pi \pi_{t+1}^C + M_t, \tag{5}$$

where N_t, C_t, μ_t, π_t^C, and i_t are the number of products, demand, markup, CPI inflation rate, and nominal interest rate, respectively. These are endogenous variables. As exogenous shocks, Z_t, $f_{E,t}$, and M_t are a productivity shock, a free entry shock, and a demand shock, respectively. As parameters, ρ, r, θ, φ, κ, and ϕ_π are separation rate, steady state real interest rate, the symmetric elasticity of substitution across goods, intertemporal elasticity of substitution in labor supply, a price adjustment parameter, and a monetary policy parameter, respectively. We define $\psi = \varphi \frac{(r+\rho)(\theta-1)+\rho}{\theta-1}$. It notes that we assume the CES preferences for the consumption aggregator. As mentioned in Bilbiie, Ghironi, and Melitz (2012), (1) determines the number of goods in a market according to a demand and a productivity shock. (2) determines a markup by the number of products and a free entry shock. (3) is a Phillips curve to determine CPI inflation rates by a markup and the number of products. These two equations show that an endogenous product entry holds clear effects on a price setting. (4) decides a demand according to a real interest rate and the number of products. A forward-looking monetary policy (5) sets a nominal interest rate as in Bilbiie, Ghironi, and Melitz (2007) and includes a demand shock.

3.2 Data and Observation Errors

We use Nikkei POS scanner data in a quarterly base over the sample from 1990Q2 to 2022Q4. The estimation uses three time series data, SBPI to π_t^C, the number of products to N_t, and real demand for products to C_t. π_t^C is given by year to year growth of SBPI. N_t and C_t data are percentage deviations from trends calculated by HP filter.

To include data into a model, we assume observation errors given by 10 percent of one standard deviation to an inflation rate, i.e., 0.068/10, the number of products, i.e., 0.04/10, and real demand, i.e., 0.2/10. Observation errors are assumed to be i.i.d. normally distributed with zero mean.

3.3 Calibrated Parameters and Shocks

We use a conventional value for a discount factor as $\beta = 0.99$ and $r = \beta^{-1} - 1$ for a quarterly model. We calibrate an exit rate as $\rho = 0.115$ as in Table 1. This is an average of exit rates from Nikkei data. As in Bilbiie, Ghironi, and Melitz (2007), we set $\phi_\pi = 1.5$.

We use three types of shocks, free entry shock $f_{E,t}$, productivity shock Z_t, and demand shock M_t, as shown in the model. We assume AR1 process with i.i.d. normally distributed disturbance as follows.

$$f_{E,t} = \rho_f f_{E,t-1} + \epsilon_t^f,$$

$$Z_t = \rho_z Z_{t-1} + \epsilon_t^z,$$

$$M_t = \rho_m M_{t-1} + \epsilon_t^m,$$

where standard deviations of ϵ_t^f, ϵ_t^z, and ϵ_t^m are given by σ_f, σ_z, and σ_m, respectively.

3.4 Prior and Posterior Distributions

Table 2 shows moments for the prior distributions of structural parameters. As prior distributions, we assume calibrated parameters in Bilbiie, Ghironi, and Melitz (2007) except shock persistences and standard deviations. For the symmetric elasticity of substitution across goods θ, the intertemporal elasticity of substitution in labor supply φ, and a price adjustment parameter κ, we assume Inverse Gamma Distribution since these parameters should be positives. Regarding a shock persistence, we assume Beta distribution with 0.5 mean. For a standard deviation of shock, we assume Inverse Gamma Distribution with 0.1 mean.

Figure 2 shows prior distributions colored by gray and estimated posterior distributions colored by black and Table 3 shows statistics for the distributions. Elasticity of substitution across goods θ and intertemporal elasticity of labor substitution φ are estimated as 7.834 and 0.486, respectively. For elasticity of substitution across goods, the estimated number is larger than a mean of prior that is calibrated in Bilbiie, Ghironi, and Melitz (2007). It implies that a variety effect is less elastic to the number of the products. A reason for it is that a variation of the product number is larger in our Nikkei data than in data that Bilbiie, Ghironi, and Melitz (2007) analyze as shown in separation rates as 0.025 in the paper and 0.115 in our paper. As shown in the estimation and variance decompositions in the next section, the product number data naturally gives fundamental quantitative effects for these.[6] For a price stickiness, a price adjustment parameter is estimated as 41.88. This is smaller than one in Bilbiie, Ghironi, and Melitz (2007). A reason is that the Nikkei data includes temporary sales and its price variations are larger than the official CPI that excludes temporary sales. We clarify it in Section 5.2. These estimation results are still reasonable numbers when comparing these to Bilbiie, Ghironi, and Melitz (2007).[7]

3.5 Variance Decomposition and Impulse Responses

As shown in Table 4, a productivity shock, a free entry shock, and a demand shock explain 38.78, 49.37, and 11.85 percent of CPI inflation rate variations, respectively. To CPI inflation rate, a free entry shock holds the largest effect. One reason for it is that a new price by a new product is directly included in SBPI without delays since SBPI inflation rate is calculated by year to year growth of price levels each period with sales weights across products as shown in Appendix A. For other variables, these shocks also play important roles.

Figure 3 shows impulse responses to a free entry shock that decreases a product entry. As discussed in Bilbiie, Ghironi, and Melitz (2007), to the shock, new entrants decrease and firm value increases since a relative price of investment goods increases. It makes consumption more attractive than investment and consumption increase in an initial period. In the long run, however, consumption decrease due to decrease in the number of products, i.e., extensive margin effect. CPI inflation rates decrease by negative PPI inflation rates due to decreasing marginal cost and by a variety effect under a product number returning to zero from negative values. Figure 4 shows impulse responses to a productivity shock. To the productivity shock, CPI inflation rates decrease due to a variety effect. Consumption increase due to an increasing product number and negative

[6] We show it by excluding the product number data in Appendix C for robust analyses.

[7] In the model of Bilbiie, Ghironi, and Melitz (2007), there is no extensive margin effect on prices since all firms set the same price each time after assuming a symmetric equilibrium. Thus, a price adjustment parameter includes an extensive margin effect in the Nikkei data and it can further decrease an estimated price adjustment parameter.

real interest rate. Figure 5 shows impulse responses to a demand shock by a monetary policy. When a nominal interest rate increases, consumption and CPI inflation rates decrease. The number of products increases since the expected return on equity increases by an increase in an interest rate.

These outcomes confirm that endogenous product entry well works for food products and daily necessities in Japan and holds essential effects on prices.[8]

4 Quantitative Effect of Product Entry

To quantitatively evaluate effects of endogenous product entry on prices in the BGM model, we use a standard New Keynesian model with Rotemberg price adjustment cost.

4.1 A Standard New Keynesian Model

This model does not include product entry nor exit. Under a similar structure of consumer's optimization problem and firm's price setting with Rotemberg price adjustment cost, a model is given by following two equations and the same monetary policy rule by (5).[9]

$$\pi_t^C = \beta \mathrm{E}_t \pi_{t+1}^C - \frac{1+\varphi}{\varphi}\frac{\theta-1}{\kappa}\left(Z_t - C_t\right), \tag{6}$$

$$C_t = \mathrm{E}_t C_{t+1} - \left(i_t - \mathrm{E}_t \pi_{t+1}^C\right). \tag{7}$$

The standard New Keynesian model does not include the number of products nor a free entry shock. Parameter structures also change and a price markup is constant.

[8]When we use SBPI, it is reasonable to interpret products in SBPI as homogeneous since these products are only food products and daily necessities in supermarkets. At the same time, we still can pay attention for heterogeneity in food products and daily necessities. For example, estimation result is shown for processed meats and seafoods in Appendix C for robust analysis.

[9]See this model's details in Appendix B.

4.2 Decomposing Price Variations by Product Entry

We quantitatively evaluate effects of endogenous product entry on prices by comparing two models for price variations. A standard New Keynesian model extracts all effects of product entry and exit. In impulse response analyses, we assume the same estimated parameters and shocks for two models as shown in Table 3.

Table 5 shows simulation results for BGM model and a standard New Keynesian model. A standard deviation of an inflation rate sufficiently changes from a standard New Keynesian model to BGM model. In a case of a CPI (PPI) inflation rate, a standard deviation decreases by 40.9 (42) percent.[10] Even when we exclude a free entry shock from BGM model, a standard deviation decreases by 56.8 percent for a CPI inflation rate. [Reason for reduction in Std] It confirms that product entry and exit hold significant effect on inflation rates and we can not ignore these effects for economic analyses using price data.

5 Nikkei Data and Official CPI

5.1 Unique Japanese Data Environment

Our question now is whether Japanese official CPI is affected by product entry and exit. Moreover, if affected, is it negligible or not? Our unique Nikkei data makes a new insight possible.

The Nikkei data is basically smaller statistic than Japanese official CPI since the Nikkei data only includes goods prices and excludes service prices. Moreover, goods samples are corrected in supermarkets, so the data excludes recreational durable goods, such as computers and cell phones. Eventually, the Nikkei data covers 170 out of the 588 items in Japanese CPI. As a sales weight, Nikkei data covers 17 percent of the prices

[10] To calculate PPI inflation rate π_t, we use an equation below as shown in Bilbiie, Ghironi, and Melitz (2007).

$$\pi_t = \pi_t^C + \frac{1}{\theta - 1}\left(N_t - N_{t-1}\right).$$

in the CPI. On the other hand, as shown in Imai and Watanabe (2015) and Watanabe and Watanabe (2014), Japanese official CPI can be interpreted as a constant sub-sample of the Nikkei POS data when we focus on these 170 items. Imai and Watanabe (2015) show that the number of products in Nikkei POS data from 2000 to 2010 year is $462,906$. Among these samples, only $70,966$ products meet the Statistic Bureau of Japan specifications for samples in the CPI. They show several experiments to make a similar inflation rate as the official CPI inflation rate from the Nikkei data. They assume virtual price collectors to pick up samples from the Nikkei data and change frequencies of shop and product replacements in samplings. Their finding is that we can make a similar inflation rate as the official CPI inflation rate from Nikkei POS data as a trend by sampling prices through infrequent shop and product replacements in the Nikkei data. To further match standard deviations, they show that an additional price stickiness by infrequent observation updating is necessary. Watanabe and Watanabe (2014) make another aggregate inflation rate from the Nikkei data. This is so called S Index of Nikkei CPINow and is updated to predict the official CPI. They show that this index can closely mimic the official CPI inflation rates.

These papers provide one objective evidence to show that the Nikkei data include necessary information to make the official CPI and the official CPI is a sub-sample of the Nikkei data.

