Understanding Law of One Price Deviations: Local Distribution Services and Price Discrimination

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Abstract

The deviation from the law of one price is often attributed to local non-traded inputs and price discrimination in local markets. This paper empirically measures the significance of these factors using panel data of disaggregated regional consumer price in Japan. Under imperfect competition, retailers charge the marginal cost of distribution and set an optimal markup that depends on local demand elasticity. In order to measure the difference in local demand elasticity, I estimate the price and income elasticity using the Almost-Ideal Demand System (AIDS) with multiple-stage budgeting. The difference in the demand elasticities across cities arises from differences in the local expenditure pattern, which may reflect local characteristics such as taste or demography. With about 200 consumer goods, the empirical models show that a part of the price difference is accounted for by local distribution costs and local demand elasticities, as the theory predicts. However, those two factors explain only 3 % of the observed price dispersion. These findings suggest that deviations from the LOP are not fully explained by differences in cost and demand, and efforts to explain these deviations need to be based on other factors.

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1 Introduction

Deviations from the Law of One Price (LOP) are substantial and highly persistent even for seemingly highly tradable goods at different levels of disaggregation.[1] Given that the LOP is the fundamental building block of any version of the Purchasing Power Parity (PPP) theory, understanding the source of these deviations has been at the center-stage of macroeconomic research.

A common explanation of the LOP deviations in the literature is based on location specific costs. In particular, the costs of local distribution services have received increasing attention. All tradable consumer goods that are highly tradable embody non-tradable costs of distribution, such as labor costs at retail stores and rental costs of operating space. The size of distribution costs (retail and wholesale) is substantial when compared to other trade costs, such as transportation costs and tariffs. Burstein, Neves, and Rebelo (2003) report that the distribution margin represents more than 40 percent of the final good price.[2] However, little research has been conducted to empirically measure the significance of the relationship between price and distribution services.

Another standard approach to explain the LOP deviations is based on price discrimination. When markets are segmented across space, monopolistic retailers can charge different markups across locations and time, depending on local demand structure. The demand elasticity is a key factor that has been emphasized in numerous studies on pricing-to-market, including the early contributions by Dornbusch (1987) and Krugman (1987). As the elasticity of consumer demand increases, the optimal markup decreases, lowering the price of the good. Consumers living in different locations may have different tastes over goods,[3] causing heterogeneity in demand elasticities and, therefore, variations in equilibrium consumer prices.

This paper empirically measures the contribution of these two hypotheses to account for LOP deviations in the framework of a static oligopoly model. In particular, I study LOP deviations by estimating a structural empirical model using highly disaggregated panel data on retail prices, local costs (wages and land prices), and household expenditure allocations for about 200 goods in 47 Japanese cities[4] from 2000 to 2005. The model allows for location specific costs and price

[1] See the survey by Rogoff (1996) and Goldberg and Knetter (1997) for a broad review. As for the evidence at disaggregated levels, see, for example, Broda and Weinstein (2008), Crucini, Telmer, and Zachariadis (2005), Crucini and Shintani (2008), Goldberg and Verboven (2005), and Parsley and Wei (2001).

[2] See also Bradford (2003), Goldberg and Campa (2004) and Anderson and van Wincoop (2004).

[3] A mechanism behind the time and/or location specific demand elasticity is different across studies. See Alessandria (2005), Atkeson and Burstein (forthcoming), and Lapham and Vigneault (2001) among others.

[4] Unlike existing studies, I focus on the price difference between cities in the same country to abstract from the costs of crossing a national border that also cause the LOP to fail. See Engel and Rogers (1996), Parsley and Wei (2001) and Baba (2007) for example. Additionally, as Engel (2002) points out, international comparison may overestimate the local cost effects due to the price stickiness in terms of the local currency.

discrimination, connecting consumer behavior, retailer behavior, and market structure in a static way. Using the empirical model, I calculate how much each explanation can account for LOP deviations.

Specifically, I construct and estimate an oligopolistic model in which retailers compete by quantity in geographically segmented markets. The key elements of the price are location specific costs of distribution,[5] local demand elasticities, and the intensity of competition.[6] The last two factors discipline the retailers' price-cost markup in equilibrium. The model is estimated in two steps: first, I estimate the demand side separately from the supply side to obtain the local demand elasticities, using the data on expenditure share and price for each good. The difference in the demand elasticities across locations arises from differences in the local expenditure pattern, which may reflect local characteristics such as taste or demography. Secondly, the supply side is estimated using the derived elasticities and local distribution costs, which are proxied by wages in distribution sector and land prices in commercial areas. I estimate the contribution of each factor to account for actual LOP deviations, simultaneously estimating the intensity of competition for each good.

The estimation results show that both local distribution costs and demand elasticities are significantly related to the observed retail price level, in the direction qualitatively consistent with the predictions of the theory. This study also shows that the quantitative effect of those factors is quite modest. In particular, the retail price of a given good is dispersed, on average, 14 percent of the consumer price. The local costs accounts for 3 percent of the price dispersion; the price discrimination explains less than 1 percent of the dispersion. There is heterogeneity across goods categories, and the model fits better for foods compared to non-food goods. In all goods groups, most of the price difference is left unexplained.

These results highlight the relative importance of other potential factors that determine deviations. Recent studies using scanner price data evidence (e.g. Nakamura (2008) and Eichenbaum, Jaimovich, and Rebelo (2008)) argue it is particularly challenging to attribute retail price variation to cost shocks or demand shocks. The key finding from the recent literature is that retail prices are

[5]The effect of difference in distribution costs is analyzed for 10 OECD countries using CPI data by MacDonald and Ricci (2003) and for European countries using car prices by Goldberg and Verboven (2001). These studies conclude that a significant portion of the retail price difference is attributable to local wage differences. In contrast, Haskel and Wolf (2001) uses the catalog price of furniture and argues that the differences in local costs are not able to account for variation across similar goods.

[6]The role of price discrimination based on demand elasticity in LOP deviations has hardly been empirically investigated with micro-level data. Exceptions are Aw (1993) for Taiwanese exporters of footwear, Goldberg and Verboven (2001) for the car industry in European countries, Hellerstein (2008) for the beer industry in the US, and Nakamura (2007) for the coffee industry in the US. Price discrimination effects are often analyzed for a narrowly defined industry, but the scope is limited within the industry. It is rarely the case that data are both highly disaggregated and extensively cover a large portion of the consumer's expenditure.

more retail-chain specific rather than product specific, implying that the form of competition or the retailer's pricing strategy that arises in a given market is more important than the shocks to costs or demands. This paper performs a structural analysis, directly connecting retail prices to observable costs and expenditure patterns that measures the contributions of the potential explanations. This paper provides evidence that both demand and cost explain some of the LOP deviations as past literature argues, but this paper also shows these factors are not enough for a complete explanation. This is consistent with the conjecture from the scanner data evidence. Given that a large fraction of the LOP deviations remains unexplained, I interpret my results as pointing to the importance of heterogeneous patterns of competition across markets as a fruitful area for research in the future.

The remainder of the paper is structured as follows: data and documentation of LOP deviations are introduced in Section 2. Section 3 presents a simple oligopolistic model and a demand system. Section 4 estimates the model. The demand side and the supply side are estimated separately. The supply side is estimated under some different specifications. The conclusion is in Section 5.

2 Preliminary Look at the Deviations from the LOP

2.1 Data

The price data are from the *Retail Price Survey* by the Statistics Bureau of the Ministry of Internal Affairs and Communications (MIC) of the government of Japan. The survey provides good-level price data for more than 700 specifications of goods and services, and this survey is the basis for the CPI in Japan. The geographical coverage is extensive, having reached 167 cities, towns and villages since 1950. I use monthly observations from 2000 to 2005 for 47 prefectural capital cities.

The MIC decides a representative specification for each good, and regular prices are surveyed in multiple retail stores in each city. For the majority of goods, the specification is highly detailed to ensure that the survey takes prices of identical goods in different outlets.[7] In the exceptional case when the specific brand or size is not available in a city, the survey substitutes the price with that of a similar good. All such substitutions are noted in the footnotes. For most groceries, the MIC divides a city into four districts, and prices are surveyed at the largest store in each district. The average price over the districts is reported as a city-level price.[8] The prices are sampled on the same day of the month nationwide. Products with volatile prices, for example, fresh food, are sampled three times a month, and the MIC reports the average. Temporary discounts (low prices that remain

[7]For example, "Tuna fish" is specified as "Big-eyed tuna, sliced, lean, unit=100g". "Tomato ketchup" is "In polyethylene container (500g), "Kagome tomato ketchup" or "Del Monte tomato ketchup"".

[8]Large cities have more districts. See the appendix for more detail.

less than a week) and bulk-discounts are excluded.

The quantity-side data on consumption at the prefecture level are available from the *Family Income and Expenditure Survey*, also administrated by the MIC. The survey provides data of the average allocation of expenditure and purchase frequency of each good in the 47 prefectural capital cities on a monthly basis. The survey samples about 100 households in each city, which report the source and the use of their income. City-level expenditures are calculated by taking a simple average over the sampled households. Once a household enters a sample, it continues reporting its income and expenditure on a monthly basis for six months. One-sixth of households are replaced every month to maintain representativeness.[9]

In this paper, I include goods that are available in both surveys. The retail price survey uses more disaggregated good definitions than the expenditure survey, but these two statistics have similar coverage of goods. The surveys are similar because data from both are used to construct the CPI in Japan. The MIC chooses a representative specification for each good or service that has more than a 0.01 % share of the consumption expenditure. The expenditure share is then used as a weight for each good to compile the overall CPI. In contrast, the expenditure survey bundles goods of infrequent purchase, such as durable goods, to avoid the problem of small sample bias.

Table 1 summarizes the number of goods that are covered in those surveys and in the following analysis. According to the expenditure survey, an average household spends a quarter of its consumption expenditure on food and 20 % on miscellaneous goods, which includes daily commodities. The following analysis does not cover consumption of housing, utilities, transportation, and education, because goods in those categories are not likely to be traded across regions and some goods have a non-linear price schedule or regulated pricing. Clothing is also excluded because most goods are highly seasonal. Excluding those categories, the retail survey covers 405 goods, and the expenditure survey has 332 corresponding goods that cover 65.2 % of the household's total expenditure. Some goods are further dropped from the sample if a good is discontinued during the sample period, if a good is not purchased frequently, if the good is not available in all 47 cities, or if the good is not available throughout the year. Ultimately, the sample consists of a total of 198 goods with five top categories and 48 middle groups, and they jointly represent 29.9 % percent of total expenditure, which is equal to 45.9 % of the total expenditure exclusive of the categories mentioned above.

Some goods in the retail price data have occasionally missing observations. Missing observations are interpolated using the previous month's price and the national average price. If a good is

[9]See the appendix for more detail.

missing more than 10 % of observations in the sample period, then it is dropped from the sample. Additionally, the MIC regularly revises the specification of a good that represents the category. These revised series are also interpolated. The price series before and after the revision are connected by adjusting their level, but the monthly changes are preserved.[10]

The other data come from the following sources. Wage data are from *Basic Survey on Wage Structure* by the Ministry of Labor. "Wage" in the following refers to the total cash earnings of all employees working at establishments with five or more employees in the wholesale and retail sectors. Land price data are from the *Prefectural Land Price Survey* by the Ministry of Land, Infrastructure, and Transport. Land price is measured per square meter of commercial area in each city. Both surveys are annually reported for each prefectural capital. Population data are constructed from *Population Census* (2000 and 2005) by the MIC and the *Annual report on current population estimates* by the Ministry of Labor.

2.2 Price Dispersion at Different Levels of Disaggregation

The price dispersion between the regions is significant at different levels of disaggregation. Table 1 reports the average of the good-level standard deviations. All prices are annualized by taking simple average over twelve months. Throughout the paper, I measure the price dispersion by the standard deviation of log price over cities l. For a given year t for a given good i, it is:

$$S_{it} = \underset{l}{Std}(\log p_{ilt} - \log \overline{p}_{it}) = \underset{l}{Std}(\log p_{ilt}), \tag{1}$$

$$where \log \overline{p}_{it} = \frac{1}{L} \sum_{k=1}^{L} \log p_{ikt} \tag{2}$$

where L is the number of cities. The good-level dispersions are then aggregated over goods and over time. Because the average price across cities is common to all cities for a given good, the standard deviation of log prices is equivalent to the dispersion of the good-level log real exchange rates relative to the national average price. The right-most column of Table 1 reports the expenditure share-weighted average over goods within the category. On average, regional prices differ by 12 % of consumer price. Fishery goods have the largest dispersion, which equals 21 % of retail price.[11]

[10] I first deflate the price series using the CPI and calculate the average price level of goods for three months before and after the revision. The ratio of the two averages is used to adjust the level of the two disconnected price series.

[11] The effect of the good selection bias is more problematic for non-food goods than for foods. In Table 1, I report the price dispersions using all available goods in the category and using only the goods that are selected for the analysis. The food price dispersions are similar in two specifications, overall 14.6 % and 14.5 % by in-sample data. However, non-food goods have smaller price dispersion than the overall dispersion. This difference arises because many non-food goods are dropped from the sample because households do not purchase these goods very often and the expenditure survey does not have a corresponding good specification. Therefore, I must interpret the results for non-food goods with caution because the result may change if I have more detailed expenditure data.

There is a weak tendency that price dispersion becomes greater for goods with smaller expenditure shares. In fact, the expenditure share-weighted average dispersion (12.4 %) is smaller than the simple average dispersion (14.5%) for foods. This pattern applies only to foods.

Although good-level price dispersion is substantial, the aggregated prices show relatively small dispersion across cities. Instead of taking the good-by-good dispersion, I calculate the dispersion of aggregate price that is defined by averaging the log prices over goods in a given city:

$$\tilde{S}_t = \underset{l}{Std}(N^{-1}\sum_{i=1}^{N} \log p_{ilt}). \tag{3}$$

In the lower half of Table 2, I report the average over the years of S_t for each group of goods. The dispersion of average price that pools all goods in my sample is 3 %. In all subcategories, the dispersion is significantly smaller than the dispersion at the good-level. The size of the dispersion depends on the number of goods used to calculate the average price. The aggregate price using all 198 goods shows the smallest dispersion. The more goods that are included, the less dispersed the average price is. Therefore, price differences seem highly idiosyncratic across goods.

In sum, at the individual good-level, the price difference is significantly large, close to 15 % of the retail price. However, the price of a basket of goods is much less dispersed, but still sizable. This pattern is consistent with evidence reported by existing literature using micro-price data. At the individual good-level, the dispersion is substantial, for example 20 % for cities within the US and within Canada (Broda and Weinstein (2008)), 25 % for tradable goods and 40 % for non-tradable goods across European countries (Crucini, Telmer, and Zachariadis (2005)). Both report that the aggregated price dispersion is on the order of 1 %. In the following analysis, I mainly focus on the dispersion at the individual good-level, but later, I also look at the dispersion of aggregated price.

2.3 Dispersion in the Long Run and in the Short Run

A part of the dispersion is transitory. The dispersion documented in Table 1 is the average of static dispersion over six years. To calculate this, I first annualize the price by taking the average over months in a given year for each good i and each city l. In the lower part of Table 2, I also report the dispersions without averaging over months in a year. The monthly dispersion is the average over 72 months of (1). It is always the case that monthly level dispersion is larger than annual level dispersion. Therefore, even within the horizon of a year, some price difference disappears.

