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Kano, Kazuko

The University of Tokyo

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Kazuko Kano†
Graduate School of Economics
The University of Tokyo
Hongo 7-3-1, Bunkyo-ku
Tokyo, 113-0033 Japan
Email : kkano@e.u-tokyo.ac.jp

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Abstract

Scrutinizing a state-dependent pricing model in the presence of menu costs and dynamic duopolistic interactions, this paper claims that the assumption about market structure is crucial for identifying menu costs for price changes. Prices in a dynamic duopoly market can be more rigid than those in more competitive markets such as monopolistically competitive one. If so, estimates of menu costs under monopolistic competitions are potentially biased upwards due to the price rigidity from strategic interactions between dynamic duopoly firms. Developing and estimating a dynamic discrete-choice model with duopoly to correct this potential bias, this paper provides empirical evidence that not only menu costs but also dynamic strategic interactions play an important role to explain the observed degree of price rigidity in data of weekly retail prices.

Key Words : Menu Cost; Dynamic Discrete Choice Game; Retail Price.
JEL Classification Number : $D43$, $L13$, $L81$.

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1. Introduction

In this paper, I study a structural state-dependent pricing model with menu costs for price changes in which brands of retail products play a dynamic game of price competition. The model provides the claim of this paper: estimates of menu costs identified under a maintained hypothesis of monopolistic competitions could be biased upwards due to the price rigidity generated from dynamic strategic interactions between two brands in a duopolistic market. Using a scanner-data set collected from a large supermarket chain in the metropolitan area of Chicago, I provide empirical evidence that not only menu costs but also dynamic strategic interactions play an important role in high-frequency movements of the weekly retail prices of the data after correcting the potential bias stated above. To my best knowledge, the bias due to dynamic strategic interactions in a duopoly market toward estimates of menu costs has not been investigated profoundly in the literature of state-dependent pricing.

Following past studies, this paper defines menu costs as any fixed adjustment costs a price setter has to pay when changing its price, regardless of the magnitude and direction of the price change. Several papers provide evidence that menu costs are empirically important to understand retail price dynamics. Constructing direct measures of physical and labor costs in large supermarket chains in the United States, Lévy, Bergen, Dutta and Venable (1997) claim that menu costs play an important role in the price setting behavior of retail supermarkets. Estimating menu costs as structural parameters of single-agent dynamic discrete-choice models in monopolistic competitive markets, Slade (1998) and Aguirregabiria (1999) find that their estimates of menu costs are positive and statistically significant. More recently, with a dynamic oligopoly competition model, Nakamura and Zerom (2009) observe that menu costs are crucial to explain price rigidity in the short run, while their estimates of menu costs are small.

As frequently observed in the literature of macroeconomics, monopolistic competition is the market structure most commonly adapted by past studies of price rigidity.[1] This maintained hypothesis of market structure, however, is problematic if the market under study is dominated by a small number of firms. In this case, duopolistic/oligopolistic competition may be a more appropriate market structure for studying pricing behaviors of firms. More importantly, if duopolis-

[1] The seminal paper that applies a monopolistic-competition model to aggregate price rigidity is Blanchard and Kiyotaki (1987).

tic/oligopolistic competition prevails in the market of investigation, estimates of menu costs identified under the maintained assumption of monopolistic competition is potentially biased due to possibly tighter strategic interactions among firms. For exposition, suppose that there are just two dominant firms in a market, which compete with respect to their prices. Although monopolistic competition models create a degree of strategic complementarity among firms' prices, each firm perceives its own market power so small that it recognizes the average price to be exogenous. By contrast, in a duopoly market, firms take into account strategic interactions between them explicitly. Because this would lead to a stronger degree of strategic complementarity, firms may prefer less aggressive price competition. Due to their tighter strategic interactions, the equilibrium price of the market might be rigid to some extent *regardless of the existence of menu costs*. Within such markets with tighter strategic interactions among firms, the working hypothesis of monopolistic competition spuriously results in overestimates of menu costs. This means that, to draw a precise inference on menu costs, it is essential to identify the market structure of a product under investigation properly and allow for dynamic duopolistic/oligopolistic interactions among the firms in the market.