5.2 Introducing CPI Sampling Features into SBPI

In this section, we show cases in which we introduce sampling features in the official CPI into SBPI and confirm that such sampling natures do not change estimation results in previous sections.

Trend for SBPI

Watanabe and Watanabe (2014) point out that the price index by the Nikkei data is more volatile than the official CPI due to temporary sales. To mitigate its effect on prices, they suggest to decompose the Nikkei data into a trend part and a cyclical part.

We replace SBPI by a trend component of SBPI. In particular, we use HP filter with a smooth parameter of 1600 as a simple method to make a trend component of SBPI. As shown in Table 1, standard deviations of SBPI inflation rate decrease from 0.068 to 0.041 by applying HP filter. New setting for estimation is to set observation error for CPI inflation rate as 0.041/10 and other settings do not change from Section 3.

Table 6 reports summarized statistics for posterior distributions. Elasticity of substitution across goods θ and intertemporal elasticity of labor substitution φ are estimated as 7.212 and 0.744, respectively. Elasticity of substitution across goods does not change from Table 3 for SBPI. Intertemporal elasticity of labor substitution slightly increases from Table 3. For a price stickiness, a price adjustment parameter κ is estimated as 68.71. It implies that CPI inflation rates are less volatile by taking trend and a model replicates it by a larger price adjustment parameter.

Matched-products SBPI

In the official CPI, inflation rates are calculated from individual product prices and then are aggregated to make the index. Here, we naturally need to allow one year lag for year to year inflation rate to include each product into the index after these products entry into a market. We follow this procedure to make a matched-products SBPI. We show details for a matched-products SBPI in Appendix A. A clear difference from an original SBPI is that we aggregate all prices each period to make a price level index and then calculate inflation rates in the SBPI. It notes that the number of products still changes over time in this index.

As shown in Table 1, standard deviations of SBPI inflation rate decrease from 0.068 to 0.014. This decreased number is very close to ones of the official CPI inflation rate as shown in last two rows. We replace SBPI by a matched-products SBPI. New setting for estimation is to set observation error for CPI inflation rate as 0.014/10 and other settings do not change from Section 3.

Table 7 reports summarized statistics for posterior distributions. Elasticity of substitution across goods θ and intertemporal elasticity of labor substitution φ are estimated as 7.849 and 0.679, respectively. Elasticity of substitution across goods does not change from Table 3 for SBPI. Intertemporal elasticity of labor substitution slightly increases from Table 3. For a price stickiness, a price adjustment parameter κ is estimated larger as 59.71.

6 Product Entry and Official CPI: Experiments

6.1 First Experiment

We suggest a new approach for price analyses by combining Japanese macro-level official CPI data with micro-level Nikkei data. We estimate BGM model for the limited official CPI inflation rate that corresponds to product categories in the Nikkei data.[11] Here, the official CPI is interpreted as random samples from the Nikkei data which works as population data as shown in Imai and Watanabe (2015). For a real demand, we use real gross domestic product (GDP) gap since it is a total demand for Japanese economy corresponding to macro-level official CPI.[12]

After applying the symmetric equilibrium assumption in BGM model, an individual price is the same for all products and is determined by aggregate demands and the number of products for whole products. It is a mechanism that an endogenous product entry changes an individual price setting through a variable markup. Thus, if the official CPI correctly reflects the population data of the Nikkei data, we can use the official CPI to π_t^C in a model though the official CPI has a constant basket and seems to be not affected by product entry and exit.[13] In other words, we evaluate whether the official CPI is affected by product entry and exit or not using BGM model. A point here is not

[11]See details of the official CPI that corresponds to product categories in the Nikkei data in Appendix A.

[12]A real GDP data is available in National Accounts of Japan that is published by Economic and Social Research Institute, Cabinet Office.

[13]In the model of Bilbiie, Ghironi, and Melitz (2007), there is no extensive margin effect on prices and all prices are the same. Thus, the model is rather suitable to use the official CPI with a constant basket and no extensive margin effect.

a model and is about precision in sampling for the official CPI.

In details, we apply the limited official CPI inflation rate to π_t^C, the number of products to N_t from the Nikkei data, and the GDP gap to C_t. π_t^C is given by year to year growth of the limited official CPI. N_t and C_t data are percentage deviations from trends calculated by HP filter. The sample covers from 1994Q1 to 2021Q2. In an estimation, we follow the same setting in Section 3 as shown in Table 2. For observation errors, we assume 10 percent of one standard deviation to the limited official CPI inflation rate, i.e., 0.015/10, the number of products, i.e., 0.035/10, and GDP gap, i.e., 0.016/10.

Table 8 and Figure 6 show estimation results. All parameters are well estimated and an endogenous product entry effect works for the official CPI. Elasticity of substitution across goods θ and intertemporal elasticity of labor substitution φ are estimated as 10.07 and 0.644, respectively. For a price stickiness, a price adjustment parameter is estimated as 54.13. Intertemporal elasticity of labor substitution and a price adjustment parameter are very close to the case using the trend SBPI in Table 6 and the matched-products SBPI in Table 7. It notes that the limited official CPI excludes temporary sales and its price variations are smaller than ones of SBPI as the trend SBPI. Elasticity of substitution across goods is slightly larger in the case of the limited official CPI than in the cases of SBPIs. However, this difference is negligible as shown in impulse response analysis in the next section.

Table 9 show variance decomposition in percent contributions. A productivity shock, a free entry shock, and a demand shock explain 53.96, 20.77, and 25.27 percent of the limited official CPI inflation rate, respectively. A free entry shock still holds a non-trivial effect as about 20 percent on the macro-level official CPI and a product entry has a clear effect on inflation rates. For other variables, these shocks also play important roles.

These result suggests that the limited official CPI is affected by a product entry and including the number of products into an estimation for macro variables works well to explain price dynamics. Moreover, we confirm that the official CPI including limited samples corresponding to the Nikkei data is a precise sample of population data of the Nikkei data and at least reflects product entry and exit effects.

6.2 Second Experiment

In the last section, we show that the number of products holds quantitatively significant effect on the limited official CPI that corresponds to items included in the Nikkei data. We extend this result to all CPI items including service prices and other goods prices that are not included in the Nikkei data. Here, we have a strong assumption that the same product entry effect holds for services and other goods. Estimation result, however, justifies this assumption though we need to clarify this point further.

In details, we apply the official CPI inflation rate for all goods and service to π_t^C, the number of products to N_t, and the GDP gap to C_t. π_t^C is given by year to year growth of the official CPI. N_t and C_t data are percentage deviations from trends calculated by HP filter. The sample covers from 1994Q1 to 2022Q4. Figure 7 shows these three data.

We assume observation errors given by 10 percent of one standard deviation to a CPI inflation rate, i.e., 0.0097/10, the number of products, i.e., 0.035/10, and GDP gap, i.e., 0.016/10. Observation errors are assumed to be i.i.d. normally distributed with zero mean. Calibrated parameters are the same as shown in Section 3.3 and prior distributions are the same as shown in Table 2.

Table 10 shows estimation results for BGM model. Elasticity of substitution across goods θ, intertemporal elasticity of labor substitution φ, and a price adjustment parameter κ are estimated as 10.661, 0.669, and 59.98, respectively. These estimations are almost the same as the limited official CPI. When we compare elasticity of substitution across goods to the cases using the Nikkei data, the estimated number is slightly larger. This difference, however, is too small to change impulse responses. Figures 8 shows impulse responses to one standard deviation productivity shocks for BGM model with official CPI data including all items. When comparing Figure 4 to Figure 8, impulse responses are the almost same for CPI inflation rates and demands in two figures after adjusting the size of shocks. An impulse response of the number of products is little bit smaller in a case of Nikkei data than a case of the official CPI data. We have the similar impulse responses for two cases even to demand shocks though we do not show figures. As shown in Table 11, a productivity shock, a free entry shock, and a demand shock explain 56.79, 15.88, and 27.33 percent of CPI inflation rate variations, respectively. A free entry shock still holds a non-trivial effect as about 15 percent on the macro-level official CPI. For other variables, these shocks also play important roles. A product entry has a clear effect on inflation rates even when we use the official CPI including all items.

7 Implications to Economic Analysis: Examples

Estimation and simulation results give new and strong implications for economic analysis. Product entry and so variable number of products are fundamental elements to analyze prices. Here, we show several implications to economic analyses.

7.1 Product Entry Effect on Official CPI

By comparing a BGM model with a standard New Keynesian model, we show quantitative implications to macro economic analysis in Japan. For it, we again use a standard New Keynesian model as in Section 4.2. We assume the same estimated parameters and shocks for two models as shown in Table 10. It notes that a free entry shock is excluded in a standard New Keynesian model.

Table 12 shows simulation results for BGM model and a standard New Keynesian model. A standard deviation of CPI inflation rates in BGM model is 40.9 percent smaller than one in a standard New Keynesian model. For a demand, a standard deviation increases by 24.1 percent. If we ignore a product entry effect on prices, a model and economic analyses quantitatively suffer from serious misidentification problems as shown in Section 7.3 below.

7.2 Quantitative Role of Free Entry Shock on Historical Inflation

Figure 9 shows a historical variance decomposition using estimated BGM model in Section 6.2. We confirm that a free entry shock significantly contributes to inflation and deflation in Japan. In some periods, the free entry shock changes inflation rates more than one percent positively and negatively. This is impossible finding in a model that discards product entry and exit.

As shown in an impulse response to a free entry shock in Figure 10, CPI inflation rates decrease as the number of products decreases. In details, when we see period from 20 to 50 in Figure 6, lowered product numbers make negative effects on inflation rate and induce chronic deflation in the historical decomposition given by Figure 9. Moreover, a large drop of the product number from 60 to 70 induces a deep deflation. On the other hand, an inflation rate surges with increasing number of products around the end of the sample period. In Japan, non-negligible part of inflation rates can be explained by product entry.

7.3 Model Selection Failure in Price Analysis

An endogenous product entry makes quantitatively significant effects on price and demand. A standard New Keynesian model, however, discards an endogenous product entry. We estimate a standard New Keynesian model using our Nikkei data and show outcomes by a misidentification due to gaps between the model and data. In particular, we evaluate effects of two misidentifications in an estimation. The first one is that a price setting does not depend on an endogenous product entry. In a standard New Keynesian model, a price markup is constant and is not related to the number of products. The second one is that there is no extensive margin effect in product supply and demand. In a standard New Keynesian model, a variety of the product is one and constant.