To consider the possibility that deviations from the LOP disappear in the long run, I calculate the long-run level of dispersion. An autoregressive model is fit to each good, pooling the observations across cities l and across months t. The following AR(k) model is applied to each good i separately.

$$\log p_{ilt} = \mu_{il} + \mu_{it} + \sum_{j=1}^{k_{il}} \rho_{ij} \log p_{il,t-j} + \epsilon_{ilt} \tag{4}$$

$$= \mu_{il} + \mu_{it} + \rho \log p_{il,t-1} + \sum_{j=1}^{k_{il}-1} \zeta_{ij} \Delta \log p_{il,t-j} + \epsilon_{ilt}, \tag{5}$$

where μ_{il} is a city-specific good price, μ_{it} is a time-specific good price, k_{il} is a city-specific lag order and $\rho = \sum_{j=1}^{k} \rho_j$ is the sum of autocorrelation coefficients (SARC). The time- and good-specific dummy variables μ_{it} are equivalent to the national average log price of good i at time t. In other words, equation (5) can be rewritten as the AR(k) process of log real exchange rates relative to the national average.

Assuming all cities have the same AR coefficients for a given good, I use Levin, Lin, and Chu (2002)'s estimate of ρ to measure the persistence. The half-life is calculated by $-\log(2)/\log(\rho)$. The lag length k_{il} is calculated based on the following criterion. The univariate ADF is fitted to each city, and the optimal lag length is decided by the Schwarz Information Criterion (SIC). The initial ADF allows lags up to 12 months. The optimal lag length is city-specific. The long-run variance is estimated using Newey-West's technique. The choice of kernel bandwidth follows Andrews (1991).

Table 3 summarizes the panel unit root results. For each good i, the number of observations is 47 cities $\times$ 72 months, or 3384 total observations. The reported values are the simple averages over goods in a given category. Overall, shocks to the prices are transitory. The average SARC is 0.80 and the average half-life is 6.6 months. The null hypothesis that the data is a unit root is rejected in most cases. The rest of the columns report the summary statistics for subgroups. Goods are categorized into five groups: fresh food, processed food, electric appliances, other goods, and services. There is great heterogeneity across the groups. Fresh foods have an average half-life as short as two months, while services have an average half-life of about one and a half years.[12]

Having estimated the AR model, I then calculate the long-run level of dispersion. Basically, I use a city$\times$good-specific intercept μ_{il} to gauge the long-run level of dispersion. Because most series are stationary, the long-run level of city-specific price is obtained by setting $\log p_{ilt} = \log p_{il}$ in all periods. For simplicity, let the lag length $k_l = 1$.[13] Then the long-run level of dispersion is obtained

[12]These estimates are within a range comparable to that given by literature using micro-level price data. Examples of half-lives of shocks are: 19 months across OECD cities (Crucini and Shintani (2008)), less than two quarters across US cities (O'Connell and Wei (2002)), 1.3 - 1.6 years for the European car market (Goldberg and Verboven (2005)). Choi and Matsubara (2007) reports that the median half-lives across cities in Japan are less than two years using more aggregated CPI indices.

[13]The optimal lag length based on the SIC is in fact 1 for most of the cases.

by $\bar{\mu}_{il} = \mu_{il}/(1-\rho_i)$. This level's standard deviation $\sigma_{i0} = Std(\bar{\mu}_{il})$ is used as a measure of long-run dispersion for good i in city l.

Most price dispersion persists in the long run. The average dispersion is 12.6% in the long run and 13.7 % in the short run. Only 8 % of price difference is transitory, and most dispersion does not disappear in the long run. Figure 1 displays the relationship between the long-run dispersion and the short-run dispersion for all goods in the sample. Each dot represents a good. It is clear these two measures are very close. The least square fit is $\sigma_i = .95\bar{\sigma}_i - .02$ ($R^2 = .94$). The long-run dispersion, which is on the vertical axis, is only slightly smaller than the short-run dispersion.

Figure 2 breaks down the dots into groups of goods. Because fresh foods are less persistent (their average SARC is the smallest), their long-run dispersion is smaller than their short-run dispersion. However, services find that the long-run dispersion is as large as the short-run dispersion because the prices are very persistent.

The lower half of Table 3 considers possible bias from the sampling scheme. Because a higher number of retail prices are sampled to calculate the average price for large cities, one might argue that the prices in large cities and small cities are not directly comparable. To check robustness, I perform the same calculation excluding 12 large cities. The MIC takes more price samples for large cities to calculate the average price, so large cities may have lower persistence than small cities.

Overall, Table 3 confirms the expectation that deviations across small cities are slightly more persistent than deviations overall, but the difference is small. Additionally, dispersions among small cities are relatively larger than those for all cities. These differences seem to come from the notion that the law of large numbers applies better to large cities because retail prices in large cities are based on a higher number of price quotes. At the same time, except for services, the difference between these two specifications is quite small. Not only is the difference small, the exclusion of large cities from the sample does not affect the qualitative result. Although the results focusing on small cities are not reported in this paper, I confirm that the data set which excludes large cities qualitatively produces the same result.

In sum, the data shows the average dispersion across cities is as large as 14 % of the retail price and it is persistent. The persistence of the dispersion motivates the use of a static model to analyze the absolute deviation. In the following section, I introduce a simple static model of imperfectly competitive pricing under an arbitrary demand structure.

3 Model

The basic structure of the model is: A country has L separated local markets, and each of them, $l \in L$, is called a city. A city is characterized by a representative consumer and retailers. A consumer's preference is summarized by a demand function that is defined later. The supply side is characterized by a static partial equilibrium model of retailers. Input prices are given outside of the model. The number of retailers in each market is exogenously given by R_l, and there is no exit/entry decision. Location subscript l is dropped for convenience.

Retailers do not produce goods by themselves. Instead, they purchase goods from a manufacturer at a common (across retailers) price.[14] They buy good i from the producer at c_i and sell in the local market at p_i using local inputs whose unit cost is d. Retailers also incur the cost of transporting goods from the manufacturer to the consumption location. There are R symmetric retailers in each city, and they play a static Cournot quantity competition game.

3.1 Oligopolistic Retailers' Problem

Assume, for simplicity, that each retailer sells one good, so that he does not consider the cross-price effect on other goods. Given the local household's demand structure, a profit-maximizing retailer chooses the input of manufacturer's good q_i^M, whose unit price is c_i, and the input of local distribution service q_i^D, whose unit cost is d_i, subject to their Cobb-Douglas form technology constraint. Additionally, assume that the inverse demand function for each good $p_i(Q)$ is differentiable. For each of retailers $r = 1, 2, ..., R$, the maximization problem is described by:

$$\begin{aligned} max \qquad & p_i(Q_i)q_{ir} - c_i q_{ir}^M - d_i q_{ir}^D && (6) \\ s.t. \qquad & q_{ir} = \frac{1}{(1-a_i)^{1-a_i} a_i^{a_i}} (q_{ir}^M)^{1-a_i} (q_{ir}^D)^{a_i} && (7) \end{aligned}$$

where $Q_i = \sum_{r=1}^{R} q_{ir}$ is the aggregate amount of good i in a city.

The first-order conditions imply:

$$p_i(Q_i) + \frac{\partial p_i}{\partial Q_i}\frac{\partial Q_i}{\partial q_{ir}} q_{ir} = mc_{ir} = (c_i)^{1-a_i}(d_i)^{a_i}. \tag{8}$$

To further simplify the expression, let $\theta_{ir} \equiv \partial Q_i / \partial q_{ir}$ measure the retailer's conjectures about competitor behavior. This represents the retailer r's expectation about the responses from other

[14] The distribution sector typically includes both wholesale and retail trade, but I only consider retailing activity in the following. One can conceptualize wholesaling as a part of the manufacturer's activity in this model. A retailer purchases goods from a wholesaler. Wholesaling is not done locally in many cases, so the impact of wholesaling on regional price differences should be limited.

retailers to a change in quantity of good i. The conjecture may be formed through a repeated pricing game with the competitors. The first order condition is then rewritten as:

$$p_{it}(1 + \frac{\theta_{ir}}{e_{it}}) = mc_{ir}, \tag{9}$$

where $e_i = \frac{d \log q_i}{d \log p_i}$ is the price elasticity of demand. Therefore, the retail price of good i is decided by the marginal cost of retailing (the right hand side) and the markup, which depends on the degree of competitiveness and the demand elasticity.[15] Under the assumption of Cournot oligopoly and symmetry across retailers ($\forall r,\ q_{ir} = Q_i/R$) in a given city, the conduct parameter θ is equal to the inverse of the number of retailers R^{-1}. If the market is perfectly competitive, $\theta = 0$ and the price is equal to the marginal cost. If the market is under monopoly or collusion, $\theta = 1$.

Let me add two assumptions. A retailer's technology is good-specific, so the parameter a_i that measures the share of non-tradable input to sell a unit of good i is common across retailers in any location. Additionally, all retailers in a city face the same unit input price for distribution services regardless of the type of goods they are selling; therefore d_l is location l-specific but not good-specific.[16] Then log price of good i in location l at time t is written by

$$\log p_{ilt} = \log m_{ilt} + (1 - a_i) \log c_{ilt} + a_i \log d_{lt}, \tag{10}$$

$$m_{ilt} = (1 + \frac{\theta_{il}}{e_{ilt}})^{-1} : \text{ markup.} \tag{11}$$

The equation implies that a good i sells for a more expensive price in city l if the demand is less elastic, the market is less competitive or the local distribution service is costly. The LOP at the manufacturer's level implies that the manufacturer price c_{ilt} is common to all cities ($\forall l,\ c_{ilt} = c_{it}$).

This leads to the key pricing equation that I take to the data. The pricing equation to be estimated is specified as:

$$\log p_{ilt} = \log m_{ilt} + a_i \log d_{lt} + (1 - a_i) \log c_{it} + \epsilon_{ilt}. \tag{12}$$

The error term ϵ_{ilt} captures unobserved components of retail costs. The parameter a_i is the share of distribution inputs in the final price. This equation demonstrates the retailer's pricing depends

[15] The retailer might set prices of his assortment of goods to maximize his total revenue, instead of good-by-good. The case of joint maximization can be considered in terms of the consumer's substitutability to other goods. In principle, the markup term is expressed by the matrix form that summarizes the cross-price effect from the other goods. Since the data in this work is more aggregated than the product level, the estimation result in the following indicates that most goods are unrelated to each other. Therefore, the analysis in the following does not consider those cross-price effects.

[16] This assumption is plausible when the labor is immobile across locations. In Japan, the wage level is more city-specific than industry-specific.

on three factors: the marginal cost that the retailer pays to the manufacturer level (c_{it}), the cost of distribution services (d_{lt}), and price-cost markups (m_{ilt}).

The manufacturer price c_{it} is not directly observable. However, the LOP at the manufacturer level implies that this cost component is common to all cities. By using a panel structure of data, I can have a good $\times$ time-specific fixed-effects μ_{it} which control for this component, even in the absence of marginal cost data at the manufacturer level.

I proxy the unit cost of distribution $\log d_{lt}$ mainly by wage and rent. This decomposition is based on the *Survey on Business Accounts of Small and Medium Companies* in Japan. According to the survey, more than 50 % of the retailer's operating costs is paid in the form of personnel expenses, and rental costs of operating space are the second largest component of the total cost (10 %). Freight costs compose less than 2 % of the total cost. Although the transportation cost is often considered to be one of the major components of distribution margin, its effect on price through the distribution activity is likely limited. The *2000 Input-Output Tables* of Japan report that the share of transportation margin in private consumption is quite small, 2.4 %, compared to the share of the wholesale- and retail-trade margin (39.7 %). Therefore, I focus on the role of local wage and rent, but I also consider transportation cost later.

The final component, the markup, depends on the local consumer's demand structure that is summarized by price-elasticities. To estimate the role of price discrimination, I have to obtain consistent estimates of demand elasticity. To this end, I specify the form of the demand system in the next subsection.

3.2 Household's Budgeting Problem

A representative consumer in each city maximizes his utility from consumption of goods and services; his preference is characterized by the Almost Ideal Demand System (AIDS) proposed by Deaton and Muellbauer (1980a). The AIDS model has some desirable features, such as a flexible cross-price substitution pattern and non-constant elasticities. Another advantage of choosing the AIDS is that this system is designed to work with revenue shares, instead of quantities of consumption. Because the goods in the sample cover many different categories, using revenue shares allows me to avoid the difficulty in defining the quantity unit that is comparable across different goods. The AIDS model gives an arbitrary second-order approximation to any demand system and satisfies the necessary properties of demand functions (add-up, homogeneity of degree zero in price and income, symmetric substitution matrix).[17]

The drawback of flexibility is the dimensionality problem, which is solved by the multi-stage budgeting approach. With N goods in a demand system, one has to estimate N^2 own- and cross-price parameters, at least. Deaton and Muellbauer (1980b) argue that the AIDS model satisfies weak separability, so it is possible to work it out with hierarchic decision making. The consumer's optimization problem is divided into several stages. At the top level, a consumer decides how to allocate his disposable income into consumption of the top groups. Then, he decides the allocations in the sub-groups. For example, top level demand is defined for segments such as food, housing, furniture, clothing, transportation and recreation. At the middle level, the consumer splits segment expenditure into groups such as fish, meat, dairy products, vegetables, fruits, snacks and beverages in the food sector. Finally, at the bottom level, the consumer allocates the group expenditure to goods in the meat group, for example, beef, pork, chicken, ham and sausage. This approach has the advantage of reducing the number of parameters to estimate but it also has a disadvantage in limiting cross-substitution patterns a priori by the grouping decision. At the bottom level of the hierarchical structure, consumption patterns are highly flexible, and one price directly affects the other good's consumption within the same group of goods. At the middle level, the allocation decision is only a function of the segment expenditure and the price indexes of the following groups. Once goods are classified in different groups, a change in price of a good only indirectly affects the consumption of the other good through the change in budget allocation to the group.

The bottom level demand for good i in group (g) is written by:

$$s_{(g)ilt} = \alpha_{il} + \sum_{j \in g} \gamma_{ij} \log p_{jlt} + \beta_i \log \frac{y_{(g)lt}}{P_{(g)lt}} + Z_{it}\iota + \epsilon_{ilt} \tag{13}$$

where $s_{(g)ilt}$ denotes the expenditure share of good i in group (g) expenditure in city l at period t, α_{il} is the city-good specific fixed effect, y_{lt} is the group expenditure, Z_t is the vector of seasonal

[17] There are several alternatives for the demand specification. CES demand functions are often used in theoretical models, but they are too restrictive because the cross-price elasticities must be equal by construction.

The translog demand system is equally flexible, but its estimation is more difficult due to the non-linearity in the price index. Additionally, Wang, Halbrendt, and Johnson (1996) show the estimates by the AIDS and the translog are very close. Furthermore, the elasticity obtained from the AIDS model has similar properties to the Translog model.

Discrete choice models over characteristics space with logit, nested logit and random coefficient logit are often used for the estimation of demand for differentiated goods. These models are suitable for closely related goods. However, given that the purpose is to estimate demand for goods and services, it is difficult to project products over a space of characteristics.

variables and P_{glt} is the price index for the group and is approximated by Stone price index[18]:

$$\log P_{(g)lt} = \sum_{i \in (g)} s_{(g)il} \log p_{ilt}, \tag{14}$$

where the weights s_{il} are fixed over time to make the price index unit-free.[19] All prices and expenditures are deflated using the CPI. The general requirements for demand are imposed by setting $\gamma_{ij} = \gamma_{ji}$ (Slutsky symmetry), $\sum_j \gamma_{ij} = 0$ (homogeneous of degree zero), and $\sum_i \alpha_{il} = 1$ and $\sum_i \beta_i = 0$ (adding up).