Although a slew of empirical papers study price rigidity using micro data, a few of them investigate the relationship between the price rigidity of a product and its market structure taking into account the effect of dynamic duopolistic/oligopolistic interactions.[2] Slade (1999) estimates thresholds of price changes as functions of strategic variables using a reduced-form statistical model. Assuming that firms follow a variant of (s, S) policy, she observes that strategic interactions among firms engaging a dynamic oligopolistic competition exacerbate price rigidity. This observation suggests a potential upward bias of the estimates of menu costs, as discussed above. In this paper, I go beyond the reduced-form model of Slade (1999) by developing a fully-structural dynamic discrete-choice model equipped with menu costs and dynamic duopolistic interactions. Since the effect of dynamic duopolistic interactions on equilibrium prices is captured by the strategies of two firms in the model, the rigidity due to menu costs is separately inferred from that caused by

[2]Carlton (1986), Cecchetti (1986), and Kashyap (1995) are among the empirical studies on price rigidity with micro data. For more recent studies, see Nakamura and Steinsson (2008) and the references cited there. For theoretical studies that deal with duopolistic/oligopolistic competitions in the presence of fixed adjustment costs, see Dutta and Rustichini (1995) and Lipman and Wang (2000). Unfortunately, it is not straightforward to construct econometric models from their theoretical implications.

dynamic strategic interactions. Another important exception is Nakamura and Zerom (2009), who investigate the sources of the incompleteness of the pass-through of wholesale prices to retail prices observed within a coffee industry. They construct an empirical model under dynamic oligopolistic competition among manufacturers and identify menu costs at the wholesale level. Their estimation shows that the size of menu costs is negligible but the menu costs are important to explain the price rigidity observed in the short run. Notice that the objective of this paper is different from theirs: in this paper, I examine how an empirical inference on menu costs might be affected when the underlying market structure is misspecified.

Scrutinizing a small product market of graham crackers, I estimate menu costs under monopolistic competition as well as dynamic duopoly. The former is the benchmark and the latter is the minimum extension of monopolistic competition with dynamic strategic interactions. It is worth noting that the main claim of this paper is not a theoretical consequence of a dynamic-duopolistic competition: in the estimation under the assumption of the dynamic duopoly, no restriction leading to price rigidity is imposed. Thus, the estimated size of the menu cost can be either greater or smaller than that of the monopolistic-competition model. I find that the estimates of menu costs are statistically significant under the two market structures. The comparison between the estimation results from the two specifications supports the main claim of this paper: dynamic strategic interactions between brands result in an upward bias of the estimate implied by the benchmark specification of monopolistic competition.

The next section describes the data I analyze. Section 3 introduces the dynamic discrete-choice model of duopoly. Section 4 reports the empirical results. Section 5 concludes.

2. Data

I examine the weekly scanner data set collected in the branch stores of Dominick's Finer Food (DFF, hereafter), the second largest supermarket chain in the metropolitan area in Chicago during the sample period from September 1989 to May 1997.[3] The data set contains information on actual transaction prices, quantities sold, indicators of promotions (simple price reductions and

[3] The data set is publicly available online at the website of the James M. Kilts Center, Graduate School of Business, University of Chicago. The website also provides the links to papers that describe the pricing practice of DFF.

bonus-buys), and a variable called average acquisition cost (AAC, hereafter), which is a weighted average of wholesale prices of inventory in each store, across stores and Universal Product Codes (UPC, hereafter)[4]. The products in the data set are basically priced on a weekly basis, which matches the sampling frequency of the data. The fact that prices are actual transaction ones is ideal to study the price rigidity since the frequency and timing of price changes are most important moment in this study.