An estimation procedure is basically the same as in Section 3. Differences are to uses two time series data, SBPI to π_t^C and real demand for products to C_t, and to assume two types of shocks, productivity shock Z_t and demand shock M_t. Figure 11 shows prior and posterior distributions and these summarized statistics are reported in Table 13. Elasticity of substitution across goods θ and intertemporal elasticity of labor substitution φ are estimated as 8.536 and 1.793, respectively. For a price stickiness, a price adjustment parameter κ is estimated as 75.198. However, when we see prior and posterior distributions in Figure 11, distributions for φ and κ seems to well overlap. It implies that estimation does not work well due to inconsistency between a model and data.[14]

By misidentifications, estimated parameters are not well estimated and could be biased. A price adjustment parameter are estimated larger to reduce price variations in a standard New Keynesian model than in BGM model. This is because price variations are constrained by a variable price markup due to an endogenous product entry in BGM model. Regarding shocks, a standard deviation of productivity shock becomes double to replicate economic variations since a standard New Keynesian model can not include a free entry shock.

Impulse responses quantitatively show effects of misidentifications for economic dynamics. Figure 12 show impulse responses to a productivity shock for a standard New Keynesian model. CPI inflation rates are more elastic to the shock in comparing to those for BGM model. On the other hand, a demand is less elastic to the shock. About a demand shock, two models show the similar size of impulse responses for an initial period though impulse response persistences are longer, almost two times, in BGM model as shown in Figure 13. These outcomes imply that misidentifications make quantitatively significant errors in economic analysis when we apply a model discarding an endogenous product entry to data showing relationships among product entry, price, and demand.

We can apply a model selection failure problem to the official CPI for all items and GDP gap since behind these data, there exists a product entry and the number of products change over time. Table 14 shows summarized statistics for posterior distributions for a standard New Keynesian model. In estimation, we use the official CPI inflation rate for all goods and services to π_t^C and the GDP gap to C_t, and other settings are the same as in Section 3. Figure 14 shows impulse responses to one standard deviation productivity shock. When we compare Figures 8 and 14, CPI inflation rates are less

[14]To check robustness, we estimate one of these three parameters separately under given jointly estimated other two parameters and we confirm that our conclusion here does not change. Please see details in Appendix C.

elastic to the shock in a standard New Keynesian model than in BGM model.

8 Concluding Remark

In this paper, we evaluate whether the official CPI is affected by a product entry and the number of products in a market. We make use of Japanese unique data environment where the Nikkei data including larger samples than the official CPI is available for analysis. Our conclusion is that a product entry holds quantitatively significant effect on the official CPI as on the Nikkei data through an intensive margin effect though the official CPI has a constant basket and seems to exclude a product entry effect. The official CPI is a precise sample to correctly reflect a product entry effect in Japanese product market.

The outcome that the official CPI is affected by the number of products gives several questions. Among those, we need to ask whether a model discarding a product entry and assuming a constant price basket suffers from misidentification for economic analysis. Our result shows that this misidentification is quantitatively large and makes serious misunderstandings for estimation, variance decomposition, and impulse responses.

Our future works include evaluations on a product entry effect in the official CPI by using another types of models such as an oligopoly model for pricing. Evaluations on a product entry effect by rich general equilibrium models including a variety of frictions are necessary for robust analyses. Extending analysis to other countries is mandatory since we observe product entry and exit every day in supermarkets. Moreover, we can focus on service prices since new services come into a market and old services exit from a market.

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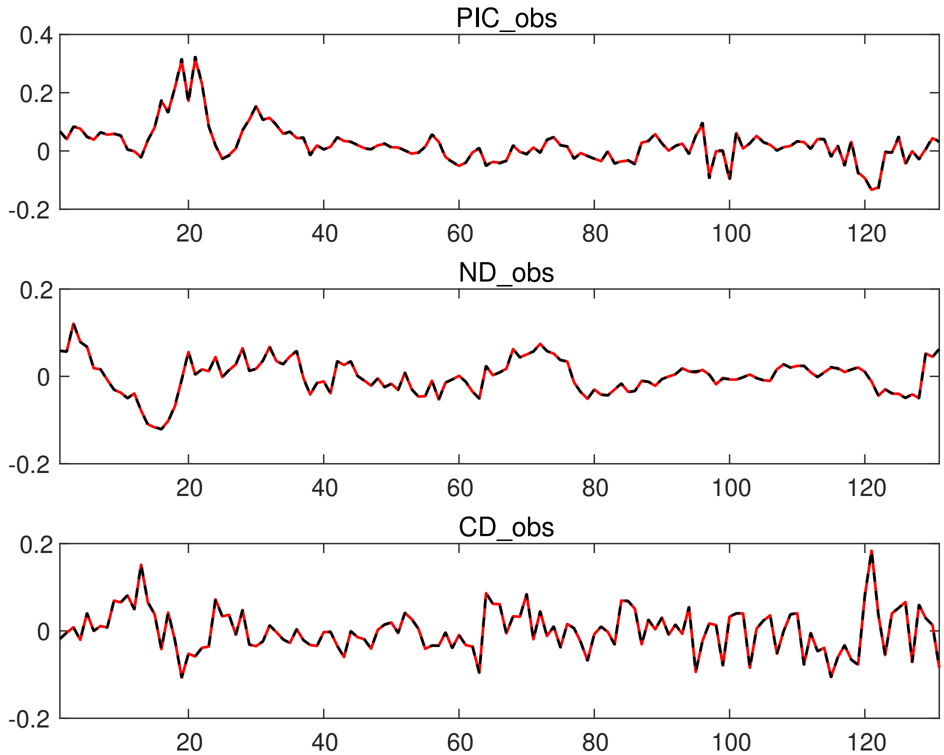

Figure 1: Inflation Rate, Number of Product, and Demand

Note: PIC_obs: SBPI inflation rate, ND_obs: Number of products, CD_obs: Demand.

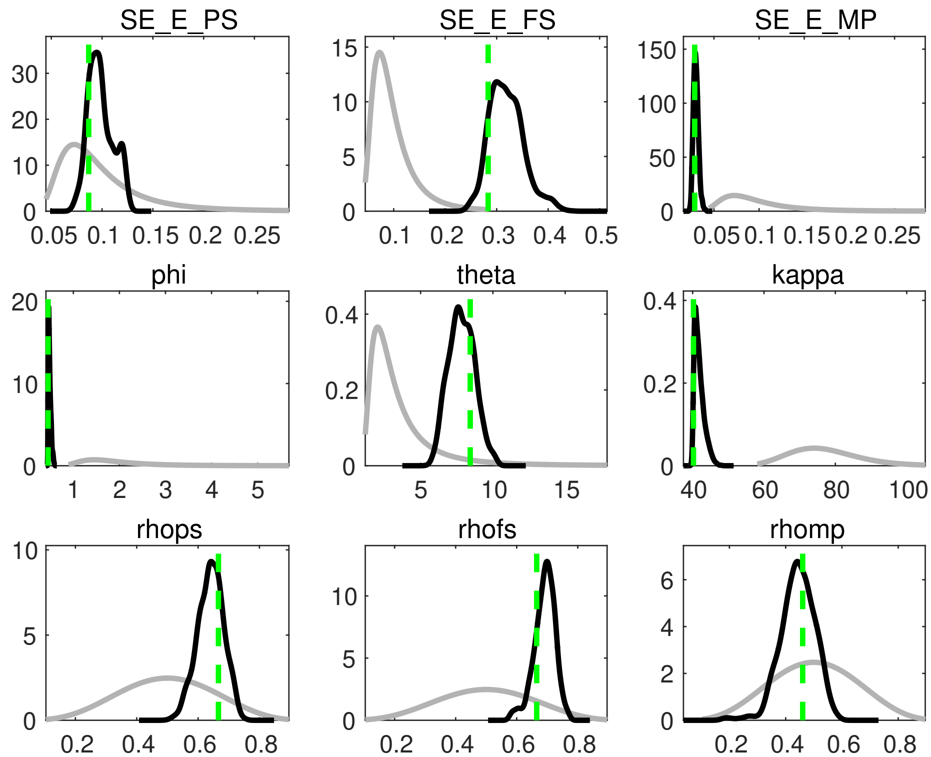

Figure 2: Posterior Distributions

Note: SE_E_PS, SE_E_FS, and SE_E_MP denote σ_z, σ_f, and σ_m, respectively. phi, theta, and kappa denote φ, θ, and κ, respectively. rhops, rhofe, and rhomp denote ρ_z, ρ_f, and ρ_m, respectively. Prior distribution is colored by gray and estimated posterior distribution is colored by black.

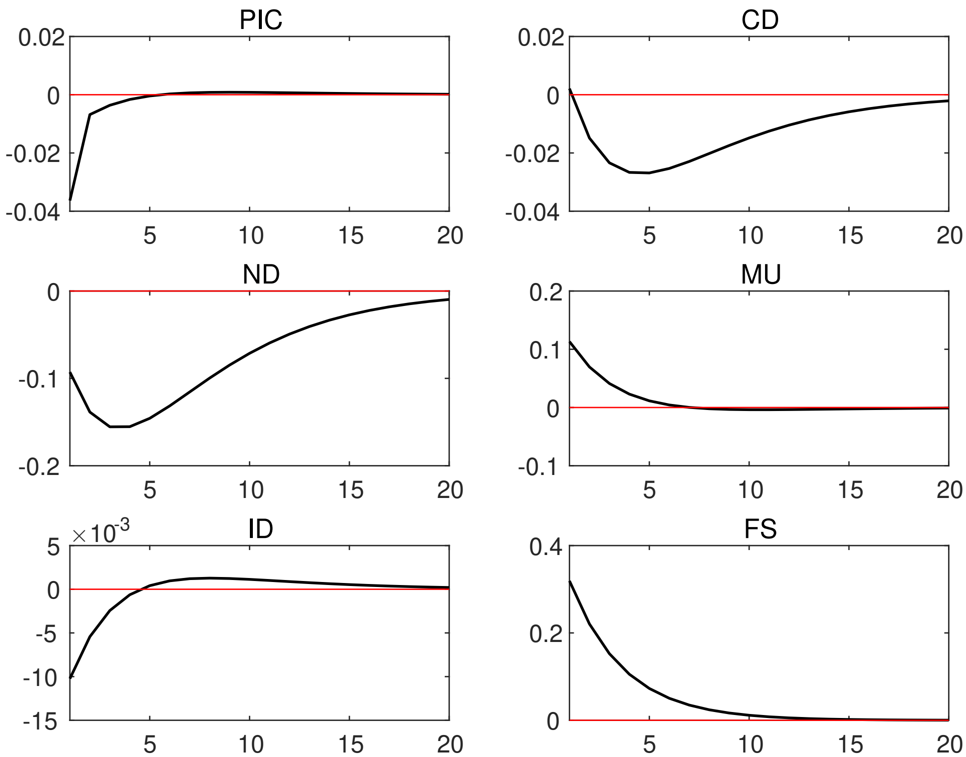

Figure 3: Impulse Response to Free Entry Shock

Note: PIC: SBPI inflation rate, ND: Number of products, CD: Demand, ID: Nominal interest rate, and FS: Free entry shock. Impulse responses to one standard free entry shock with AR1 persistence as shown in Table 3.