The γ and β parameters measure the responsiveness of expenditure share of good to the change in real income and price. $\beta > 0$ indicates that goods are luxuries because the expenditure rises disproportionately to the rise in income. α measures the share at the subsistence expenditure level.

The allocations of expenditures across groups are calculated by treating a group as an individual good, with its price being the price index for the group. Each stage of the upper hierarchy is specified by the same AIDS form as in equation (13). At the top stage, the budget is equal to the total disposable income, and the household divides its income over the top segments.

The conditional own- and cross-price elasticities of demand between good i and j that belong to the same bottom group (g) are obtained by:

$$\tilde{\eta}_{(g)ilt} \equiv \frac{d \log q_{ilt}}{d \log y_{(g)lt}} = 1 + \frac{\beta_i}{s_{(g)itl}} \tag{15}$$

$$\tilde{e}_{(g)ijlt} \equiv \frac{d \log q_{ilt}}{d \log p_{ilt}}|_{y=\bar{y}} = (\gamma_{ij} - \beta_i s_{(g)jl}) \frac{1}{s_{(g)ilt}} - \delta_{ij}. \tag{16}$$

Note δ_{ij} is Kronecker delta that is equal to one when $i = j$. This elasticity is conditional on a constant expenditure for each group.

The overall (unconditional) price elasticities must consider the effect of price change on the group price index and hence on the group expenditure, which is obtained by incorporating the results from all stages of estimation. Following Edgerton (1996), the multiple-stage budgeting is denoted by $[a], [b]$ segments for the top stage, $(g), (h)$ groups for the middle stage and i, j goods for the bottom stage. Then, the unconditional income elasticity η_i of good i and the unconditional price elasticity

[18]The exact form of price index is

$$\log P = \alpha_0 + \sum_k \alpha_k \log p_k + \frac{1}{2} \sum_j \sum_k \gamma_{jk} \log p_k \log p_j.$$

Using this exact form requires techniques to solve a non-linear system. Deaton and Muellbauer (1980a) argue that using the approximation does not substantially affect the result.

[19]Moschini (1995).

e_{ij} between good i and j are characterized by the following:

$$\eta_{il} = \tilde{\eta}_{[a](g)i} \cdot \tilde{\eta}_{[a](g)} \cdot \eta_{[a]} \tag{17}$$

$$\begin{aligned} e_{ij} &= \tilde{e}_{[a](g)ij} \cdot \delta_{[a][b]} \cdot \delta_{(g)(h)} \\ &\quad + s_{[a](g)j} \cdot \tilde{\eta}_{[a](g)i} \cdot \tilde{e}_{[a](g)(h)} \cdot \delta_{[a][b]} \\ &\quad + s_{[b](h)j} \cdot s_{[b](h)} \cdot \tilde{\eta}_{[a](g)i} \cdot \tilde{\eta}_{[a](g)} \cdot e_{[a][b]}. \end{aligned} \tag{18}$$

where time subscript t and city subscript l are dropped for convenience. If two goods belong to the same group, or $(g) = (h)$, their unconditional substitution is obtained by adding their conditional elasticity at the bottom group to the group's own elasticities at the upper stages. On the other hand, if two goods are in different top segments, one in segment $[a]$ and the other in segment $[b]$, for example, their substitution is equal to the elasticity of substitution between segment $[a]$ and $[b]$.

There is a potential endogeneity problem in the demand estimation. Price-setting retailers may be able to observe some demand shocks that are unobservable to the analyst; then, price and demand shocks may be involved in a feedback loop where each is simultaneously affecting the other. This problem is addressed by employing instrumental variable methods. Here I use two different sources of instruments.

Wholesale prices of goods are used as instruments for retail price. From the supply-side pricing equation, it is clear that manufacturer/wholesale prices c_{it} are correlated with retail prices p_{ilt}. But it is less likely that wholesale prices at the national level are correlated with local shocks to demand. The problem that arises from this approach is that wholesale price data are not available for all of the goods in my sample. The wholesale price index is used as an instrument only when I find a corresponding index in *Corporate Price Index* published by the Bank of Japan.

Another set of instruments is obtained by using the panel structure of the data. Hausman, Leonard, and Zona (1994) propose using prices in other cities to instrument for prices in a city. In the retailer's pricing, specified by equation (12), retail prices in all cities have a common cost factor c_{it} that is the manufacturer's price. Therefore, prices in neighboring cities are valid instruments as long as unobservable demand shocks are independent across locations. In the estimation, the prices of the same good in two neighboring cities are used.

4 Estimation Result

4.1 Demand System

The system of equations (13) is estimated by GMM three-stage least squares (3SLS). The parameter restrictions are imposed during the estimation. The demand is estimated with a panel data set that pools all cities, although the system can be estimated for each city separately as well. I chose not to use the city-by-city regression because the estimates are not always robust.[20] I use the coefficients from the pooled estimation to derive the implied markup. The price elasticities (18) are city-specific because they are evaluated at a city-specific budget share, but not because the estimates of parameters are different. The only city-specific parameter in the estimation is the intercept, α_{il}. Since elasticities are not constant by construction, the following tables report only the results that are evaluated at national average expenditure shares. Autocorrelation-consistent standard errors are reported below the estimates.[21]

The top stage budgeting decision is made over five segments: food, household durable goods, medical goods, recreational goods, and miscellaneous goods. Table 4 shows the top-stage estimation result. Instead of reporting the point estimates of parameters, the table reports the implied elasticities to facilitate interpretation. The elasticities are evaluated at the national average expenditure shares and their standard errors are calculated using the delta method. The third column shows the income elasticity of demand for each segment, and the remaining columns present price elasticities.

The income elasticities are all positive, implying that these goods are normal goods. The estimated income elasticity of food is less than one, which satisfies Engel's law of demand, so an increase in income leads to a decrease in the share of income allocated to food. For all segments, estimated own price elasticities found on the diagonal of price elasticities are significantly less than zero at 5 % level. The off-diagonal entries are the cross-price elasticities. Food, medical goods, and miscellaneous goods are relatively elastic, while furniture and recreational goods are inelastic. Because inelastic sectors include many durable goods that people do not purchase frequently, it may be the case that this form of static demand system is not appropriate for those categories.

Middle stage results are reported from Table 5a to 5e. The food segment is followed by an

[20] In city-by-city regressions I sometimes find insignificant own-price elasticities whose point estimates are unreasonable. Less than half of price elasticities are statistically significant even at the 10 % level.

[21] I tested serial correlation by the autoregressive coefficient of time-demeaned residuals (p.275, Wooldridge (2002)) and confirmed that it is significant in almost all groups. The inclusion of lagged expenditure share in the form of Edgerton (1996) helps eliminate the problem of serial correlation but does not substantially affect the estimates of elasticities. In this paper, I avoid using the dynamic specification because its effect on the estimates is limited, and having a lagged term could cause a time inconsistency in the retailer's optimal pricing strategy.

additional three-stage decision and non-food segments are followed by a two-stage decision. The tables report the results for the highest stage of food segment and the upper stage of the other segments. At the segment level, consumer demand is not very sensitive to price. The own-price elasticities are negative in all sub-segments, but in many cases they are around unity in absolute value.

Bottom-stage results are summarized in Table 6. To save space, I only report the summary statistics of the own-price elasticities in the table. The left half of the table reports conditional price elasticity that assumes a constant group expenditure (Equation (16)), and the remaining half reports unconditional elasticities (Equation (18)). Some groups have an "other good" entry that bundles minor products into one good. Because no price information is provided to this category of good, the price index for the whole group is calculated excluding the "other good" category, while the total group expenditure includes the expenditure on "other" goods. Basically, the coefficients related to this good are calculated from the adding-up conditions.[22]

For many goods, own-price elasticities are around one in absolute value. To facilitate the comparison with existing literature, I examine the result for the alcoholic beverage group. There are five goods in the group: sake, beer, low-malt beer, whisky, wine and other liquor. Beer has an inelastic demand where the point estimate of own-price elasticity is -0.51. In contrast, low-malt beer's own-price elasticity is -3.06, which is one of the most elastic goods in the data. Those values are smaller, in absolute value, than the value estimated in existing literature that uses product-level data. Hausman, Leonard, and Zona (1994), for example, use product-level beer consumption data in the US and find a price elasticity between -3.8 and -6.2 at the product-level, but at more aggregated levels, the price elasticities are less elastic.

The inelastic problem is not specific to foods. The lower half of Table 6 presents the results for non-food goods. Daily commodities, mainly cosmetics, include some exceptions that show a relatively high level of elasticity. Additionally, I do not find significant cross-price elasticities. This observation is more evident for non-food goods. Those goods are "unrelated," giving some rationale for assuming that the retailer's pricing rule to one good does not depend on the other good's demand.

There are some possible reasons behind obtaining inelastic demand. The consumer's elastic substitution behavior might be found at more disaggregated levels, such as among different brands of beer or among different segments of beer. Indeed, with the same multi-stage AIDS budgeting model, Chaudhuri, Goldberg, and Jia (2003) find that the lower-stage demand is more elastic than

[22] Another way of treating "other goods" is to exclude them completely. I tried this specification and confirmed that the point estimates were not substantially different for many cases.

the higher stage using India's pharmacy data. Hausman, Leonard, and Zona (1994) observe the same pattern. Deaton and Muellbauer (1980b) also argue that demand system estimation using aggregated data tends to generate low elasticity. Unfortunately, I do not have observations for further disaggregated goods.

It is also known that the AIDS estimate of elasticity depends on the goods grouping decision. I tried several different grouping patterns; but grouping does not help in obtaining elastic demand, and the estimates are quite robust.

4.2 Supply Side Estimation with Good-level Heterogeneity

4.2.1 Measure of Markups

The pricing equation (12) is estimated by pooling cross-sectional observations for six years. The price data is then annualized by taking the average over months. The supply side is estimated with annual data for two reasons. First, annual price can alleviate the effect of price rigidity. On a monthly basis, there are many cases in which prices stay constant for several months, and this stickiness is likely to be driven by factors other than local costs or taste dependent markups.[23] In fact, the average of monthly price differences is about 10 % greater than the annual average price difference, implying that the monthly dispersion is affected by transitory price differences. The other practical reason is that some variables used as proxy for local costs are only available annually.

The markups defined by (11) depend on two factors: demand elasticities and competitiveness. I use two different methods to calculate the implied markup. First, I estimate the index of competitiveness θ from the data, along with other parameters on local distribution costs. Alternatively, I estimate the pricing equation assuming that the underlying conduct is Cournot competition. In the case of Cournot competition, the markup depends on the elasticity and the number of retailers in the local market, which are observable in the data.

The number of stores in each city is taken from the *Commerce Survey*, available from the Ministry of Economy, Trade and Industry (METI). To limit attention to stores that are likely to have substantial market power, I use the number of large scale retail stores whose workforce is fifty employees or more. I normalize the number of retailers in each city per 30,000 of population. Roughly speaking, 30,000 is the number of people living within a two-kilometer radius in the prefectural capital cities. The data on the number of stores and population size are available for each city. With this normalization, the average number of retailers across cities is ten, and the overall average of

[23]See Higo and Saita (2007) for the evidence of price stickiness in Japan using the same data.

markups across goods and across cities is around 1.12, implying that the share of profits is 10.7 % of sales.[24] This value matches the data. According to the *2000 Input-Output Tables* of Japan, the net operating profit is about 10.3 % of the distribution sector's total production. The *Business Accounts of Unincorporated Enterprises*, published by the MIC, reports that net operating profits per total sales was, on average, 10.7% between 2000 and 2005.

Demand elasticities are obtained by evaluating the unconditional elasticity (18) with annual expenditure shares in each city. I treat imprecise estimates in the following way. If the point estimate of price elasticity evaluated at the national average expenditure share is not significant at the 5 % level, then the corresponding good is dropped from the sample. The demand elasticities have occasional outliers when they are evaluated at the actual shares for each city. Especially if a city has an exceptionally low share in expenditure on a certain good, then their demand elasticity tends to be large in absolute value. To control those cases, a city-specific elasticity that lies outside of five standard deviations range is replaced by the national average elasticity. In the end, 26 goods (10 foods and 16 non-food goods) are dropped from the sample because they either have insignificant demand estimates or too many outliers. Therefore, when these goods are dropped, the sample covers 125 foods and 47 non-foods, totaling 172 goods. I also run the regressions including these outliers to check the robustness.

4.2.2 Heterogeneous Degree of Competitiveness

I start with estimating the pricing equation by treating the conduct parameter θ as a value to be estimated. This specification includes other possible forms of competition, from perfect competition to the monopoly.[25]

I estimate the non-linear pricing rule (11) and (12) by the least square method. After re-labeling the notations, (12) is rewritten by:

$$\log p_{ilt} = \log(1 + \frac{\theta_i}{\hat{e}_{ilt}}) + X_{lt}\phi_i + \mu_{it} + \epsilon_{ilt}. \tag{20}$$

p_{ilt} denotes the retail price of good i in city l at time t, $\hat{e}_{ilt}$ is the demand elasticity obtained from the demand estimation, and X_{lt} is a set of distribution cost proxies that include the retailer's wage and rent. A good-time effect, μ_{it}, controls for any good- and time-specific unobservable shock that

[24]The calculation is the following:

$$\frac{\text{Net Operating Profit}}{\text{Total Sales}} = \frac{\text{Unit Price - Unit Cost}}{\text{Unit price}} = \frac{p - mc}{p} = 1 - \frac{1}{m}. \tag{19}$$

This ratio is 10.7 % when the markup is 1.12.

[25]See Reiss and Wolak (2007) and Bresnahan (1989) for a potential problem of using this method.

is common to all cities within the nation. It also captures the manufacturer price that is common across all retailers if the LOP holds at the manufacturer-level. I consider the case that treats the good-city specific effect later. The frequency of observation is annual from 2000 to 2005.

The parameters of interest are θ and ϕ. θ_i measures the competitiveness for a good i. ϕ_i is a product of the distribution share in the final price a_i and each factor's share in the unit cost of distribution.[26] It is likely that different goods need different amounts of labor input to distribute, which causes ϕ_i to be good i-specific. To allow for this possibility, I also use a type of random coefficient model. Here, I assume each good has a different coefficient on distribution costs, but its slope is drawn from a certain distribution.

$$\phi_i = \phi + \nu_i, i = 1, ..., N. \tag{21}$$

ν_i are assumed to have zero mean and constant covariances. It is assumed ν_i's are distributed independently of the regressors for all i, l and t. The overall performance is analyzed by the value of ϕ. I also assume a similar distribution for θ_i.

The equation is estimated by the Non-linear Least Square (NLLS) method separately for each good. To analyze overall performance, I use the Mean Group (MG) estimate (Hsiao and Pesaran (2008)), which is simply the average over the goods, i.e. $\hat{\phi} = N^{-1}\sum_{i=1}^{N}\hat{\phi}_i$ and $\hat{\theta} = N^{-1}\sum_{i=1}^{N}\hat{\theta}_i$. The standard errors are obtained by the bootstrap method. The conjectural variation (CV) parameter θ is restricted between 0 (perfect competition) and 1 (monopoly).