I choose standard graham crackers as the product to be analyzed by the following three reasons: (1) a small number of firms dominate the market; (2) there is only one similar size of package; (3) a box of graham crackers is a minor product so that I can avoid the possibility that pricing is affected by competitions among retailers due to, for example, a loss-leader motivation. There are four brands in this market: two national brands (Keebler and Nabisco), one local brand (Sarelno), and one private brand (Dominick's). The market share of the four brands is about 97 percent of the total sales of standard graham crackers. The size of a package is of either 15 or 16 ounces. Importantly, DFF buys graham crackers directly from manufacturers.[5] Price levels of a product is fairly uniform across stores. This means that the DFF does not adopt the zone pricing, which assigns stores into one of three categories of high, middle, and low priced stores. The zone pricing are used for products that generate large sales-volume. These facts suggest that the decisions of the manufacturers are more likely to be reflected in retail prices, and the retailer is relatively neutral in the price competition among brands of graham crackers.

Figure 1 plots the shelf prices of the four brands in a representative store. The figure shows the following important aspects of the data. First, the shelf prices discretely jump both upwards and downwards. Second, the prices stay at the same level for a certain period of time although temporary price reductions or 'sales' are observed quite frequently. Third, the price levels vary over time for each brand. These patterns suggest that the price decision can be decomposed into two aspects; the discrete decision of whether or not to change prices and the continuous one for which level to set price. This feature makes it important to incorporate a discrete decision of price change in the model.

[4]For the details of AAC, see Peltzman(2000).

[5]The data set provides a code that shows whether DFF buys a product directly from manufacturers or through wholesalers.

Figure 1 also reveals another important aspect of the data: the pricing patterns of the two national brands, Keebler and Nabisco, are similar to each other, but quite different from those of the other two brands. Observe that the prices of the two national brands move quite frequently around higher levels for most of the sample period, while the prices of the other two brands move less frequently around lower levels. Tables 1 and 2 provide further evidence to support this claim. Table 1 reports several summary statistics of the data across brands: the fourth column of the table shows the market shares in terms of revenue; the fifth column the means of the prices in the U.S. dollars per ounce; and the sixth column the means of the quantities sold in terms of ounces. While the two national brands, Nabisco and Keebler, have very different market shares, their price levels are similar to each other. Table 2 summarizes descriptive statistics related to frequencies of price changes: the third column shows the frequencies of price changes in terms of percentage; the fourth column those of downward price changes; the fifth column those of upward price changes; and the sixth column the average numbers of price changes per year. It is clear that the two national brands change their prices with similar frequencies as high as 33 % on average. The frequencies of downward and upward price changes of the two national brands are close to each other, but those of the other two brands are, by comparison, much lower. These observations lead to an inference that Keebler and Nabisco are engaged in a dynamic competition that can be described by similar strategies, while the other brands are not.

As discussed above, the most of downward price changes are temporary reductions: 'sales.' Since sales are conducted repeatedly, some consumers may expect that sales follow some cycle. If so, taking into account such consumer behavior can impact the estimated size of the demand elasticity. One way to capture such behavior is to incorporate the information of duration between sales. Using the store-level data, Pesendorfer(2002) find that the duration between sales is positively correlated with quantity sold [6]. Hendel and Nevo (2003) show that the duration between promotions is important to derive the correct inference on on the relationship between sales and stockpiling behavior. From these findings in the literature, I use an indicator of promotional activity provided in the data set, and the duration between promotions to capture the effect of stockpiling behavior.

[6] Using a household purchase data, the recent literature of dynamic structural estimation of demand find that controlling for such demand-side dynamics is crucial to identify the demand elasticity correctly (Erdem, Imai, and Keane 2003, Hendel and Nevo 2006). Incorporating such a fully dynamic demand behavior is, however, beyond the scope of this paper.