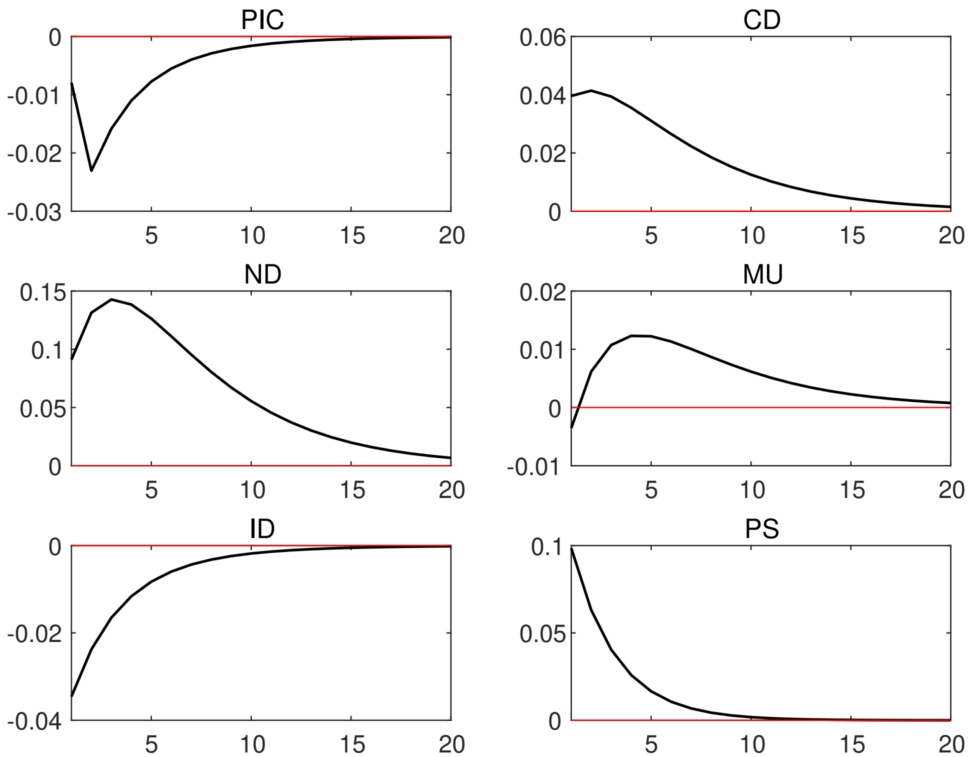

Figure 4: Impulse Response to Productivity Shock

Note: PIC: SBPI inflation rate, ND: Number of products, CD: Demand, ID: Nominal interest rate, and PS: Productivity shock. Impulse responses to one standard productivity shock with AR1 persistence as shown in Table 3.

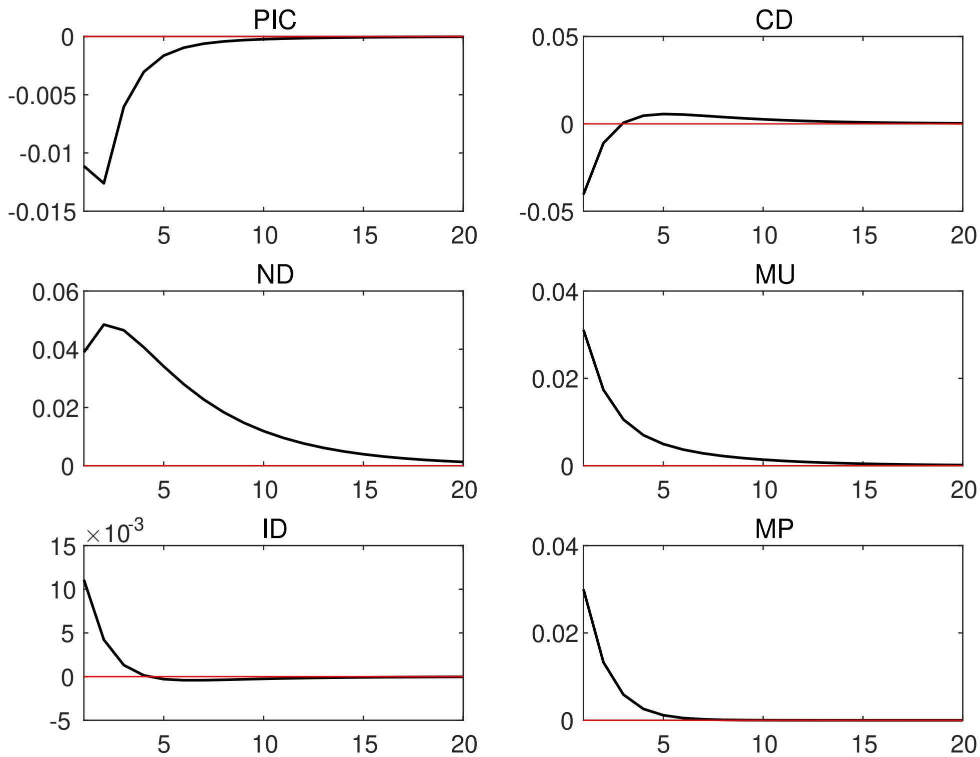

Figure 5: Impulse Response to Demand Shock

Note: PIC: SBPI inflation rate, ND: Number of products, CD: Demand, ID: Nominal interest rate, and MS: Demand shock. Impulse responses to one standard demand shock with AR1 persistence as shown in Table 3.

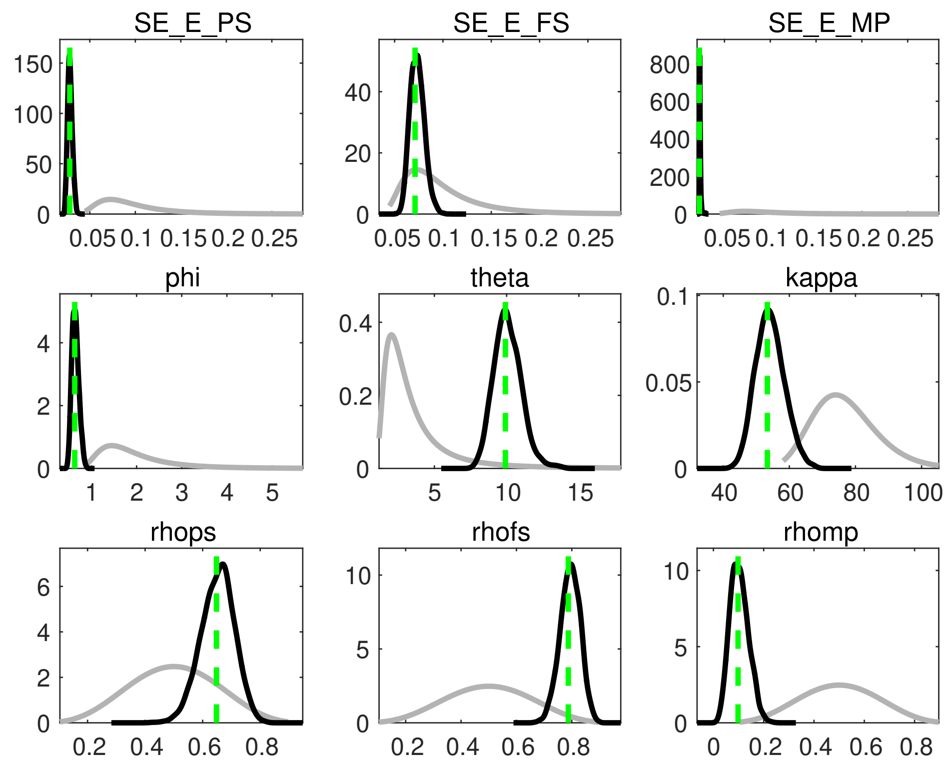

Figure 6: Posterior Distributions for BGM Model with Limited Official CPI

Note: SE_E_PS, SE_E_FS, and SE_E_MP denote σ_z, σ_f, and σ_m, respectively. phi, theta, and kappa denote φ, θ, and κ, respectively. rhops, rhofe, and rhomp denote ρ_z, ρ_f, and ρ_m, respectively. Prior distribution is colored by gray and estimated posterior distribution is colored by black.

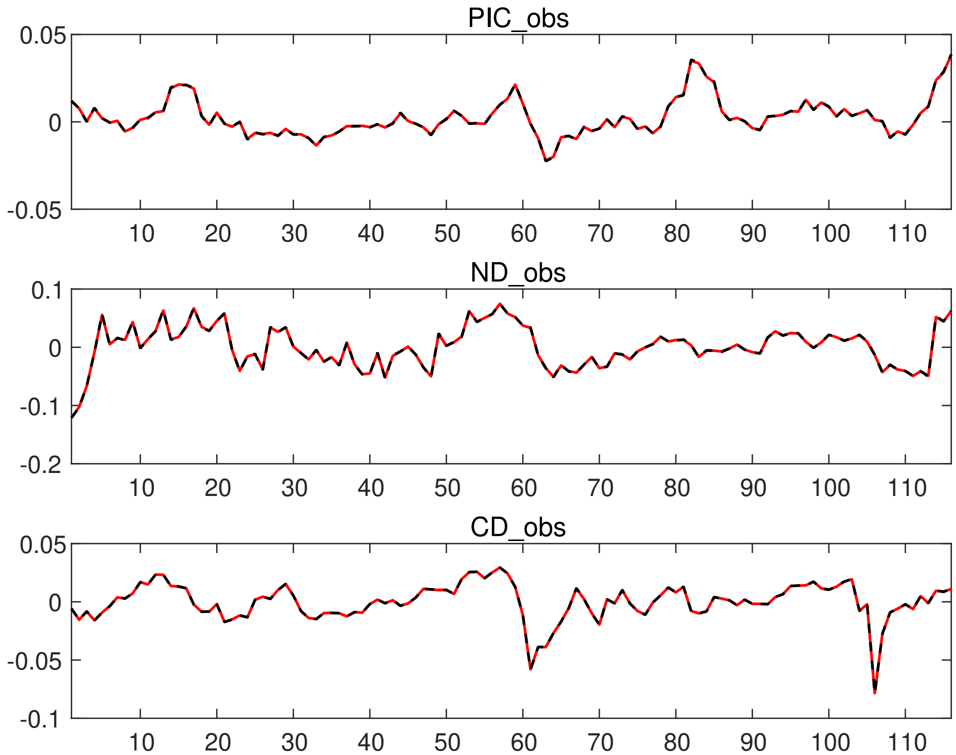

Figure 7: Official CPI Inflation Rate, Number of Product, and GDP Gap

Note: PIC_obs: Official CPI inflation rate, ND_obs: Number of products, CD_obs: GDP Gap. The sample covers from 1994Q1 to 2022Q4.