A summary of the results is reported in Table 7. The upper half restricts the coefficients on local costs to be positive, while the lower half does not restrict them. The MG estimate of θ is .08. There are many goods that find $\theta = 0$, implying that retailers do not price discriminate across locations for those cases. The coefficients on the wage and the land price are both positive and statistically significant. Figure 3 shows the density of the individual coefficients when imposing the positive sign restriction. The density is highly skewed for all regressors due to the positive sign restrictions. The density shows that many goods have zero coefficients on the cost variables, implying that local cost variables are not always related to the price as the theory predicts.

The remaining columns of the table report the corresponding estimates for subgroups. Fresh foods have relatively large market power. For electric appliances, the market is quite competitive, but this estimate may be imprecise because the number of goods in this group is limited. Local wage

[26] The values of the parameters imply the following values of ϕ, on average. The average distribution margin a is 40 % of the final price. Typical shares of inputs in the retailer's operating cost are 50 % for wage and 10 % for rent. Therefore, the expected value of ϕ is .2(=.4×.5) for wage and .04(=.4×.1) for rent.

and land price account for the price difference in all groups except for electric appliances. The value of CV θ under the Cournot competition with ten retailers in a market is 0.1. The estimated values of θ are close to this, except for electric appliances. For three out of five groups, fresh foods, processed foods and services, the null hypothesis of Cournot competition is not rejected.

At the good level, many fresh seafood, fresh meat and food services have a relatively large point estimate of CV. Fresh seafood is a category that indeed has the largest price dispersion in Table 1. Part of the large price dispersion for fish and shellfish can be attributed to price discrimination based on demand elasticity. In contrast, for the majority of electronic appliances, none of the cost factors or CV is significantly related to the price.

This relationship is consistent with the finding of Baba (2007). Using the data from Japan and Korea, Baba (2007) argues that the absolute dispersion of perishable goods is wider than the dispersion of durable goods[27]. The dispersion of perishable goods is explained by the geographical distance, but the dispersion of durable goods is not. Although geographical distance is not explicitly included in the pricing equation, both distribution costs and demand elasticities are cross-sectionally correlated with distance between cities. In other words, people living in a nearby city tend to have similar tastes and wage levels. These factors significantly account for the price of perishable goods (seafood and meats) but do not account for the price of durable goods (electronic appliances).

Although price discrimination and local costs are statistically significant, the qualitative significance is limited. The bottom of Table 7 reports standard deviations of the errors that are left unexplained by the markup and the local costs. For a good i, the original price dispersion is defined by the standard deviation across cities in equation (1). The remaining dispersion after accounting for markup difference is defined by the standard deviation of $(\log p_{ilt} - \log \hat{m}_{ilt})$. Similarly, the remaining dispersion after accounting for differences in both costs and markups is calculated by $\underset{l}{Std}(\log p_{ilt} - \log \hat{m}_{ilt} - X_{lt}\hat{\phi}_i) = \underset{l}{Std}(\hat{\epsilon}_{ilt})$. The ratio of these dispersions to the original dispersion measures the goodness of fit and is analogous to R^2. The average and median of the ratios over goods are reported in the table.

The original price dispersion is 14.1 %, of which the demand based markup explains less than 1 % and local costs explain 2 %. The dispersion of residuals is 13.8 %, which corresponds to a 2 % reduction from 14.1 %. The actual reduction in dispersion is different across goods such that, for the best case, the dispersion is reduced by 17 %, while in another case, the dispersion does not shrink at all. To summarize the changes at the good level, I plot the level of original price dispersion and the

[27] Because the price data in this paper cover a narrower range of durable goods than Baba (2007), this pattern is less evident in this paper.

dispersion after accounting for the markups (Figure 4) and the combination of both markups and local costs (Figure 5). The horizontal axis of each figure shows the original level of dispersion, and the vertical axis shows the remaining dispersion after fitting the model. Each dot represents a good, and its distance from the 45-degree line indicates the goodness-of-fit. On the 45-degree line, the good's dispersion remains unchanged before and after fitting the model. When the price dispersion for a good shrinks after accounting for the difference in local costs and elasticities, the good's dot is located below the 45-degree line.

The figures clearly show that most goods are on the 45-degree line. The markups do not reduce the dispersion for most cases. At the same time, goods that originally have larger dispersion tend to have a greater reduction, particularly seafood. To understand the performance for disaggregated groups, I decompose the change in dispersion into five subgroups in Figure 6. The figure clearly shows that the model is able to explain the price difference for foods and services, but not for non-foods.

When the negative slope is allowed, as is reported in the lower half of Table 7, the model is able to account for 3% of the price dispersion on average. However, the coefficient on wage is not significant. This is most likely due to a correlation between the regressors, wage and land price. In the following subsection I discuss the single regression result and the multiple regression result under the setting of Cournot competition in more detail.

When city-good fixed effects are included, most coefficients have very small impacts or are even insignificant, as shown in Table 8. Most coefficients are still significant if I impose positive sign restrictions. Once I allow fixed effects to enter the equation, then the model is basically testing the relative version of LOP because the permanent deviations from parity in levels are allowed. As the analysis in the previous section shows, the dispersion is highly persistent. Therefore, allowing the good-specific dispersion for each city simply implies that these fixed-effects take away most of the significant static dispersions. Indeed, the dispersion that remains after controlling city-good fixed effects is around 10 % of the original. The results in Table 8 imply that the role of local distribution costs is even more difficult to reconcile in the relative LOP.

To check robustness, results without controlling outliers in the demand estimation are reported in Table 9. Originally, I exclude the price elasticities that lie outside of five standard deviations. To investigate the effect from the treatment of outliers, I estimate the same equation allowing for outlier elasticities to be in the data. The results are robust to the existence of outliers. The average CV is around 0.08, and the wage and the land price significantly account for the retail price. Demand-based markups explain less than 1% of the dispersion and local costs explain about 2-3 % of price dispersion.

In sum, the differences in local distribution costs and consumer demand elasticities affect the price of goods. The conduct of retailers is characteristic of Cournot competition. Furthermore, these factors explain the dispersions for food better than for non-food goods. Finally, however, the effect is small.

4.2.3 Cournot Competition

I then estimate the pricing equation, assuming the conduct is Cournot and considering the number of retailers. The markup is defined by (11), with R_l being equal to the number of stores per 30,000 people in each city. Specifically, the pricing equation is written as:

$$\log p_{ilt} = \log m_{ilt} + X_{lt}\phi_i + \mu_{it} + \epsilon_{ilt}, \tag{22}$$

and

$$\phi_i = \phi + \nu_i, i = 1, ..., N. \tag{23}$$

ν_i are assumed to have zero mean and constant covariances. It is assumed that ν_i's are distributed independently of the regressors for all i, l and t.

The model is estimated by Swamy (1970)'s specification, using the feasible GLS estimator. At the individual level, the consistent $\hat{\phi}_i$ is obtained by applying OLS on a good-by-good basis. With the consistent estimates, the weights are calculated from the residuals. In a linear framework, the MG estimate and Swamy's GLS are asymptotically equivalent. See Swamy (1970) and Hsiao and Pesaran (2008) for the statistical inferences.

The results in Table 10 confirm the pattern obtained from the CV model. I estimate the equation by changing the set of regressors. In simple regressions, both wage and land price have the expected sign and are statistically significant. When wage and land price are jointly included in the regression, only the land price is significant. This may be because the land price and the wage correlate cross-sectionally (correlation coefficient = 0.7). The coefficients are robust to the inclusion of markups. I include the markups in two different ways. When the Cournot markups (11) are included in the set of regressors, there is no significant change in the result. But the assumption of Cournot conduct for all goods is rejected. When I restrict the coefficient on the markup to one, which is equation (12), both wage and land price are significantly related to price.

Slope coefficients are highly heterogeneous across goods. Figure 7 shows the kernel estimate of the distribution of ϕ_i from the regression that includes wage, land price and markup as regressors. In linear regressions, I do not impose the sign restrictions, so there are many goods that have negative slope coefficients on the local cost variable.

The model is able to explain about 3 % of price dispersion when it includes both wage and land price. When I impose the Cournot markup, the implied price dispersion is greater than the original dispersion. Figure 8 replicates the change in dispersion that is analogous to Figure 5. The change in dispersion is similar across the two specifications. The results in Table 10 and Figure 7 are for foods only, but the result is robust when all goods are included. The right half of Table 10 reports the result when all available goods are pooled.

4.3 Analysis on Average Price Difference

In this subsection, I consider the role of distribution costs and markups in the dispersion of the aggregated price. Recall that the dispersion of average price is smaller than the dispersion at the individual good-level, but it is still sizable. To investigate the role of costs and demand elasticity at the aggregated level, I calculate the average price level of the city by taking a simple average over goods to obtain the measure of aggregated price and then look at its relationship to local costs and demands. This aggregated price measures the price of a basket of goods, so its deviations are understood as deviations from Purchasing Power Parity (PPP), rather than as deviations from the LOP.

Without the markups, the regression is specified as:

$$N^{-1}\sum_{i=1}^{N}\log p_{ilt} = X_{lt}\phi + \mu_t + \epsilon_{lt}. \tag{24}$$

It is worth noting that the regression on the city average price is mathematically equivalent to the analysis of the regression that pools all goods in equation (22) but restricting the same slope coefficients. This is because all regressors are common across goods.

The benchmark results in Table 11 confirm the robustness of the overall result obtained from the good-level dispersion. The left-most column of Table 11 shows the estimates obtained from the single regression. The slope coefficients on wage and land price are close to those reported in Table 10.

In addition to the wage and the land price, I also consider the roles of city remoteness and population. Remoteness is included to capture the transportation cost from a good producer. Population is included to indirectly measure the demand side difference, in the sense that people living in places with similarly sized populations have similar taste. Remoteness is approximated by distance from

Tokyo or distance from a nearby large city like Nagoya or Osaka. I measure the remoteness in this way with a conjecture that the distribution network has its hubs in large cities, so a distributor incurs more transportation cost if a city is far from a large city. For example, at least for fresh foods, the largest hub is in Tokyo because *Metropolitan Central Wholesale Market* in Tokyo is the largest wholesale market in Japan. Distributors trade about 10 % of the national fresh food consumption here.

Columns (1) through (4) of Table 11 report results from the multiple regressions. As in the good-level analysis, wage does not significantly explain the retail price if it is jointly included with the land price. The distance from Tokyo has a significantly positive relationship with the price. Thus, the retail prices are less expensive in Tokyo than in other cities, once we control for some local inputs. When city fixed effects are controlled, neither wage nor land price is statistically significant. The regression with the city fixed effects is reported in columns (5) and (6) of Table 11. Population is the only variable that remains significant.

The results for food are reported in Table 12. I allow a variation in the coefficients between fresh food and processed food. For fresh food, all variables enter with the expected sign. The local wage level and the fresh food prices are positively correlated across cities. The distance from Tokyo also enters with a positive, significant sign, implying that the farther a city is from Tokyo, the higher the price level is, after controlling the effects from wages and land prices. This result is expected because Tokyo has a large wholesale market for fresh food, and much of fresh food in Japan is distributed to the countryside from the market in Tokyo. However, processed food has a negative sign on wage and is even statistically significant at the 5 % level. Furthermore, the regression result for non-food in Table 12 is different from that for food. The non-food good price is positively related to wage level. It has a significant negative sign on land price. However, as I noted before, there is a relatively small number of non-food goods in the sample and they do not seem to represent the whole sample well. Therefore, the result for non-food goods is not robust. With more non-food goods in sample, the average price in a city is likely to be affected.

Table 13 displays the estimation results that include the Cournot markups:

$$N^{-1}\sum_{i=1}^{N}\log\frac{p_{ilt}}{m_{ilt}} = X_{lt}\phi + \mu_t + \epsilon_{lt}. \tag{25}$$

The markups are obtained assuming symmetric Cournot competition. Overall, considering markups, measures of the local cost enter with their expected sign, and most of them are significant. Column (1) reports the benchmark result. The implied marginal cost of processed food is positively related to local costs. The distance from a large city still enters with a negative sign for processed food but is not statistically significant.

The result here indicates that the implied markup has a negative relationship with wage. This is mainly because in a place where the wage level is high, a city tends to have a more competitive retail market, making markups lower. This effect from competition is more important than the effect from different elasticities between cities. To illustrate this point, I run the same regression with different specifications of markups. The second specification simply assumes that all cities have the same degree of competitiveness. The average number of retailers in each city is around ten, so I fixed the number of competitors to ten nationwide. With this specification of markups, the implied marginal costs basically retain the same property observed for the retail price without markups. On the other hand, if I fix the elasticity across goods and cities (set at -0.95, i.e., the simple average) but allow for different levels of competitiveness across cities, then the parameters are very similar to what I obtained for the benchmark case.

In the bottom of each table, I report the dispersion of aggregated prices before and after fitting the model. The dispersion of average price is measured by the average over time of $\tilde{S}_t = \sigma(N^{-1} \sum \log p_{ilt})$. For food, the dispersion of average price is around 5 %, while the average of good-level dispersions is as large as 14 %. After fitting the model, the dispersion of average price falls by 0.5 %, from 4.6 % to 4.0 %, implying that those factors account for about 15 % of the difference in aggregated prices.

Therefore, the analysis for the aggregated price confirms the robustness of the good-level analysis to the other explanatory variables. It also shows that, at the aggregated level, about 15 % of deviations from PPP is accounted for by differences in distribution costs and demands.

5 Conclusion

I construct a simple static model to analyze the good-by-good deviations from the LOP and apply the model to Japanese regional price data. Deviations from the LOP are associated with differences in local costs of distribution and in markups that are set by imperfectly competitive retailers. The markups for goods in each city are derived from the local demand structure, which is estimated from the AIDS demand system with multiple-stage budgeting.

Overall, empirical results confirm the relationship implied by the theoretical model. Both local distribution costs and local demand heterogeneity account for a part of the dispersion and they are shown to have a statistically significant relationship to the retail price.

However, contrary to what the standard models predict, the price dispersion that is attributable to the differences in local costs or demand is very limited. The estimated model implies that local costs significantly explain the retail price dispersion across cities, and the relationship is stronger if the markup, which is a function of demand elasticities and market competitiveness, is controlled. However, on average, local costs account for only 2-3 % of the price dispersion.

The finding of this paper is consistent with the recent literature that use a scanner data set.[28] A common conclusion that arises from the literature is that neither demand shocks nor cost shocks sufficiently account for price dynamics. A similar pattern is documented in this paper, although the main focus is on static dispersion rather than the dynamics of price. The effect from differences in demand or cost is shown to be inadequate in accounting for the observed price dispersion. Therefore, the key to understanding LOP deviations at the good-level is more likely to lie in understanding the market structure, if not cost or demand.

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[28] See Nakamura (2008) and Eichenbaum, Jaimovich, and Rebelo (2008), among others.

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A Retail Price Survey

The Retail Price Survey samples prices in the following way. First, the statistical agency decides the survey districts in each city. The number of price survey districts is decided based on the population size of the city. Tokyo is divided into 42 districts. Five cities (Osaka, Yokohama, Nagoya, Kyoto, Kobe) have 12 districts. Six cities (Sapporo, Sendai, Saitama, Chiba, Hiroshima, Fukuoka) have 8 districts. The remaining 35 cities have 4 districts respectively.