The data set provides an indicator of in-store promotional activity called bonus-buy. Bonus-buy may be associated with an advertisement, in-store display, or promotions such as 'buy-one-and-get-one-free.' Table 3 shows the frequency of bonus-buy and its mean duration by brands. Keebler and Nabisco are put on bonus-buy for 28 and 21 percent of the time, respectively. The mean length of bonus is about two weeks for both brands. The problem using this indicator is that it may overlap the period of a price reduction, and, if it is included in the demand estimation along with price, bonus may absorb a part of price variation leading to a bias of the demand elasticity[7]. To see how much it overlaps the period of the price reduction, I decomposed the price into 'regular' price and 'sale' price. First, I look at the price of the two products at a representative store, store 73. I define the regular price as the modal price in 5 weeks, and the sale price as the price which is lower than the regular price by any amount. Among 763 observations, price is kept lower than the regular price for 243 times. Among them, the bonus takes place just for 177 weeks. In addition, bonus-buys take place even with the regular price for 21 weeks. Thus, the bonus-buys and price reductions are not necessarily overlap. I, however, examine whether or not this degree of overlap biases the estimated parameter of the demand elasticities in the section of the demand estimation.

As a common problem in scanner data, some observations are missing when no purchase is made, when the product is stocked out, or when there is no data recorded[8]. In particular, in the case of graham crackers, there are about 20 weeks in which no record is available for all the brands in all the stores. While it is possible to impute missing prices assuming no-purchase and using prices in previous periods, such imputation can cause spurious price rigidity. Therefore, in this paper, I choose removing observations when they are missing including their lagged observations (i.e., list-wise deletion). As a result, I have an unbalanced panel data with the sample number of 13120 from 20 stores for the two brands[9].

When necessary, prices and other nominal monetary values are deflated by using a constant inflation rate.[10] For the inflation rate, I use the mean of Consumer Price Index (CPI) for food

[7] The data set contains another indicator of in-store promotion: a simple-price reduction. This variable is not used in the analysis since there is no additional announcement effect on the demand.

[8] Other well-known scanner data such as A.C. Nielsen data also contain missing data in their original data. For the problem due to the missing data in the Nielsen data, see Erdem, Keane, and Sun (1999).

[9] The numbers of the stores chosen are 12, 18, 44, 47, 53, 54, 56, 59, 73, 74, 80, 84, 98, 107, 111, 112, 116, 122, 124, 131.

[10] The constant inflation rate stems from the assumption of the models in this paper. From September 1989 to

obtained from the Bureau of Labor Statistics (BLS) web-site.

In order to solve the profit maximization problem of each brand, I need a measure of marginal costs to produce graham crackers. I construct a measure of production costs combining information from a box of graham crackers, the Input-Output table, and the PPI. The main ingredients of graham crackers consist of wheat flour, whole grain wheat flour, sugar, and oil. According to the Input-Output table, besides these ingredients, cardboard for package, wage, and wholesale trade are major production factors in cookies and crackers industry. Obtaining the PPI of these items, I combine them according to the ratios shown in the Input-Output table for cookies and crackers industry. To derive the monetary value per unit, the AAC from DFF data set is used as a proxy of the wholesale price for the starting period. By construction, the production cost explains about 35% of the level of price on average. The data appendix discusses the detail of the construction of the cost. The constructed series is monthly in unit of dollars, and common to brands. Table 4 shows the summary statistics of the constructed cost. Particularly, as shown in the third column, the standard deviation of the constructed cost is fairly reduced when it is deflated.

3. Model

This section introduces the structural model of this paper. I describe only the duopoly model in this section. The monopolistic-competition model is described in the appendix. The difference between the two models is whether or not a brand takes into account the impact of its own action on rival's reactions and the future strategic interactions.

In the following model, I model the dynamic competition between two brands to maximize their own profits from each store. Brands set wholesale prices each period, and each store maximizes its joint profit from the products of the two brands. The main competition is the one between two brands within each store, but stores are allowed to set prices discretionally to some extent.