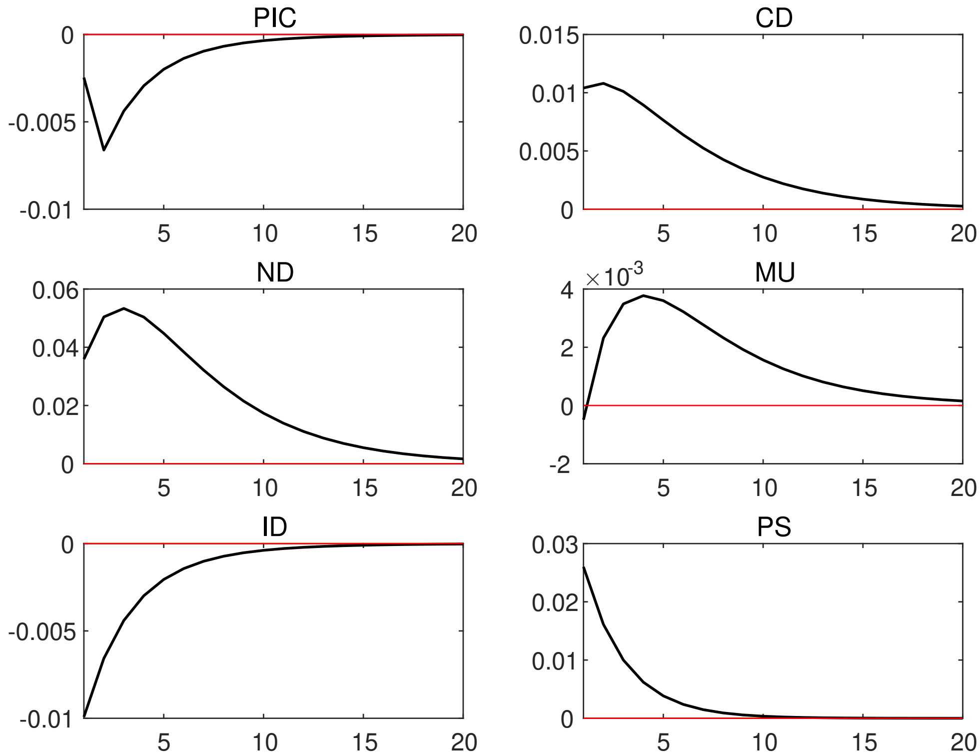

Figure 8: Impulse Response to Productivity Shock for BGM Model with Official CPI

Note: PIC: Official CPI inflation rate, ND: Number of products, CD: GDP Gap, ID: Nominal interest rate, and PS: Productivity shock. Impulse responses to one standard productivity shock with AR1 persistence as shown in Table 10.

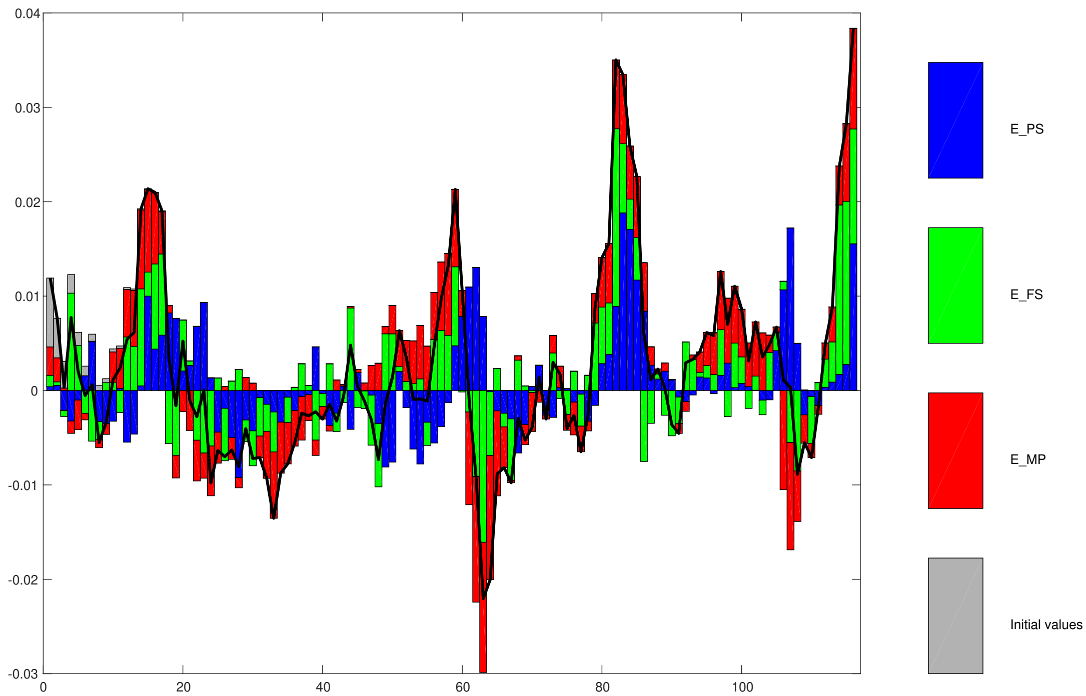

Figure 9: Historical Decomposition for Official CPI using BGM Model

Note: E_PS, E_FS, and E_MP denotes productivity shock, free entry shock, and demand shock. Initial values denotes an effect by initial condition.

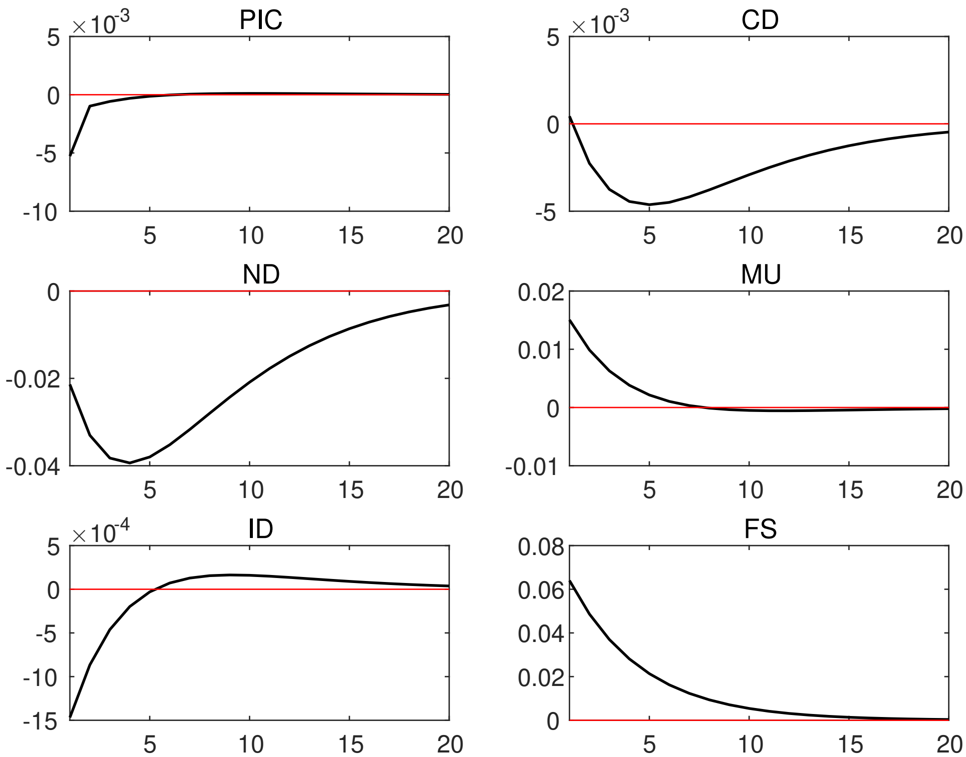

Figure 10: Impulse Response to Free Entry Shock for BGM Model with Official CPI

Note: Note: PIC: Official CPI inflation rate, ND: Number of products, CD: GDP Gap, ID: Nominal interest rate, and FS: Free entry shock. Impulse responses to one standard productivity shock with AR1 persistence as shown in Table 10.

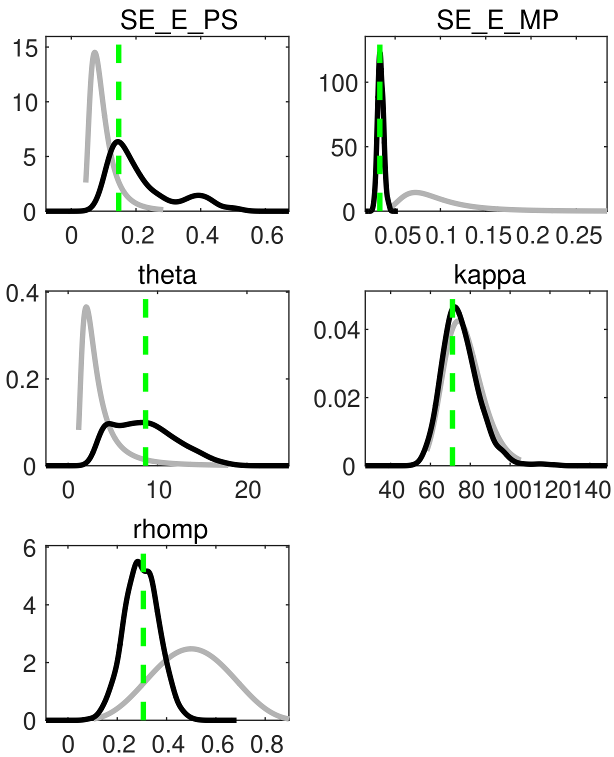

Figure 11: Posterior Distributions for New Keynesian Model with SBPI

Note: SE_E_PS and SE_E_MP denote σ_z and σ_m, respectively. phi, theta, and kappa denote φ, θ, and κ, respectively. rhops and rhomp denote ρ_z and ρ_m, respectively. Prior distribution is colored by gray and estimated posterior distribution is colored by black.