Second, goods are divided into six groups based on consumer behavior, nature of commodities and variation of prices among stores and other characteristics. The prices of goods in Group A, mostly grocery, are surveyed in all districts. Group B consists of goods that households usually buy at a mall or large stores, such as clothing or electric appliances, and their prices are surveyed in a subset of districts. 21 out of 42 total price districts in Tokyo are surveyed, all 12 districts are surveyed in Osaka, 6 out of 12 districts are surveyed in Yokohama, Nagoya, Kyoto and Kobe. For the other six large cities, 4 out of 8 districts are surveyed. For the remaining 35 cities, 3 out of 4 are surveyed. Group C consists of goods with less price dispersion, such as seasoning and recreational goods, and their price is surveyed in 12 (Tokyo), 6 (Osaka), 2 (all other cities) districts in each city. Group D consists of goods whose price is reasonably common within a city, such as utilities and medical cares. Only one price is sampled in each city.

Third, from each district, the representative outlet is chosen based either on their amount of sales or on the number of employees.

The prices are sampled once a month on Wednesday, Thursday or Friday of the week that includes the 12th of the month. Group D goods are sampled on Friday of the week. Fresh foods and fresh flowers are surveyed three times in a month (Wednesday, Thursday or Friday of the week with 5th, 12th and 22nd) and in each time the reported price is the average of three days before the survey date. So the actual price is the average of three observations, each of which is the average of three days.

The survey excludes prices when goods are on "sale". If the sale is temporary, or the low-price lasts for less than a week, then the regular price is instead reported. If the sale lasts more than 8 days, then that price is reported.

Further detail of the outline of the survey and the sampling process is available at: `http://www.stat.go.jp/English/data/kouri/pdf/outline.pdf`

B Family Income and Expenditure Survey

The survey covers all consumer households except for single households of students. Approximately, 9000 households are randomly sampled for the survey out of 43 million households. The number of surveyed households is 96 for most prefectural capitals, except Tokyo (408 households), Yokohama (144), Nagoya (132), Osaka (192), and Naha (168).

Data are collected by questionnaires. Sample households fill in the *Family Account Books* with daily income and expenditures. They keep accounts of all the transactions everyday. If a household is new to the sample, then it is also requested to measure the quantity of the purchase using the scale. A household stays in a sample for six months and is then replaced by another household. Every month one sixth of the sample is renewed.

The city level expenditure data is calculated by a weighted average over households. The weight is decided based on the sampling ratio of each stratum.

Further detail of the outline of the survey and the sampling process is available at: `http://www.stat.go.jp/english/data/kakei/pdf/p2.pdf`

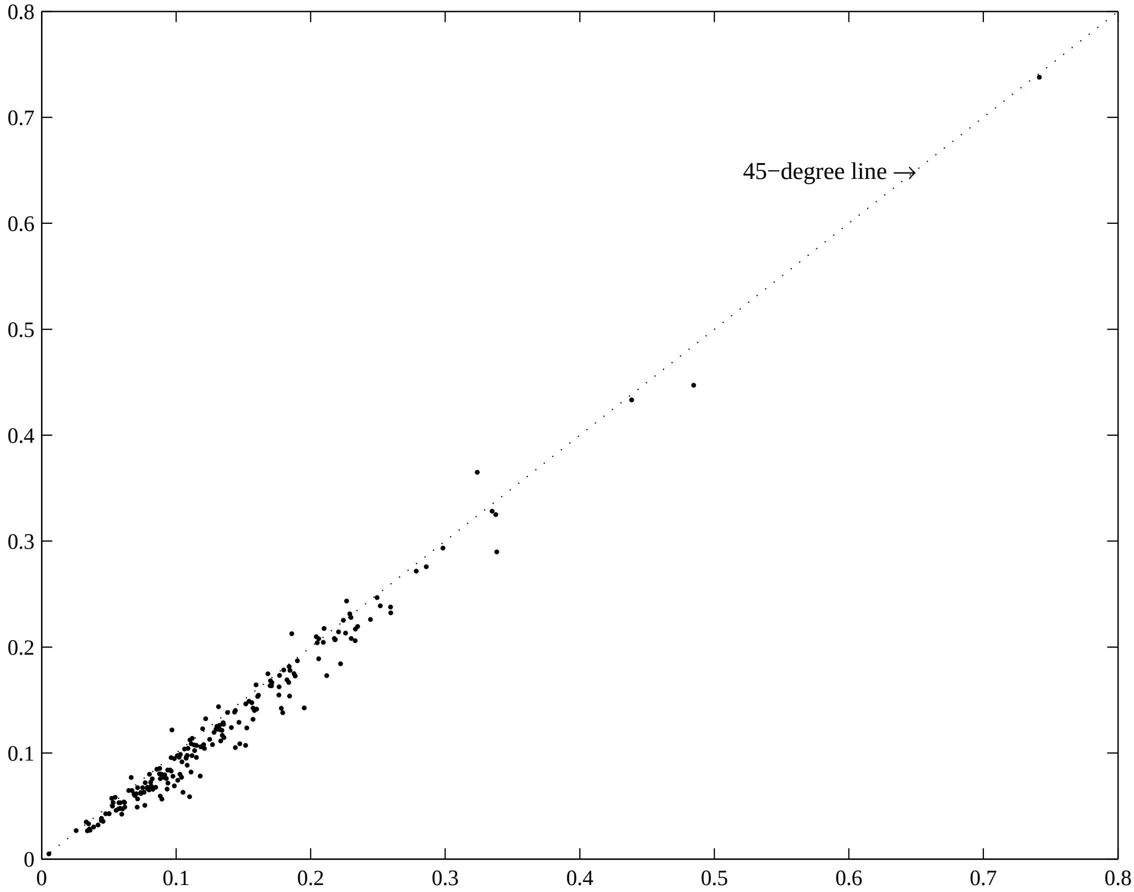

Figure 1: Dispersion in the short-run (x-axis) and the long-run (y-axis)
Notes: Each dot represents a good. The short-run dispersion is calculated by the average of static dispersion over years. The long-run dispersion refers the dispersion of the long run price level obtained from AR(k) models.

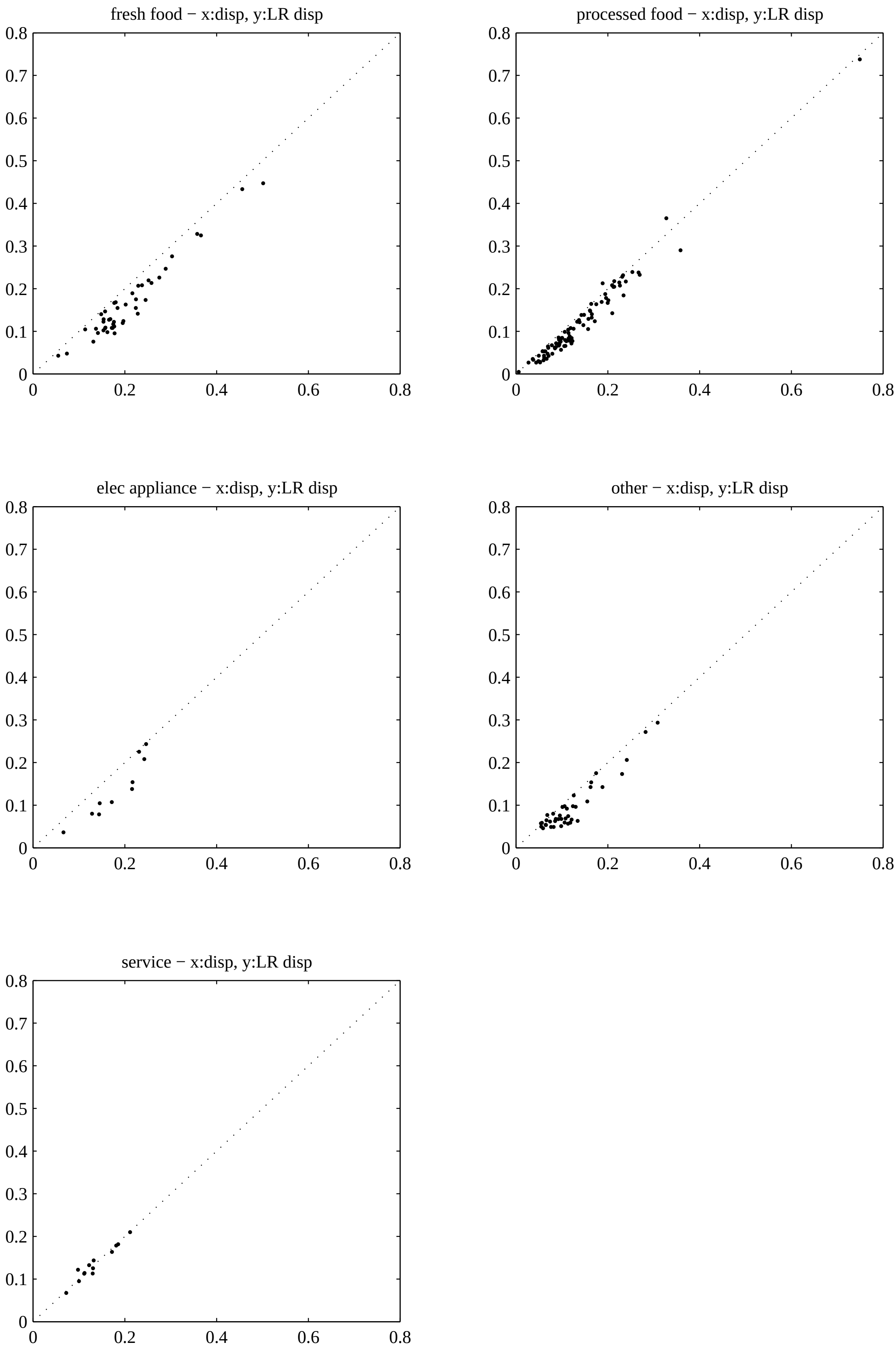

Figure 2: Long Run Dispersion by Group
Notes: Each dot represents a good. x-axis represents the short-run dispersion and y-axis represents the long-run dispersion.

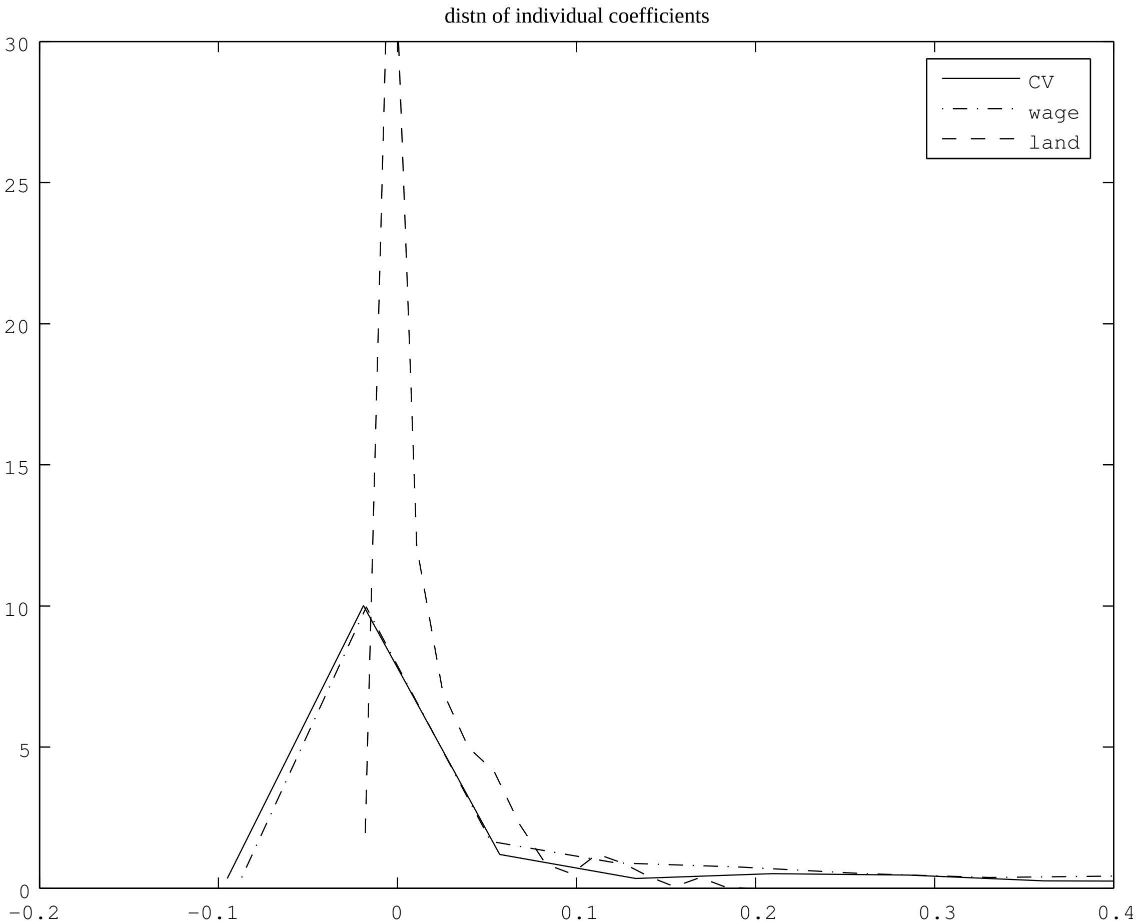

Figure 3: Distribution of Individual Coefficients from NLLS
Notes: The figure plots the kernel density of individual coefficients obtained from applying the NLLS to each good.

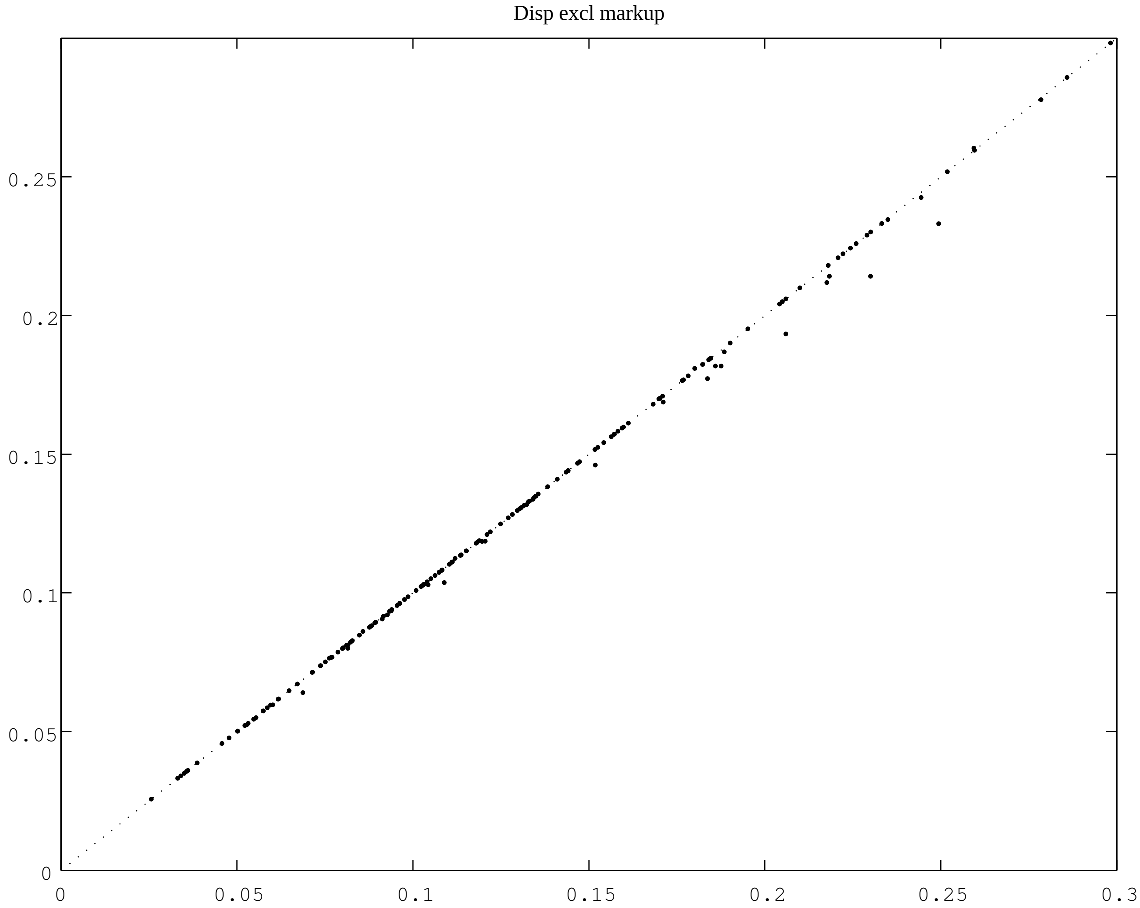

Figure 4: Change in Dispersion by Implied Markup
Notes: The figure plots the original price dispersion (x-axis) and the remaining dispersion (y-axis) after accounting for the difference in the demand elasticities. Each dot represent a good. Distance between the dot and the 45-degree line represents the goodness-of-fit of the model.