Suppose that store $s \in \{1, ..., S\}$ sells the products of the two brands $i \in \{1, 2\}$. For simplicity, I assume a static linear demand function. Let q_{ist}, p_{ist}, rp_{ist}, and e_{ist} stand for the quantity, the real price, the price of the rival brand, and the demand shock of the product of brand

May 1997, the average weekly monthly rate is 0.2 %. I converted it to weekly rate of 0.06 %, on average.

i at store s in week t, respectively. The demand elasticity is allowed to be asymmetric between brands. Defining a brand dummy variable that takes zero for brand 1 and one for brand 2 by br, the asymmetricity of own price elasticity is expressed by including a cross term, $p_{ist} \times br$. In the same manner, $rp_{ist} \times br$ allows an asymmetric rival price elasticity. The demand shock e_{ist} is assumed to be mean-zero and decomposed into a store-brand specific component and an idiosyncratic shock: $e_{ist} = \xi_{ist} + \varepsilon_{ist}$. Define another variable, demand condition d_{ist}, to include other demand shifters. The demand condition, for example, includes an in-store promotional variable such as bonus-buy and the number of customers who visit store s in week t as a measure of the size of potential purchase. More detail on d_{ist} will be addressed in the section of demand estimation and the construction of the state variables. The demand for the product of brand i then is

$$q_{ist} = d_{ist} - b_0 p_{ist} + b_1 rp_{ist} + (b_2 p_{ist} + b_3 rp_{ist}) \times br + e_{ist}, \tag{1}$$

where $b_0 \geq 0$, $b_1 \geq 0$, $b_1 < b_0$.

Store s is a multi-product local monopolist who maximizes the joint profit generated by the two branded products each period. Given wholesale prices w_{ist}, a store sets real retail prices p_{ist} of brand $i \in \{1, 2\}$ and puts the products on shelf. The current-period profit of the store s in week t is

$$\pi_{st} = \sum_{i \in 1,2} (p_{ist} - w_{ist}) q_{ist}. \tag{2}$$

Solving for p_{1st} and p_{2st} yields the following optimal retail prices:

$$p_{1st} = \lambda_1^{-1}[2(b_0 - b_2)\tilde{d}_{1st} + (2b_1 + b_3)\tilde{d}_{2st} + \lambda_2 w_{1st} - b_3(b_0 - b_2)w_{2st}], \tag{3}$$

and

$$p_{2st} = \lambda_1^{-1}[(2b_1 + b_3)\tilde{d}_{1st} + 2b_0\tilde{d}_{2st} - b_0 b_3 w_{1st} + \lambda_3 w_{2st}], \tag{4}$$

where where $\tilde{d}_{ist} = d_{ist} + e_{ist}$, $\lambda_1 = 4b_0(b_0 - b_2) - (2b_1 + b_3)^2$, $\lambda_2 = 2b_0(b_0 - b_2) - b_1(2b_1 + b_3)$, and $\lambda_3 = 2b_0(b_0 - b_2) - (b_1 + b_3)(2b_1 + b_3)$.

Given the decision rule of stores, brands compete with respect to wholesale prices, which are unobservable to the other one, over infinite periods. Each period, brand i observes the previous own and rival's real retail prices, p_{ist-1} and rp_{ist-1}, current real production cost c_t which is common to brands, and the previous level of demand conditions d_{ist-1} for both brands. Brands observe the one-period lagged demand conditions as state variables since the demand conditions are assumed to be realized during a week. The expectations with respect to the realizations of the demand conditions are identical between brands. At the same time, each brand receives private information ε_{ist} that affects its profitability. I assume that the store-level demand shock e_{ist} is not observable to brands at the time of wholesale pricing decision.

Observing the state variables, brands simultaneously take their actions on real wholesale prices w_{ist}, which are drawn from a continuous support. At the same time, suppose that each brand suggests a 'range' of retail price to each store. The middle value of the suggested price range takes one of L discrete elements, $\mathbf{p}_{ist} \in \{p_1, ..., p_L\}$. Having the suggested price ranges, stores set shelf prices drawn from a continuous support. This structure assumes that the main price setters are brands, but allows retailers to exhibit some power to affect prices accounting for various conditions in the stores. A small number of L allows more discretion by stores.