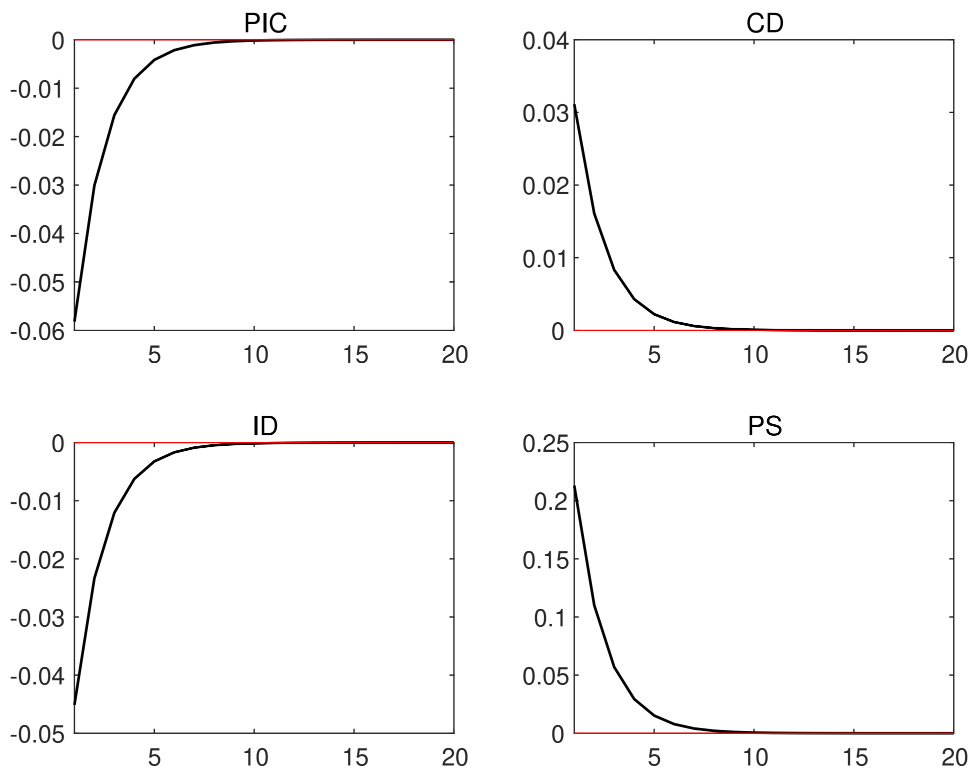

Figure 12: Impulse Response to Productivity Shock for New Keynesian Model with SBPI

Note: PIC: Limited Official CPI inflation rate, ND: Number of products, CD: Demand, ID: Nominal interest rate, and PS: Productivity shock. Impulse responses to one standard productivity shock with AR1 persistence as shown in Table 3.

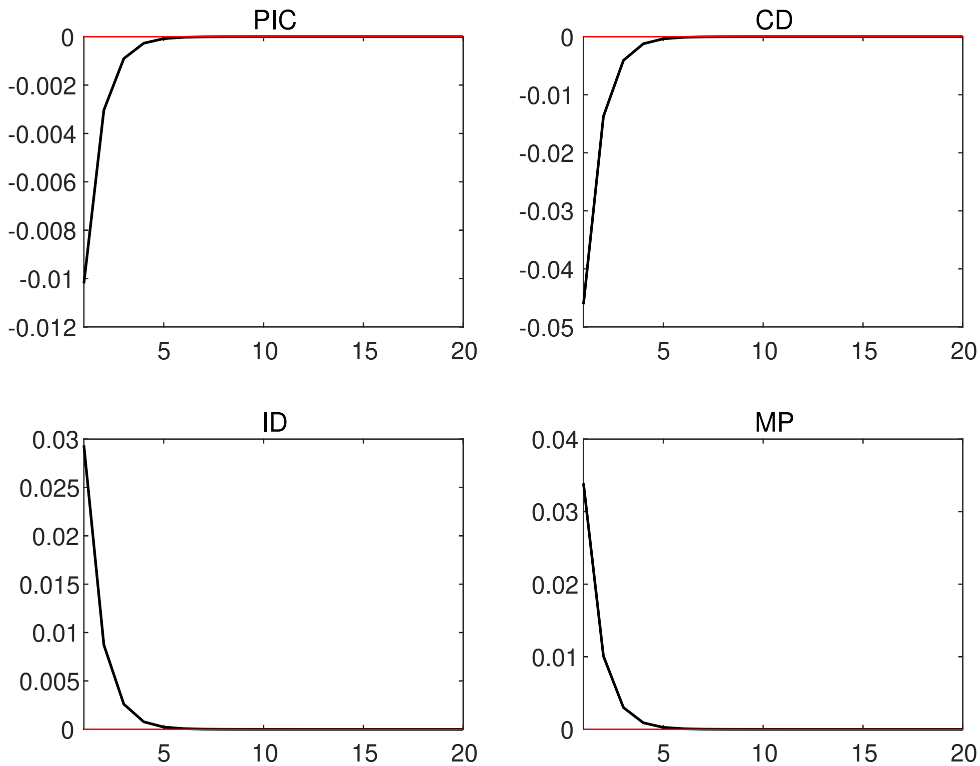

Figure 13: Impulse Response to Demand Shock for New Keynesian Model with SBPI

Note: PIC: SBPI CPI inflation rate, ND: Number of products, CD: Demand, ID: Nominal interest rate, and MS: Demand shock. Impulse responses to one standard demand shock with AR1 persistence as shown in Table 3.

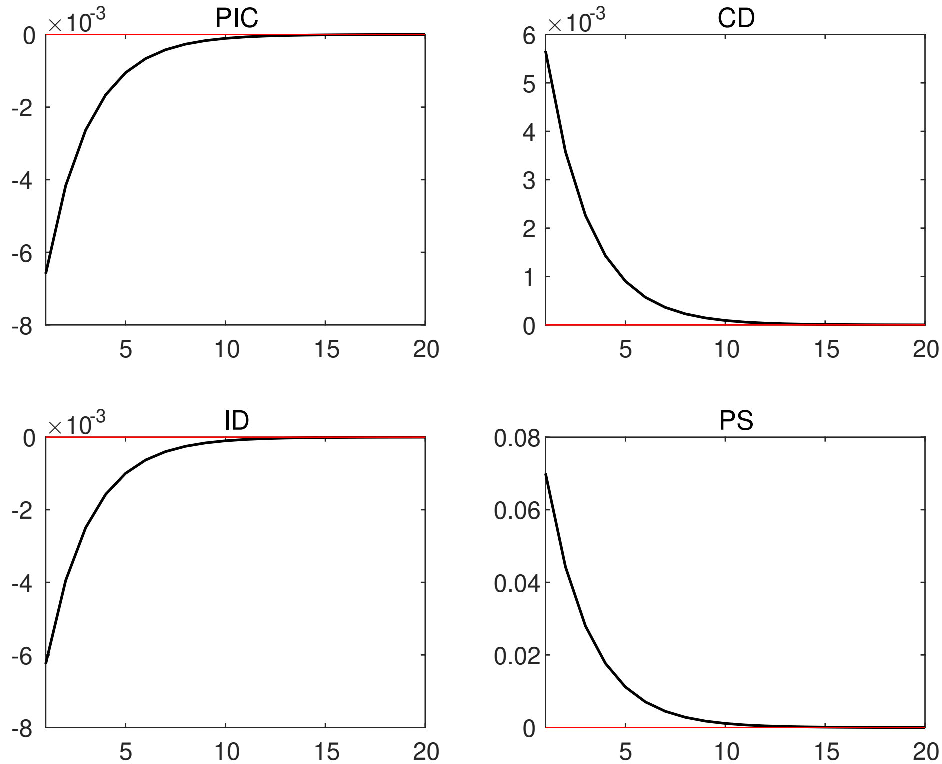

Figure 14: Impulse Response to Productivity Shock for New Keynesian Model with Official CPI

Note: PIC: Official CPI inflation rate, ND: Number of products, CD: GDP gap, ID: Nominal interest rate, and PS: Productivity shock. Impulse responses to one standard productivity shock with AR1 persistence as shown in Table 14.

Table 1: Basic Statistics

	Average	Standard deviation
Number of products	52884.32	15438.89
Entry rate	0.122	0.018
Exit rate	0.115	0.01
Nominal sales amount	4354313201	750835205
Real sales amount	6830135	940731
SBPI inflation	0.024	0.068
Trend SBPI inflation	0.024	0.041
Matched-products SBPI inflation	-0.006	0.014
Limited official CPI inflation	0.004	0.016
Official CPI inflation	0.002	0.011

Note: Quarterly base. A sample period for the number of products is from 1988Q2 to 2022Q4. A sample period for entry rate is from 1988Q3 to 2022Q4. A sample period for exit rate is from 1988Q2 to 2022Q3. A sample period for matched-products SBPI price inflation, trend SBPI price inflation, SBPI price inflation, limited official CPI inflation, sales amount, and real sales amount is from 1990Q2 to 2022Q4. A sample period for official CPI is from 1994Q1 to 2022Q4.

Table 2: Prior Distributions

Parameters	Description	Mean	S.D.	Distribution
θ	Elasticity of substitution across goods	3.8	5	Inv. Gamma
φ	Intertemporal elasticity of labor substitution	2	1	Inv. Gamma
κ	Price adjustment parameter	77	10	Inv. Gamma
ρ_f	Persistence of free entry shock	0.5	0.15	Beta
ρ_z	Persistence of productivity shock	0.5	0.15	Beta
ρ_m	Persistence of demand shock	0.5	0.15	Beta
σ_f	S.D. of free entry shock	0.1	0.05	Inv. Gamma
σ_z	S.D. of productivity shock	0.1	0.05	Inv. Gamma
σ_m	S.D. of demand shock	0.1	0.05	Inv. Gamma

Note: S.D. denotes a standard deviation.

Table 3: Posterior Distributions

Parameters	Mean	90 percent interval
θ	7.834	[6.358, 9.221]
φ	0.486	[0.452, 0.525]
κ	41.88	[40.24, 43.85]
ρ_f	0.691	[0.636, 0.744]
ρ_z	0.641	[0.579, 0.72]
ρ_m	0.443	[0.347, 0.534]
σ_f	0.319	[0.269, 0.372]
σ_z	0.099	[0.082, 0.212]
σ_m	0.03	[0.026, 0.034]
MDD	470.998	

Note: MDD denotes marginal data density.