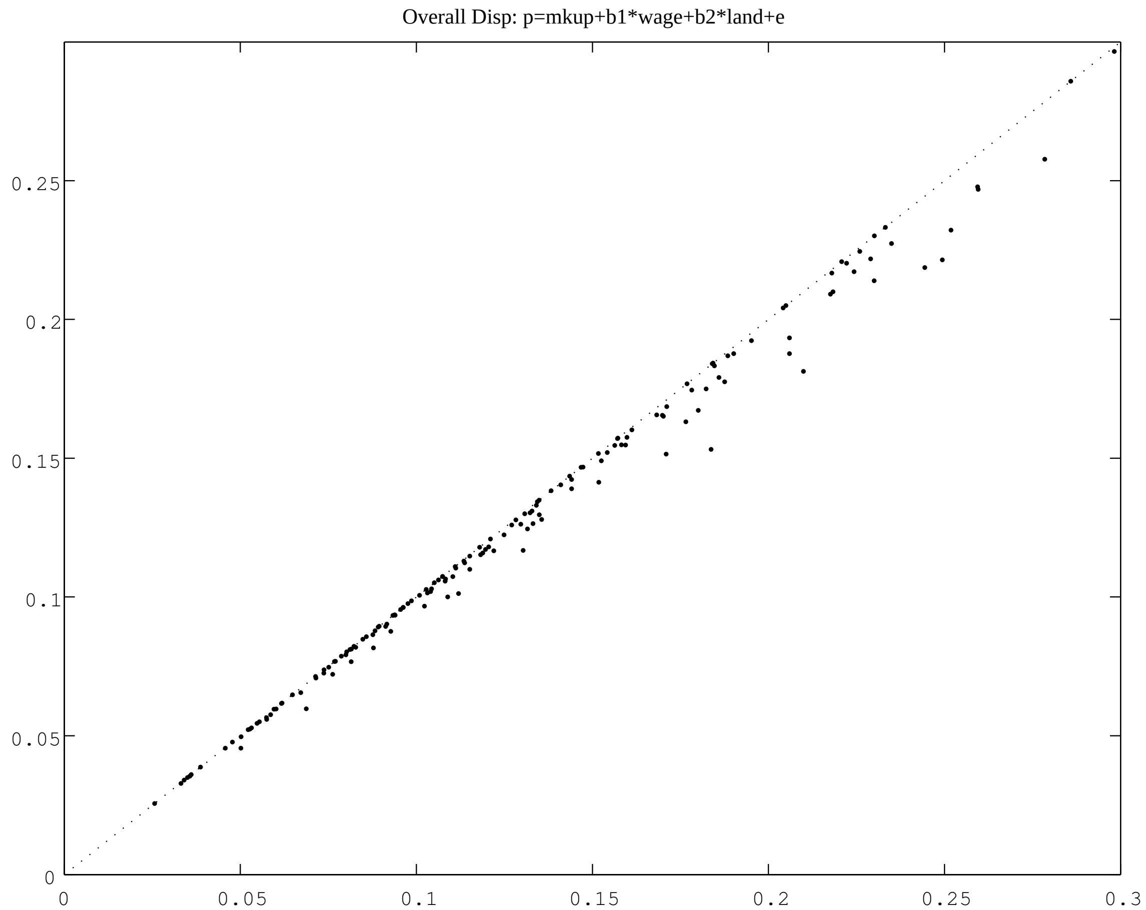

Figure 5: Overall Change in Dispersion
Notes: The figure plots the original price dispersion (x-axis) and the remaining dispersion (y-axis) after accounting for both the demand elasticities and the local costs. Each dot represents a good. Distance between the dot and the 45-degree line represents the goodness-of-fit.

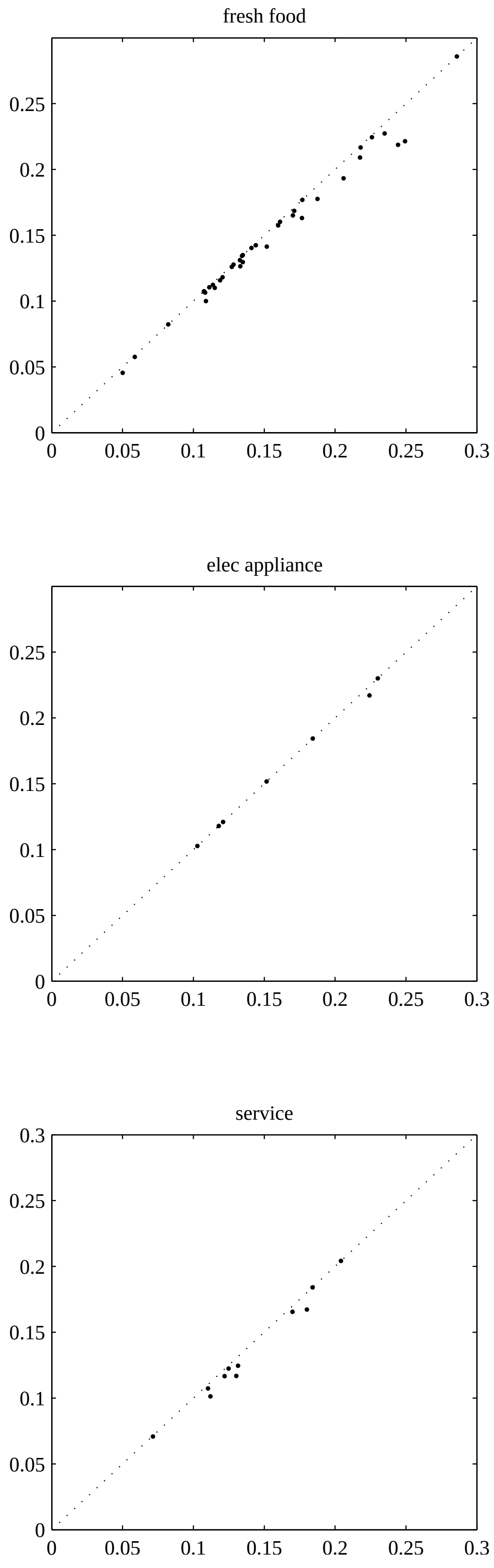

Figure 6: Overall Change in Dispersion by Group
Notes: The figure plots the original price dispersion (x-axis) and the remaining dispersion (y-axis) for good-groups. Each dot represents a good.

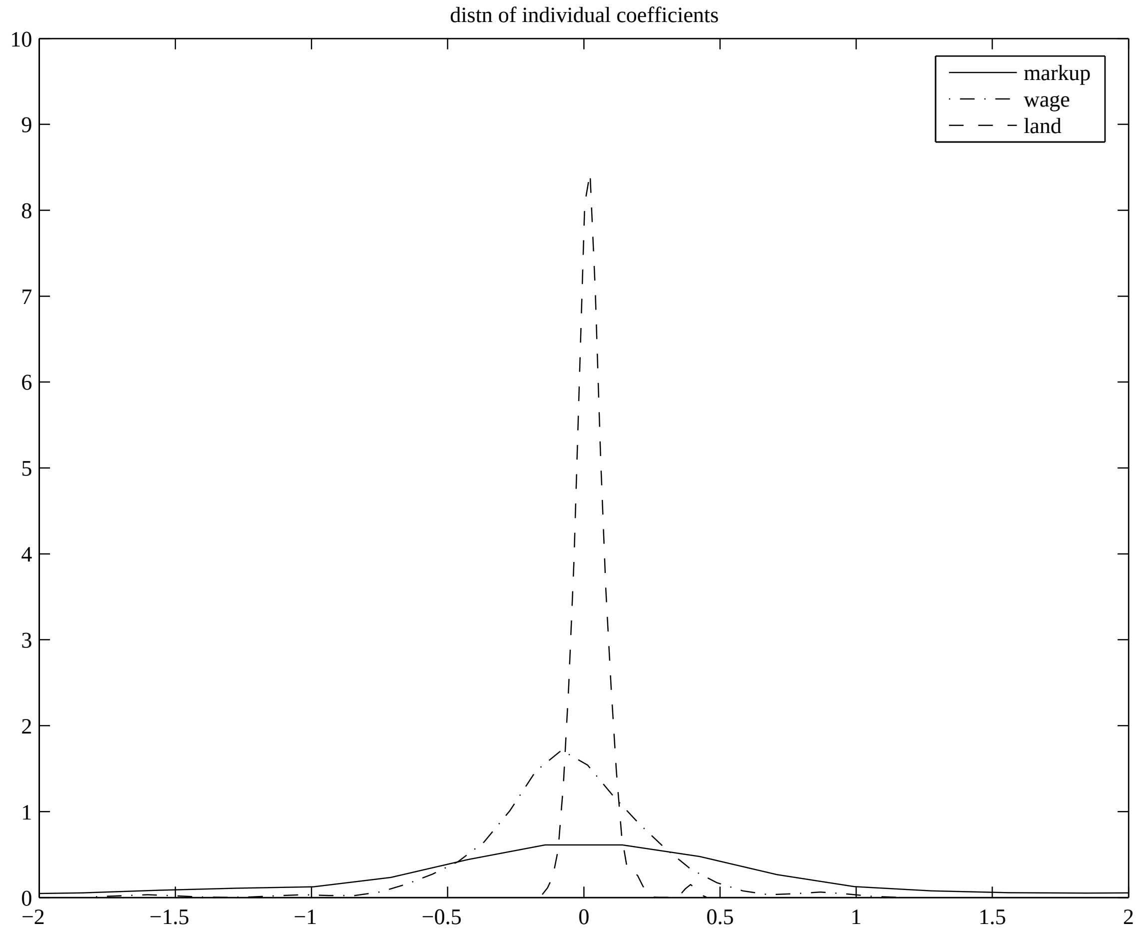

Figure 7: Distribution of Individual Coefficients from OLS
Notes: The figure shows the kernel density estimate of individual coefficients obtained from applying the POLS to each good separately.

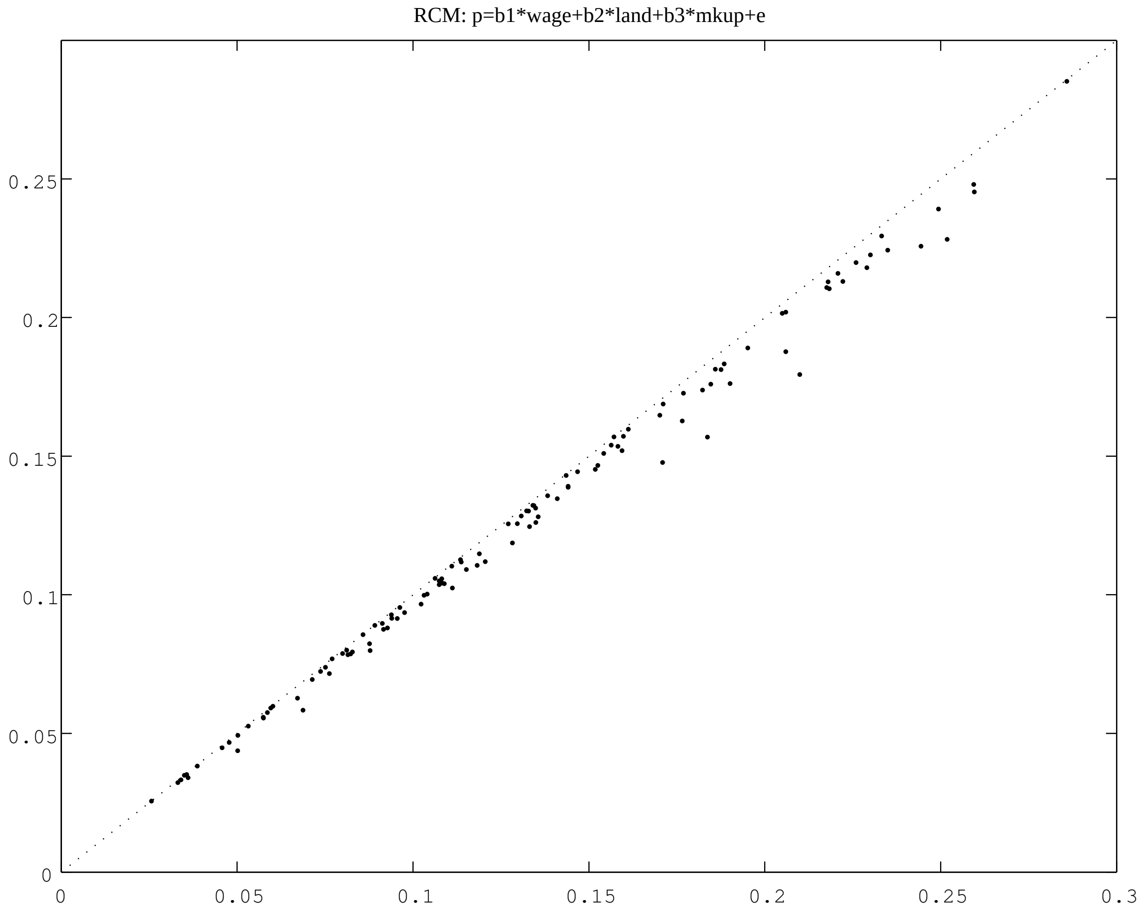

Figure 8: Change in Dispersion in Random Coefficient Model
Notes: The figure shows the change in dispersion from the original (x-axis) to the residuals (y-axis) under the Cournot competition. Each dot represents a good.

Table 1: Summary Statistics of Expenditure Shares and Cross Sectional Price Dispersion

	Share[1)]	#goods[2)]			Dispersion by Std (log P) [3)]		
		(Retail)	(Expd)	(in sample)	(Retail)	(in sample) simple avg	(in sample) weighted avg
Food	25.2%				0.146	0.145	0.124
Cereals	9.2%	13	12	10	0.101	0.100	0.082
Fish & Shellfish	10.6%	31	31	24	0.233	0.225	0.212
Meat, Dairy products & Eggs	12.8%	18	13	11	0.124	0.098	0.116
Vegetables & Seaweeds	11.7%	43	39	37	0.171	0.174	0.165
Fruits	4.5%	20	13	-	0.141	-	
Oil, Fats and Seasonings	4.2%	16	16	16	0.080	0.080	0.087
Confectionery, Snack & Cooked fo	19.2%	31	26	25	0.127	0.131	0.119
Beverages & Alcoholic beverages	9.8%	28	16	12	0.093	0.086	0.081
Eating out	17.9%	20	11	10	0.164	0.137	0.130
Furniture and Household utensils	3.5%				0.186	0.155	0.160
Household durables	47.7%	29	22	8	0.215	0.178	
Domestic non-durables	43.8%	25	13	13	0.154	0.147	
Domestic services	8.5%	3	3	-	0.169	-	
Medical goods and services	4.0%				0.104	0.107	0.116
Medicines	24.9%	11	7	6	0.070	0.071	
Medical supplies & appliances	18.9%	8	5	5	0.140	0.143	
Medical services	56.1%	9	5	-	0.114	-	
Recreation	10.6%				0.200	0.089	0.075
Recreational goods	46.6%	41	40	6	0.125	0.089	
Recreational services	53.4%	22	23	-	0.340	-	
Miscellaneous	21.9%				0.112	0.093	0.097
Miscellaneous	31.7%	24	19	12	0.119	0.085	
Miscellaneous Services		13	13	3	0.099	0.122	
Allowance	68.4%	0	5	-			
	Total	405	332	198		0.137	0.123

Notes:
1) Expenditure share of each segment is in percentage of the total consumption expenditure. The value for each subgroup is the expenditure share within the segment.
2) The number of goods in each survey is reported. Discontinued goods and new goods are dropped.
3) Cross sectional price dispersions are measured by all available goods and by in-sample goods. The in-sample goods dispersion is further measured by simple arithmetic average over goods (left) and the expenditure share weighed average over goods (right).

Table 2: Aggregated and Disaggregated Price Dispersion

	Overall	Fresh Foods	Processed Foods	Electronic Appliances	Other goods	Services
#goods	198	44	91	10	40	13
Annual Price Dispersion						
Good-Level	0.137	0.175	0.130	0.158	0.110	0.134
Aggregated	0.027	0.059	0.033	0.089	0.030	0.059
Good-Level Dispersion for Different Time Horizons						
Monthly	0.152	0.206	0.139	0.181	0.120	0.135
Annual	0.137	0.175	0.130	0.158	0.110	0.134
Long Run	0.126	0.164	0.119	0.137	0.095	0.135

Notes:

1) Jan 2000-Dec 2005. 47 cities. The number of goods in each category is reported in the top pa

2) The good-level dispersion is the average standard deviation of the good-level price differences across 47 Japanese cities. The aggregate dispersion is the standard deviation of the aggregate log prices. The lower half of table shows the good-level dispersion calculated from monthly prices, the annual average price and the long-run dispersion that is obtained from applying an autoregressive model.

Table 3: Persistence of Price Dispersion

Group Name		Overall	Fresh Foods	Processed Foods	Electronic Appliances	Other goods	Services
#goods		198	44	91	10	40	13
All Cities	SARC	0.797	0.594	0.831	0.810	0.887	0.951
	Half-life (months)	6.613	2.050	6.163	4.884	9.102	18.884
	Reject Unit Root	173	44	83	9	31	6
	(in %)	87.4%	100.0%	91.2%	90.0%	77.5%	46.2%
	LR Disp	0.126	0.164	0.119	0.137	0.095	0.135
	Avg of SR Disp	0.137	0.175	0.130	0.158	0.110	0.134
Small Cities	SARC	0.801	0.600	0.835	0.832	0.888	0.948
	Half-life (months)	7.419	2.116	6.113	4.775	9.099	31.376
	Reject Unit Root	163	44	77	10	27	5
	(in %)	82.3%	100.0%	84.6%	100.0%	67.5%	38.5%
	LR Disp	0.131	0.169	0.123	0.145	0.096	0.156
	Avg of SR Disp	0.141	0.181	0.133	0.166	0.112	0.136

Notes:
1) The summary results are obtained by applying the Levin-Lin-Chu test for each good separately. The values in the table are the average over goods. Period: Monthly, Jan 2000-Dec 2005. 47 Japanese cities. The number of goods in each category is reported in the top part.
2) Subsample regression "Small cities" excludes 12 large cities from 47 cities with prefectural capital.

Table 4: Estimates from the Demand System, Top Level Elasticities

	Segments:	Avg share	Income Elas	Price Elasticity 1	2	3	4	5
1	Food	78.1%	0.820 **	-1.128 **	0.023 **	0.035 **	0.006 **	0.244 **
			(0.006)	(0.025)	(0.004)	(0.005)	(0.003)	(0.026)
2	Furniture and Utensils	6.7%	1.930 **	-0.597 **	-0.868 **	-0.183 **	0.045 **	-0.327 **
			(0.047)	(0.057)	(0.045)	(0.032)	(0.018)	(0.052)
3	Medical care	5.6%	1.913 **	-0.363 **	-0.216 **	-1.740 **	0.004	0.402 **
			(0.056)	(0.069)	(0.038)	(0.075)	(0.022)	(0.076)
4	Reading and Recreation	2.2%	1.646 **	-0.418 **	0.159 **	0.026	-0.699 **	-0.714 **
			(0.071)	(0.103)	(0.057)	(0.058)	(0.050)	(0.084)
5	Miscellaneous	7.4%	1.183 **	2.278 **	-0.243 **	0.345 **	-0.196 **	-3.367 **
			(0.033)	(0.257)	(0.047)	(0.058)	(0.024)	(0.282)

Notes:
1) The elasticities are evaluated at average expenditure shares.
2) Autocorrelation consistent standard errors are reported in parentheses.
3) '**' and '*' indicate the estimate is significant at 5 % and 10 % respectively
4) The systems of equations estimated by 3SLS. Sample period: Jan 2000 - Dec 2005 (72 months). 47 cities. The regression also includes city-dummies and 12 seasonal dummies for each good.

Table 5a: Estimates from the Demand System, Middle Level Elasticities, Food Segment

		Avg share	Income Elas	Price Elasticity 1	2	3	4	5	6	7	8
1	Cereals	9.8%	0.935 **	-0.185 **	-0.003	-0.063 **	-0.092 **	0.051 **	-0.051 **	-0.186 **	-0.408 **
			(0.019)	(0.026)	(0.013)	(0.017)	(0.013)	(0.008)	(0.022)	(0.022)	(0.035)
2	Seafood	11.3%	1.161 **	-0.024 **	-0.423 **	-0.053 **	-0.012	0.020 **	-0.236 **	-0.320 **	-0.114 **
			(0.014)	(0.011)	(0.017)	(0.011)	(0.009)	(0.007)	(0.015)	(0.017)	(0.026)
3	Meat and Dairy	13.6%	0.798 **	-0.032 **	-0.003	-1.110 **	-0.006	0.008	0.167 **	0.030 **	0.147 **
	products		(0.011)	(0.012)	(0.009)	(0.019)	(0.008)	(0.006)	(0.014)	(0.015)	(0.026)
4	Vegetables	12.5%	0.785 **	-0.058 **	0.032 **	-0.004	-0.500 **	-0.023 **	-0.013	-0.077 **	-0.143 **
			(0.011)	(0.010)	(0.009)	(0.009)	(0.015)	(0.005)	(0.013)	(0.014)	(0.021)
5	Oil, Fats and	4.5%	0.723 **	0.133 **	0.099 **	0.034 *	-0.056 **	-1.358 **	-0.006	0.041 **	0.390 **
	Seasoning		(0.016)	(0.017)	(0.017)	(0.019)	(0.013)	(0.046)	(0.026)	(0.020)	(0.058)
6	Confectionery	20.4%	0.826 **	-0.014	-0.093 **	0.108 **	-0.013	-0.006	-0.748 **	0.114 **	-0.175 **
	and Cooked food		(0.010)	(0.010)	(0.008)	(0.009)	(0.008)	(0.006)	(0.029)	(0.011)	(0.034)
7	Dining out	17.5%	1.431 **	-0.152 **	-0.237 **	-0.063 **	-0.135 **	-0.021 **	0.010	-1.097 **	0.264 **
			(0.018)	(0.013)	(0.011)	(0.011)	(0.010)	(0.005)	(0.013)	(0.026)	(0.029)
8	Beverage	10.5%	1.145 **	-0.402 **	-0.121 **	0.145 **	-0.216 **	0.148 **	-0.406 **	0.492 **	-0.785 **
			(0.021)	(0.032)	(0.028)	(0.032)	(0.025)	(0.025)	(0.064)	(0.046)	(0.100)

Notes:
1) The elasticities are evaluated at average expenditure shares.
2) Autocorrelation consistent standard errors are reported in parentheses.
3) '**' and '*' indicate the estimate is significant at 5 % and 10 % respectively
The systems of equations estimated by 3SLS. Sample period: Jan 2000 - Dec 2005 (72 months). 47 cities. The regression also includes city-dummies and 12 seasonal dummies for each good.

Table 5b: Estimates from the Demand System, Middle Level Elasticities, Furniture+Utensils Segment

		Avg share	Income Elas	Price Elasticity 1	2	3
1	Household durables	25.1%	2.830 **	-1.340 **	-0.256 **	-1.234 **
			(0.024)	(0.069)	(0.035)	(0.058)
2	Domestic utensils	38.3%	0.562 **	0.402 **	-0.856 **	-0.109 **
			(0.014)	(0.023)	(0.032)	(0.032)
3	Domestic non-durabl	36.5%	0.201 **	-0.188 **	0.024	-0.037
			(0.009)	(0.039)	(0.032)	(0.051)

Table 5c: Estimates from the Demand System, Middle Level Elasticities, Medical goods Segment

		Avg share	Income Elas	Price Elasticity 1	2
1	Medicines	57.2%	0.765 **	-0.702 **	-0.063
			(0.014)	(0.053)	(0.054)
2	Medical supplies and appliances	42.8%	1.314 **	-0.398 **	-0.916 **
			(0.018)	(0.071)	(0.073)

Table 5d: Estimates from the Demand System, Middle Level Elasticities, Recreational goods Segment

		Avg share	Income Elas	Price Elasticity 1	2
1	Recreational durables	69.6%	1.200 **	-1.080 **	-0.121 **
			(0.007)	(0.041)	(0.042)
2	Recreational goods	30.4%	0.541 **	0.183 *	-0.724 **
			(0.017)	(0.094)	(0.097)

Table 5e: Estimates from the Demand System, Middle Level Elasticities, Miscellaneous goods Segment

		Avg share	Income Elas	Price Elasticity 1	2	3
1	Beauty salon and products	43.6%	0.881 **	-1.476 **	0.205 **	0.390 **
			(0.014)	(0.042)	(0.024)	(0.053)
2	Toilet articles	18.9%	0.829 **	0.494 **	-1.866 **	0.542 **
			(0.026)	(0.055)	(0.119)	(0.142)
3	Cosmetic products	37.4%	1.225 **	0.305 **	0.199 **	-1.729 **
			(0.016)	(0.060)	(0.070)	(0.114)

Notes:
1) The elasticities are evaluated at average expenditure shares.
2) Autocorrelation consistent standard errors are reported in parentheses.
3) '**' and '*' indicate the estimate is significant at 5 % and 10 % respectively
4) The systems of equations estimated by 3SLS. Sample period: Jan 2000 - Dec 2005 (72 months). 47 cities. The regression also includes city-dummies and 12 seasonal dummies for each good.

Table 6: Summary of Estimates from the Demand System, Bottom Level Elasticities

	Own Price Elasticities (conditional)				Own Price Elasticities (unconditional)				#goods	
	(average)	(median)	(Min)	(Max)	(average)	(median)	(Min)	(Max)	(all)	(sig)
Food										
Cereals	-1.16	-1.10	-1.49	-0.88	-0.97	-1.06	-1.22	-0.48	10	9
Fish & Shellfish	-1.06	-0.99	-1.84	-0.42	-1.05	-0.99	-1.90	-0.42	24	24
Meat, Dairy products & Eggs	-1.05	-0.84	-2.88	-0.46	-1.01	-0.82	-2.84	-0.42	11	10
Vegetables & Seaweeds	-0.90	-0.94	-1.77	-0.33	-0.88	-0.94	-1.77	-0.28	37	37
Oil, Fats and Seasonings	-0.92	-0.94	-1.94	-0.16	-0.91	-0.89	-1.92	-0.15	16	14
Confectionery, Snack & Cooked f	-1.11	-1.06	-1.86	-0.54	-1.12	-1.08	-1.88	-0.54	25	25
Eating out	-1.06	-1.07	-1.77	-0.34	-1.13	-1.12	-1.78	-0.34	10	10
Beverages & Alcoholic beverages	-1.28	-0.84	-3.56	-0.38	-1.35	-0.87	-3.58	-0.48	12	12
Furniture & Household utensils										
Household durables	-1.09	-1.03	-1.57	-0.71	-1.12	-1.08	-1.59	-0.72	8	8
Domestic utensils	-0.96	-0.98	-1.19	-0.69	-0.93	-0.96	-1.17	-0.68	7	7
Domestic non-durables	-0.79	-0.73	-1.23	-0.43	-0.69	-0.66	-1.15	-0.25	6	6
Medical care										
Medicines	-1.02	-1.00	-1.43	-0.63	-1.02	-1.01	-1.43	-0.63	6	4
Medical supplies & appliances	-1.54	-1.08	-3.24	-0.93	-1.61	-1.10	-3.37	-0.95	5	5
Recreation										
Sport equipment	-1.12	-1.12	-1.30	-0.94	-1.05	-1.05	-1.27	-0.84	2	2
Recreational goods	-1.29	-1.06	-2.24	-0.82	-1.21	-0.92	-2.22	-0.79	4	4
Miscellaneous										
Beauty salon	-1.99	-2.19	-2.36	-1.42	-2.21	-2.51	-2.55	-1.56	3	3
Toilet articles	-1.06	-1.09	-1.65	-0.42	-1.19	-1.19	-1.82	-0.56	7	7
Cosmetic products	-2.21	-2.03	-4.43	-0.92	-2.37	-2.29	-4.54	-0.97	5	5

Notes:

1) The own price elasticity for each good is evaluated at the national average expenditure share. The summary statistics are calculated over goods in the same group.

2) 'Min' corresponds to the price elasticity of the most elastic good and 'Max' to that of least elastic one.

3) The insignificant estimates are excluded before calculating these statistics. The right-most column reports the final number of goods with significant values for own price elasticities.