Table 4: Variance Decomposition in Percent

Variable	Productivity	Free entry	Demand
π_t^C	38.78	49.37	11.85
C_t	58.08	30.01	11.91
N_t	41.58	54.65	3.77
μ_t	4.17	89.22	6.61

Note: Productivity, Free entry, and Demand denote productivity shock, free entry shock, and demand shock, respectively.

Table 5: Product Entry Effect on CPI/PPI

Model	S.D. of inflation rate	S.D. of demand
BGM model	CPI 0.052 [-40.9 %]	0.12 [46.3 %]
	PPI 0.051 [-42 %]	
BGM model + no $f_{E,t}$	CPI 0.038 [-56.8 %]	0.1 [22 %]
NK model	CPI & PPI 0.088	0.082

Note: S.D. denotes a standard deviation. [ ] denotes percent change from NK model.

Table 6: Posterior Distributions for Trend SBPI

Parameters	Mean	90 percent interval
θ	7.212	[6.352, 8.164]
φ	0.744	[0.569, 0.906]
κ	68.71	[58.3, 78.78]
ρ_f	0.97	[0.955, 0.985]
ρ_z	0.854	[0.816, 0.892]
ρ_m	0.593	[0.526, 0.658]
σ_f	0.088	[0.075, 0.102]
σ_z	0.055	[0.049, 0.062]
σ_m	0.026	[0.023, 0.029]
MDD	791.733	

Note: MDD denotes marginal data density.

Table 7: Posterior Distributions for Matched-products SBPI

Parameters	Mean	90 percent interval
θ	7.849	[6.814, 8.792]
φ	0.679	[0.541, 0.812]
κ	59.71	[51.86, 67.92]
ρ_f	0.832	[0.781, 0.89]
ρ_z	0.872	[0.84, 0.907]
ρ_m	0.248	[0.162, 0.345]
σ_f	0.088	[0.074, 0.102]
σ_z	0.057	[0.051, 0.063]
σ_m	0.029	[0.025, 0.034]
MDD	815.092	

Note: MDD denotes marginal data density.

Table 8: Posterior Distributions for BGM Model with Limited Official CPI

Parameters	Mean	90 percent interval
θ	10.07	[8.503, 11.46]
φ	0.644	[0.523, 0.769]
κ	54.13	[47.2, 61.17]
ρ_f	0.794	[0.732, 0.849]
ρ_z	0.651	[0.55, 0.737]
ρ_m	0.103	[0.05, 0.168]
σ_f	0.073	[0.061, 0.084]
σ_z	0.028	[0.024, 0.032]
σ_m	0.023	[0.023, 0.024]
MDD	831.302	

Note: MDD denotes marginal data density.

Table 9: Variance Decomposition in Percent for BGM Model with limited Official CPI

Variable	Productivity	Free entry	Demand
π_t^C	53.96	20.77	25.27
C_t	50.14	15.41	34.44
N_t	48.41	45.87	5.72
μ_t	8.11	41.08	50.8

Note: Productivity, Free entry, and Demand denote productivity shock, free entry shock, and demand shock, respectively.

Table 10: Posterior Distributions for BGM Model with Official CPI

Parameters	Mean	90 percent interval
θ	10.689	[9.195, 12.304]
φ	0.657	[0.525, 0.787]
κ	58.79	[51.01, 66.6]
ρ_f	0.76	[0.686, 0.838]
ρ_z	0.62	[0.488, 0.755]
ρ_m	0.091	[0.038, 0.144]
σ_f	0.064	[0.053, 0.075]
σ_z	0.026	[0.023, 0.028]
σ_m	0.023	[0.023, 0.024]
MDD	861.229	

Note: MDD denotes marginal data density.

Table 11: Variance Decomposition in Percent for BGM Model with Official CPI

Variable	Productivity	Free entry	Demand
π_t^C	52.91	18.51	28.59
C_t	45.51	12.14	42.34
N_t	53.79	38.6	7.61
μ_t	7.52	37.56	54.93

Note: Productivity, Free entry, and Demand denote productivity shock, free entry shock, and demand shock, respectively.

Table 12: Product Entry Effect on Official CPI

Model	S.D. of CPI inflation rate	S.D. of demand
BGM model	0.013 [-40.9 %]	0.036 [24.1 %]
NK model	0.022	0.029

Note: S.D. denotes a standard deviation. [ ] denotes percent change from NK model.

Table 13: Posterior Distributions for New Keynesian Model with SBPI

Parameters	Mean	90 percent interval
θ	8.536	[3.369, 13.627]
φ	1.793	[0.847, 2.806]
κ	75.198	[61.171, 89.882]
ρ_z	0.517	[0.458, 0.58]
ρ_m	0.298	[0.192, 0.417]
σ_z	0.213	[0.095, 0.394]
σ_m	0.034	[0.029, 0.039]
MDD	402.703	

Note: MDD denotes marginal data density.

Table 14: Posterior Distributions for New Keynesian Model with Official CPI

Parameters	Mean	90 percent interval
θ	2.972	[1.937, 4.078]
φ	1.983	[0.942, 3.225]
κ	77.38	[60.9, 91.6]
ρ_z	0.632	[0.567, 0.692]
ρ_m	0.132	[0.075, 0.195]
σ_z	0.07	[0.037, 0.099]
σ_m	0.024	[0.023, 0.025]
MDD	679.068	

Note: MDD denotes marginal data density.

Appendix

A Details of Nikkei Data

A.1 Product Identification

A barcode including the Japanese Article Number (JAN) code is printed on all products and products are distinguished by fairly detailed classifications in Nikkei POS scanner data. In the JAN code, the first seven digits indicate the company code and the last six digits indicate the individual product. When JAN codes are different for the same type of products by the same company, these products are different in terms of packaging, ingredients, etc. In addition, the barcodes provide information about the product category (such as butter, yogurt, or shampoo) and the producer of each product.

A.2 Price

The Nikkei data contains the sales values and quantities sold for each product in each shop on a daily basis. By dividing the sales values by the quantities sold, we calculate the daily price for each product. Based on these individual prices, we calculate an average price for all products. We use sales values as weights to calculate average prices.

To calculate the average prices, we use price levels. The first reason is that this is the average price that Japanese consumers face in shops to decide on purchases. The second reason is that price dispersion is not large because prices in the Nikkei data are for products in supermarkets where food products and daily necessities are sold. Figure A1 shows the price distribution for all prices in our 7 supermarket sample, where one price is defined as a yearly modal price of a product sold at a shop. The figure shows that about 70 percent of prices are between 100 yen and 999 yen. The median price and mean price are 284 yen and 622.3 yen, respectively. The minimum price and maximum price are one yen and $80,290$ yen, respectively.

In details, an average price is calculated in a following equation. We call this price index as SBPI.

$$SBPI_t = \frac{\sum_{i \in I, s \in S} price_{ist} weight_{ist}}{\sum_{i \in I, s \in S} weight_{ist}},$$

where $price_{ist}$ is a price of product i sold at shop s in a quarter t and $weight_{ist}$ is sales of product i at shop s in a quarter t. Note that our original data frequency is daily and we make a quarterly price (sales) by using these daily prices (sales). We have similar equations for an average price for new products.

Figure A2 show growth rates of price indexes, such as SBPI, trend component of SBPI, matched-products version of SBPI, the limited official CPI that includes items in the Nikkei data, and the official CPI.

A.3 Entry Rate and Exit Rate

In calculating the entry (exit) rate, we define a new (discontinued) product as one for which a transaction is firstly (finally) recorded in a given period. Then, we obtain the number of new (discontinued) products in a given period, which is divided by the total number of products in a given period to calculate entry (exit) rates. Note that these rates are not weighted by sales. We interpret that a new product enters into the market when we observe the new product in at least one shop. We interpret that an existing product exits from the market when no shops sell the existing product. Thus, entry (exit) rates are at the product level. Equations for the entry (exit) rate are given by

$$Entry\ Rate\ at\ Time\ t = \frac{Number\ of\ New\ Products\ at\ Time\ t}{Total\ Number\ of\ Products\ at\ Time\ t},$$

$$Exit\ Rate\ at\ Time\ t = \frac{Number\ of\ Discontinued\ Products\ at\ Time\ t}{Total\ Number\ of\ Products\ at\ Time\ t}.$$

A.4 Product Categories

We show average prices, sales shares, and the number of individual products for 17 product categories in our 7 supermarket sample in Table A1. The average price for a category is obtained by the average of yearly modal prices of products in a category across shops for the sample period 1989-2022. A sales share is the sales amount of each category divided by the total sales amount for the sample period. Note that the sales amount includes sales with temporary promotion prices. The number of products denotes the total number of products sold in each category in the sample period.

B Derivation of New Keynesian Model

We briefly show a derivation for a standard New Keynesian Model with a adjustment cost by Rotemberg (1978). We follow BGM model as possible as we can for structures, parameters, and notations. However, we simplify an unnecessary part of a model. A representative household only holds bond. The model only includes the CPI and keeps the number of product as one.

B.1 Aggregator

The household consumes the basket of goods C_t as

$$C_t^{\frac{\theta-1}{\theta}} = \int_0^1 c_t(i)^{\frac{\theta-1}{\theta}} di,$$

where θ is the symmetric elasticity of substitution across goods. A corresponding price aggregator is given by

$$P_t^{1-\theta} = \int_0^1 p_t(i)^{1-\theta} di.$$

Then, the household's demand for an individual good i is

$$c_t(i) = \left(\frac{p_t(i)}{P_t}\right)^{-\theta} C_t.$$

B.2 Firm

We assume a continuum of monopolistically competitive firms and each firm i produce one differentiated good i. To produce a good $y_t(i)$, a firm uses a labor $l_t(i)$ and so we have $y_t(i) = Z_t l_t(i)$, where Z_t is a productivity shock. Productivity shock is exogenous and follows an AR(1) process.