Table 7: Conjectural Variation Estimates and Change in Dispersion

	All	Fresh Foods	Proc Foods	Elec Appl	Other goods	Services
#goods	172	41	84	7	29	11
CV	0.0826 **	0.1257 **	0.0749 **	0.0196 **	0.0651 **	0.0667 *
(SE)	(0.0138)	(0.0385)	(0.0184)	(0.0096)	(0.0233)	(0.0376)
Wage	0.0758 **	0.0838 **	0.0713 **	0.0742	0.0422 **	0.1698 **
(SE)	(0.0107)	(0.0202)	(0.0169)	(0.0560)	(0.0163)	(0.0399)
Land	0.0221 **	0.0311 **	0.0248 **	0.0000	0.0070	0.0217 **
(SE)	(0.0025)	(0.0054)	(0.0036)	(0.0000)	(0.0062)	(0.0093)
Dispersion						
Original	0.141	0.177	0.134	0.162	0.108	0.140
Excl Mkup	0.141	0.175	0.134	0.162	0.107	0.140
Excl M+Costs	0.138	0.172	0.131	0.161	0.106	0.135
Reduction in Dispersion (%)						
by Mkup	0.4%	0.9%	0.4%	0.0%	0.2%	-0.1%
by Mkup+Cost	2.5%	2.8%	2.7%	0.7%	1.1%	3.9%
Min	16.8%	11.1%	16.8%	3.3%	7.5%	10.4%
Max	-0.8%	0.0%	-0.8%	0.0%	0.0%	0.0%
No restriction on Coefficient						
CV	0.1353 **	0.1966 **	0.1425 **	0.0386 **	0.0767 **	0.0670 *
(SE)	(0.0176)	(0.0450)	(0.0264)	(0.0141)	(0.0237)	(0.0400)
Wage	0.0099	-0.0298	-0.0243	0.2166 **	0.0464	0.1912 **
(SE)	(0.0208)	(0.0444)	(0.0320)	(0.0544)	(0.0310)	(0.0679)
Land	0.0238 **	0.0448 **	0.0349 **	-0.0576 **	-0.0092	-0.0004
(SE)	(0.0044)	(0.0068)	(0.0063)	(0.0087)	(0.0080)	(0.0152)
Reduction in Dispersion (%)						
by Mkup	0.4%	0.9%	0.4%	0.0%	0.2%	-0.1%
by Mkup+Cost	3.1%	3.7%	3.1%	1.4%	1.9%	5.1%
Min	16.8%	11.1%	16.8%	3.4%	7.5%	13.2%
Max	-1.1%	0.0%	-1.1%	-0.6%	0.1%	1.9%

Notes:

1) NLLS is applied to each good separately. #obs=47cities*6years for each good. The MG estimates are reported. The standard errors in parentheses are bootstrapped. All regressions include year dummies.

2) The coefficients on local costs are restricted to be positive in the upper panel.

3) The outlier price elasticities are either replaced by the national average or dropped.

Table 8: Conjectural Variation Estimates and Change in Dispersion with Outlier Control

#goods	All 172	Fresh Foods 41	Proc Foods 84	Elec Appl 7	Other goods 29	Services 11
CV	0.0259 **	0.0318	0.0266 **	0.0044	0.0198 *	0.0281
(SE)	(0.0076)	(0.0213)	(0.0100)	(0.0042)	(0.0112)	(0.0227)
Wage	0.0044 **	0.0041 **	0.0041 **	0.0010	0.0067 **	0.0047 **
(SE)	(0.0006)	(0.0010)	(0.0008)	(0.0010)	(0.0020)	(0.0022)
Land	0.0002 **	0.0002 **	0.0002 **	0.0007	0.0002 **	0.0001 *
(SE)	(0.0000)	(0.0001)	(0.0000)	(0.0004)	(0.0001)	(0.0001)

No restriction on Coefficient

CV	0.0822 **	0.0988 **	0.1035 **	0.0042	0.0312 **	0.0426 *
(SE)	(0.0146)	(0.0319)	(0.0239)	(0.0038)	(0.0115)	(0.0241)
Wage	-0.0034 *	-0.0046	-0.0038	-0.0303 **	0.0033	0.0039
(SE)	(0.0020)	(0.0044)	(0.0027)	(0.0140)	(0.0050)	(0.0047)
Land	0.0006 *	0.0005	0.0006	0.0049 **	0.0000	-0.0004
(SE)	(0.0003)	(0.0007)	(0.0004)	(0.0020)	(0.0007)	(0.0007)

Notes:

1) NLLS is applied to each good separately. #obs=47cities*6years for each good. The MG estimates are reported. The standard errors in parentheses are bootstrapped. All regressions include good*year dummies and good*city dummies.

2) The coefficients on local costs are restricted to be positive in the upper panel.

3) The outlier price elasticities are either replaced by the national average or dropped.

Table 9: Conjectural Variation Estimates and Change in Dispersion, no outlier control

#goods	All 192	Fresh Foods 44	Proc Foods 87	Elec Appl 10	Other goods 38	Services 13
CV	0.0771 **	0.0897 **	0.0574 **	0.0218	0.0858 **	0.1828 **
(SE)	(0.0133)	(0.0307)	(0.0165)	(0.0211)	(0.0290)	(0.0812)
Wage	0.0773 **	0.0907 **	0.0713 **	0.0571	0.0499 **	0.1684 **
(SE)	(0.0103)	(0.0210)	(0.0168)	(0.0424)	(0.0186)	(0.0373)
Land	0.0200 **	0.0265 **	0.0248 **	0.0004	0.0069	0.0192 **
(SE)	(0.0021)	(0.0044)	(0.0033)	(0.0004)	(0.0048)	(0.0074)
Dispersion						
Original	0.140	0.175	0.134	0.146	0.113	0.134
Excl Mkup	0.139	0.173	0.133	0.146	0.113	0.133
Excl M+Costs	0.136	0.170	0.130	0.145	0.112	0.128
Reduction in Dispersion (%)						
by Mkup	0.4%	0.7%	0.3%	0.0%	0.2%	0.3%
by Mkup+Cost	2.1%	2.6%	2.3%	0.2%	0.7%	4.5%
Min	16.1%	14.2%	15.5%	3.2%	7.4%	16.1%
Max	-2.5%	0.0%	-0.2%	-2.5%	-0.2%	0.0%

No restriction on Coefficient

	All	Fresh Foods	Proc Foods	Elec Appl	Other goods	Services
CV	0.1265 **	0.1592 **	0.1206 **	0.0187	0.1173 **	0.1650 **
(SE)	(0.0165)	(0.0397)	(0.0239)	(0.0180)	(0.0333)	(0.0809)
Wage	0.0111	-0.0197	-0.0265	0.1457 **	0.0382	0.1842 **
(SE)	(0.0200)	(0.0425)	(0.0316)	(0.0497)	(0.0307)	(0.0601)
Land	0.0219 **	0.0405 **	0.0350 **	-0.0422 **	-0.0055	0.0013
(SE)	(0.0038)	(0.0059)	(0.0058)	(0.0093)	(0.0065)	(0.0120)
Reduction in Dispersion (%)						
by Mkup	0.5%	0.9%	0.4%	0.0%	0.2%	0.3%
by Mkup+Cost	3.0%	3.4%	3.1%	1.1%	1.8%	5.2%
Min	18.1%	14.2%	15.5%	3.4%	7.4%	18.1%
Max	-2.5%	0.0%	-0.5%	-2.5%	-0.9%	0.7%

Notes:
1) NLLS is applied to each good separately. #obs=47cities*6years for each good. The MG estimates are reported. The standard errors in parentheses are bootstrapped. All regressions include year dummies.
2) The coefficients on local costs are restricted to be positive in the upper panel.

Table 10: Cournot Pricing by Swamy's GLS

	Foods					All goods		
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Wage	0.0909 **		-0.0178	-0.0106	0.0695 **	0.0793 **		0.0232
(SE)	(0.0205)		(0.0258)	(0.0267)	(0.0256)	(0.0170)		(0.0211)
Land Price		0.0301 **	0.0327 **	0.0316 **	0.0154 **		0.0219 **	0.0185 **
(SE)		(0.0037)	(0.0045)	(0.0051)	(0.0046)		(0.0035)	(0.0045)
Markup				0.0877	1.0000			0.1247 *
(SE)				(0.0910)	*restricted			(0.0717)
#obs	35250	35250	35250	35250	35250	48504	48504	48504
#CS units	125	125	125	125	125	172	172	172
Reduction in Dispersion (%)								
Avg	1.5%	1.6%	2.8%	3.6%	-2.0%	1.5%	1.6%	3.5%
Med	0.6%	0.8%	1.9%	3.0%	1.3%	0.6%	0.8%	2.9%
Min	13.6%	13.2%	14.4%	15.1%	14.5%	13.6%	13.2%	15.1%
Max	-0.1%	0.0%	0.0%	0.1%	-55.9%	-0.1%	0.0%	-3.6%

Notes:

1) Swamy's random coefficient model estimates are reported. The values in parentheses are the standard errors Annual, 2000-2005, 47 cities for each good. Good*Time dummies are included in each regression.

2) Good-level price dispersion is calculated by fitting the individual Pooled OLS estimates to each good. The reported dispersion is the remaining dispersion after fitting the model. It is expressed relative to the original dispersion and then averaged over all goods.

Table 11: Supply Estimation for Average Price, pooling all goods

	All goods							
Reg ID	Single	(1)	(2)	(3)	(4)	Single	(5)	(6)
Wage	0.0872 **	0.0101	0.0220	-0.0148	-0.0158	-0.0100	-0.0121	-0.0118
	(0.0269)	(0.0228)	(0.0273)	(0.0244)	(0.0240)	(0.0140)	(0.0135)	(0.0138)
Land Price	0.0248 **	0.0233 **	0.0249 **	0.0216 **	0.0146 *	0.0118	0.0136	0.0043
	(0.0049)	(0.0062)	(0.0071)	(0.0066)	(0.0084)	(0.0192)	(0.0186)	(0.0180)
Dist from Tokyo	-0.0056 **		0.0026		0.0054 *			
	(0.0029)		(0.0033)		(0.0033)			
Dist from Large City	-0.0076 **			-0.0046 **	-0.0067 **			
	(0.0018)			(0.0018)	(0.0022)			
Population	0.0165 **				0.0095 **	0.2414		0.2357
	(0.0035)				(0.0047)	(0.1798)		(0.1806)
City FE	No	No	No	No	No	Yes	Yes	Yes
#obs	282	282	282	282	282	282	282	282
#goods	172	172	172	172	172	172	172	172
R2		0.26	0.26	0.30	0.36		0.88	0.89
Avg Disp		0.0283	0.0283	0.0283	0.0283		0.0283	0.0283
Remain Disp		0.0245	0.0243	0.0238	0.0227		0.0093	0.0092
(ratio)		0.86	0.86	0.84	0.80		0.33	0.32

1) Pooled OLS, annual from 2000 to 2005. Good dummies and time dummies are included in regression. Values in parentheses are standard errors. "**" and "*" indicate the estimate is significant at 5% level and 10% level respectively.

2) "Single" reports the coefficients obtained from single regressions. Other columns report the regression with different sets of variables.

3) The reported R2 is the within r-squared that is obtained after controlling for good and/or city fixed effects.

Table 12: Supply Estimation for Average Price, Foods and NonFoods

	Foods				Non-Foods			
Reg ID	Single	(1)	(2)	(3)	Single	(1)	(2)	(3)
Wage								
(Fresh)	0.1132 **	-0.0269	0.0372	-0.0152				
	(0.0512)	(0.0471)	(0.0546)	(0.0268)				
(Processed)	0.0911 **	-0.0250	-0.0701 **	-0.0133	0.0576 **	0.1049 **	0.0371	-0.0062
	(0.0327)	(0.0356)	(0.0326)	(0.0255)	(0.0281)	(0.0358)	(0.0363)	(0.0223)
Land Price								
(Fresh)	0.0382 **	0.0423 **	0.0401 **	-0.0203				
	(0.0112)	(0.0130)	(0.0160)	(0.0241)				
(Processed)	0.0313 **	0.0350 **	0.0198 *	-0.0275	0.0015	-0.0143	-0.0238	0.0644 **
	(0.0047)	(0.0071)	(0.0102)	(0.0239)	(0.0084)	(0.0096)	(0.0165)	(0.0236)
Dist from Tokyo								
(Fresh)	0.0008		0.0186 **					
	(0.0067)		(0.0063)					
(Processed)	-0.0069 **				-0.0089 **		-0.0095 **	
	(0.0032)				(0.0018)		0.0039	
Dist from Large City								
(Fresh)	-0.0088 **							
	(0.0026)							
(Processed)	-0.0076 **		-0.0045 **		-0.0067 **		-0.0039	
	(0.0025)		(0.0017)		(0.0025)		(0.0029)	
Population								
(Fresh)	0.0280 **		0.0136 *	0.3957 **				
	(0.0077)		(0.0073)	(0.1934)				
(Processed)	0.0192 **				0.0017		0.0022	-0.2083
	(0.0038)				(0.0059)		0.0107	0.1995
City FE	No	No	No	Yes	No	No	No	Yes
#obs	564	564	564	564	282	282	282	282
#Fresh	41	41	41	41				
#Processed	84	84	84	84	47	47	47	47
R2		0.18	0.28	0.66		0.08	0.21	0.84
Avg Disp		0.0460	0.0460	0.0460		0.0323	0.0323	0.0323
Remain Disp		0.0411	0.0389	0.0276		0.0309	0.0287	0.0128
(ratio)		0.89	0.84	0.60		0.96	0.89	0.40

Notes:

1) Pooled OLS, annual from 2000 to 2005. Good dummies and time dummies are included in regression. Values in parentheses are standard errors. "**" and "*" indicate the estimate is significant at 5% level and 10% level respectively.

2) "Single" reports the coefficients obtained from single regressions. Other columns report the regression with different sets of variables.

4) In multiple regressions, a common coefficient on population is imposed for both fresh and processed foods.

Table 13: Pricing Equation with Markup

	Foods				Nonfoods			
		(1)	(2)	(3)		(1)	(2)	(3)
	w/o mkup	benchmark	R=10	const elas	w/o mkup	benchmark	R=10	const elas
Wage								
(Fresh)	0.0632	0.1534 **	0.0632	0.1445 **	0.0529 *	0.1270 **	0.0530	0.1342 **
	(0.0531)	(0.0502)	(0.0532)	(0.0497)	(0.0400)	(0.0466)	(0.0405)	(0.0471)
(Processed)	-0.0154	0.0702	-0.0161	0.0659 *				
	(0.0364)	(0.0436)	(0.0365)	(0.0428)				
Land Price								
(Fresh)	0.0544 **	0.0365 **	0.0552 **	0.0376 **	-0.0213 **	-0.0370 **	-0.0218 **	-0.0382 **
	(0.0133)	(0.0146)	(0.0134)	(0.0143)	(0.0096)	(0.0116)	(0.0097)	(0.0118)
(Processed)	0.0363 **	0.0192 **	0.0370 **	0.0195 **				
	(0.0083)	(0.0097)	(0.0083)	(0.0096)				
Dist from Tokyo								
(Fresh)	0.0198 **	0.0197 **	0.0202 **	0.0194 **				
	(0.0066)	(0.0065)	(0.0066)	(0.0064)				
(Processed)	0.0021	0.0019	0.0023	0.0017	-0.0114 **	-0.0119 **	-0.0116 **	-0.0118 **
	(0.0035)	(0.0046)	(0.0036)	(0.0045)	(0.0037)	(0.0041)	(0.0038)	(0.0041)
Mean Markup		1.12	1.13	1.12		1.10	1.11	1.11
#obs	564	564	564	564	282	282	282	282
#goods	125	125	125	125	47	47	47	47
R2 (within)	0.2564	0.1939	0.2600	0.1980	0.1893	0.2574	0.1926	0.2562
Disp of Avg	0.0460	0.0506	0.0463	0.0496	0.0323	0.0383	0.0325	0.0392
Remain Disp	0.0395	0.0456	0.0396	0.0445	0.0290	0.0330	0.0292	0.0338
(ratio)	0.86	0.90	0.86	0.90	0.90	0.86	0.90	0.86

1) Pooled OLS, annual from 2000 to 2005. Good dummies and time dummies are included in regression.
2) The number of foods is 125, of which 41 are fresh and 84 are processed. The number of nonfood goods is 47.
3) "benchmark" reports the estimates without markups.