Firms face nominal rigidity in the form of a quadratic cost function, which is measured in terms of goods, to adjust prices following Rotemberg (1982) as

$$pac_t(i) = \frac{\kappa}{2}\left[\frac{p_t(i)}{p_{t-1}(i)} - 1\right]^2 \frac{p_t(i)}{P_t} y_t(i).$$

The firm maximizes following discounted profit.

$$\mathrm{E}_t \sum_{s=t}^{\infty} \Lambda_{t,t+s}\left[\frac{p_t(i)}{P_t} y_t(i) w_t l_t(i) - \frac{\kappa}{2}\left[\frac{p_t(i)}{p_{t-1}(i)} - 1\right]^2 \frac{p_t(i)}{P_t} y_t(i)\right],$$

where $\Lambda_{t,t+s} = \beta_{s-t}\frac{C_t}{C_s}$ is the discount factor. Here, all the firms set the price and produce the same output. Thus, we have $p_t(i) = p_t = P_t$, $pac_t(i) = pac_t$, $l_t(i) = L_t$, and $y_t(i) = y_t = Y_t$. This is symmetric assumption for equilibrium. Thus, the aggregate resource constraint is given by

$$Y_t = C_t + pac_t = Z_t L_t.$$

Then, the first order condition with respect to the demand function is given by

$$1 - \kappa\left(\pi_t + 1\right)\pi_t + \kappa\beta \mathrm{E}_t\left(\frac{C_t}{C_{t+1}}\right)\left[\left(\pi_{t+1} + 1\right)\pi_{t+1}\frac{Y_{t+1}}{Y_t}\right] = \theta(1 - \frac{w_t}{Z_t}), \tag{8}$$

where $\pi_t = \frac{P_t}{P_{t-1}} - 1$ and a demand function for $y_t(i)$ is given by

$$y_t(i) = \left(\frac{p_t(i)}{P_t}\right)^{-\theta} Y_t,$$

where a model assumes the same goods allocation for a price adjustment cost as consumption.

B.3 Household

A representative household maximizes the following an utility function,

$$\mathrm{E}_t \sum_{s=t}^{\infty} \beta_{s-t} \left[\ln C_s + \chi \frac{L_s^{1+\frac{1}{\varphi}}}{1+\frac{1}{\varphi}} \right],$$

subject to a budget constraint,

$$B_{t+1} + P_t C_t = (1 + i_{t-1}) B_t + W_t L_t + T_t + D_t,$$

where where C_t is consumption, i_t is the nominal interest rate, B_t is nominal bond holdings, W_t is the nominal wage rate, L_t is the labor supply, T_t are lump sum taxes, and D_t is nominal dividends. χ is the Frisch elasticity of labor supply to wage and φ is the intertemporal elasticity of substitution in labor supply. Then, we have the following first order conditions.

$$\frac{1}{C_t} = \beta(1 + i_t)\mathrm{E}_t \left(\frac{P_t}{P_{t+1}} \frac{1}{C_{t+1}} \right), \tag{9}$$

$$\frac{W_t}{P_t} = w_t = \chi C_t L_t^{\frac{1}{\varphi}}. \tag{10}$$

B.4 Closed System and Linearization

From (B.2), (B.2), (B.2), and (B.2), we have a closed system of economy for C_t, π_t, and i_t. By log-linaerizing these equations, we have a New Keynesian model.

C Robust Analysis

C.1 Estimation using two data

We show an estimation result for a case where we only use two data, SBPI and a demand, and include the product number data. In estimation, we follow the setting in Section 3.

Table A2 shows the estimation result. Estimated results are significant different from Table 3 that use three data. Table A3 shows variance decomposition in percents. Free entry shock less contribute to inflartion rate in Table A3 than in Table 4.

C.2 Estimation for Food Products and Daily Necessities

We show an estimation result for processed meats and seafoods from Table A1. Processed meats and seafoods category has 7 percent share in sales base in SBPI. An average number of products in the category is 33275 and average price is 348.6 yen.

In estimation, we follow the setting in Section 3 except several points. We newly assume observation errors given by 10 percent of one standard deviation to a inflation rate for processed meats and seafoods category, i.e., 0.032/10, the number of products, i.e., 0.064/10, and a real demand, i.e., 0.048/10. We set a separation rate as 0.127 from Nikkei data. Table A4 show estimation result for these parameters. Estimated parameters slightly change to reflect product heterogeneity from Table 3.[15]

C.3 Separate Estimation for New Keynesian Model

To check robustness for estimation for new Keynesian model using Nikkei data, we estimate parameters, φ, θ, and κ, separately. For example, when we estimate φ, we calibrate other two parameters given as in Table 13.

Table A5 shows estimation result for these parameters. Estimated parameters do not change a lot from Table 13.

[15]Basically, estimation results change by categories in Table A1. However, our conclusion that a product entry has significant effects on prices does not change. Furthermore, even when we use more detailed data, such as only processed meats, we have the same conclusion. These estimation results are available upon a request.

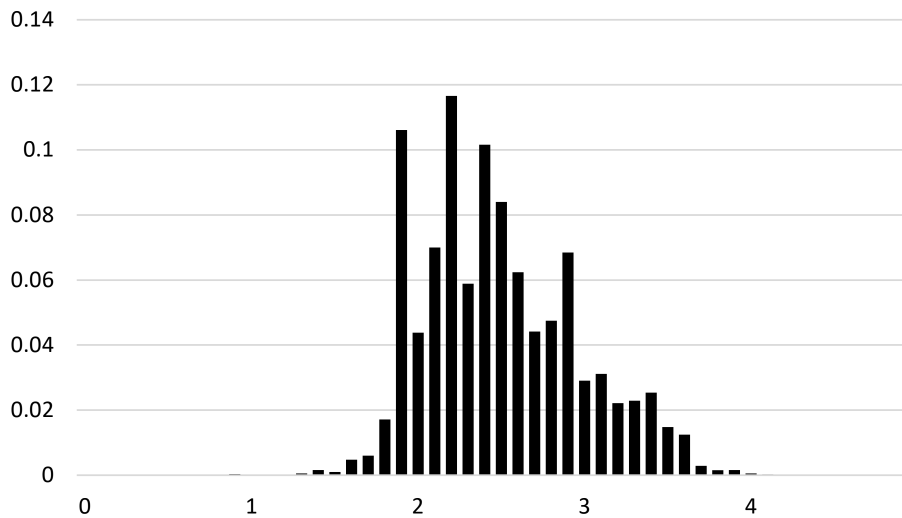

Figure A1: Price Distribution

Note: A horizontal axis is Log 10 price.

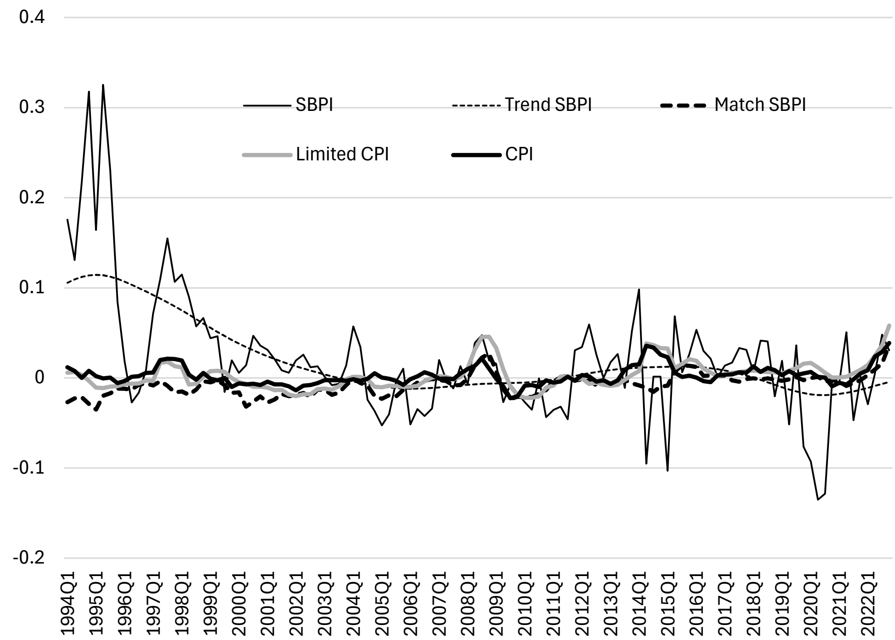

Figure A2: Price Indexes

Note: All indexes are yest to year growth rate. SBPI denotes an original SBPI. Trend SBPI denotes a trend component of SBPI. Match SBPI denotes a matched-products SBPI. Limited CPI denotes the official CPI including only items in the Nikkei data. CPI denotes the official CPI including all items.

Table A1: Product Categories: Average Price, Sales Share, and the Number of Products in Each Category

Categories	Prices	Shares	Product Numbers
Processed meats and seafoods	348.6	0.07	33275
Dairy products and milks	264.4	0.083	33929
Beverages	426.3	0.08	42907
Seasonings	273.3	0.057	21310
Instant and frozen foods	218	0.089	55529
Canned foods	249.9	0.012	6722
Breads and cakes	208.4	0.055	60505
Confectioneries	250.6	0.084	155077
Alcoholic beverages	1146.4	0.066	37893
Other foods	322.8	0.085	58347
Body/Oral care products	671.3	0.025	35675
Detergents and cosmetics	1411.6	0.077	130677
Stationeries	335	0.007	58255
Pet foods and sanitary products	403.2	0.008	17941
Other daily necessities	712.5	0.071	77659
Other agricultural products	247.7	0.06	27747
Baby foods, cereals, and eggs	1966.8	0.072	41092

Note: Price is Japanese Yen.

Table A2: Posterior Distributions When Using Two Data for BGM Model

Parameters	Mean	90 percent interval
θ	15.74	[13.41, 17.95]
φ	3.28	[1.73, 4.85]
κ	70.11	[57.07, 82.18]
ρ_f	0.339	[0.103, 0.559]
ρ_z	0.363	[0.16, 0.568]
ρ_m	0.631	[0.549, 0.702]
σ_f	0.103	[0.053, 0.149]
σ_z	0.066	[0.047, 0.087]
σ_m	0.033	[0.029, 0.037]
MDD	381.216	

Note: MDD denotes marginal data density.

Table A3: Variance Decomposition When Use Two Data for BGM Model

Variable	Productivity	Free entry	Demand
π_t^C	34.41	10.15	55.44
C_t	38.78	14.39	46.83
N_t	39.34	18.36	42.3
μ_t	16.78	38.83	44.38

Note: Productivity, Free entry, and Demand denote productivity shock, free entry shock, and demand shock, respectively.

Table A4: Posterior Distributions for BGM Model with Processed Meats and Seafoods Category

Parameters	Mean	90 percent interval
θ	12.671	[11.322, 14.413]
φ	0.562	[0.467, 0.646]
κ	54.67	[48.02, 61.08]
ρ_f	0.685	[0.608, 0.767]
ρ_z	0.764	[0.687, 0.844]
ρ_m	0.21	[0.107, 0.309]
σ_f	0.185	[0.15, 0.218]
σ_z	0.053	[0.047, 0.059]
σ_m	0.038	[0.032, 0.043]
MDD	587.109	

Note: MDD denotes marginal data density.

Table A5: Posterior Distributions by Separate Estimations

Parameters	Mean	90 percent interval
θ	3.97	[2.497, 5.469]
φ	1.989	[0.911, 3.024]
κ	78.59	[63.42, 93.34]

Note: We estimate θ, φ, and κ separately.