Changing a nominal retail price incurs a menu cost. I assume that brands pay menu costs only for price changes that reflect their suggestions $\mathbf{p}_{ist} \neq \mathbf{p}_{ist-1}$ and $P_{ist} \neq P_{ist-1}$. The changes in the suggestive prices correspond to relatively large price changes in size (e.g., taking place large discounts or terminating them). If store s implements the suggested price change, the nominal price change $P_{ist} \neq P_{ist-1}$ also occurs, and brand pays menu cost, $\gamma > 0$. Instead, reflecting changes in its retail environment, the store may change its retail price by small amount so that $P_{ist} \neq P_{ist-1}$ but $\mathbf{p}_{ist} = \mathbf{p}_{ist-1}$. I assume that brands are not responsible for paying menu costs with respect to such small price changes[11]. A real price erodes over time because of constant inflation rate $\rho > 0$. The relationship between a real price and a nominal price P_{ist} is given by $\log(p_{ist}) = \log(P_{ist}) - \rho t$.

To see the implications of the assumptions regarding price changes, I discretize the actual real prices into 5 segments so that each segment is visited with approximately equal probability. Nominal price changes occur 36 % of the time in the whole sample. Among them, 25 % of nominal price changes are associated with changes across the discretized bins in the space of real prices. The rest of the nominal price changes is categorized into small price changes which do not accompany changes in the bins in the space of real prices.

[11]This model does not describe the menu costs paid by stores. Modeling and estimating such costs requires dynamic models for both retailers and brands, which is beyond the scope of this paper.

Private information ε_{ist}^{j} is drawn randomly from a set of $J \equiv L+1$ alternatives $\{\varepsilon_{ist}^{1}, ..., \varepsilon_{ist}^{J}\}$. The first element ε_{ist}^{1} corresponds to the case of no suggestive price change, i.e., $\mathbf{p}_{ist} = \mathbf{p}_{ist-1}$, the second element ε_{it}^{2} corresponds to the case of a price change to p_1, i.e., $\mathbf{p}_{ist} = p_1$ and $\mathbf{p}_{ist} \neq \mathbf{p}_{ist-1}$, the third element ε_{ist}^{3} corresponds to the case of a suggestive price change to p_2, i.e., $\mathbf{p}_{ist} = p_2$ and $\mathbf{p}_{ist} \neq \mathbf{p}_{ist-1}$, and so on.

Let $x_{st} = \{p_{1st-1}, p_{2st-1}, d_{1st-1}, d_{2st-1}, c_t, br\}$ denote the vector stacking the common-knowledge state variables. The demand conditions and the production cost follow independent stationary first-order Markov processes with transition probability matrices independent of the actions taken by brands. Private information ε_{ist} is assumed to be i.i.d. with a known density function with unit variance $g(\varepsilon_{ist})$ common across actions, brands, and periods of time.

Given the rival's price, the one-period profit of brand i in store s in week t conditional on choosing alternative j is

$$\Pi_{ist}^{j}(x_{st}) = (w_{ist}^{j} - c_t)E_t[q_{ist}] + \varepsilon_{ist}^{j} - \gamma I(\mathbf{p}_{ist} \neq \mathbf{p}_{ist-1})I(P_{ist} \neq P_{ist-1}) \tag{5}$$

where E_t stands for the conditional expectation operator on the realization of d_{ist} conditional on the current realization of the state variable x_{st}. The one-period profit of brand i depends on the action its rival takes for its wholesale price. Brand maximizes its discounted sums of expected profits taking into account the strategy of its rival and the evolutions of the demand conditions and the production cost. The objective function of brand i in store s at period t is

$$E\{\sum_{m=t}^{\infty} \beta^{m-t} \Pi_{is}(x_{sm}) \mid x_{st}, \varepsilon_t\}, \tag{6}$$

where $\beta \in (0\ 1)$ is the discount factor, and $E\{\cdot \mid x_{st}, \varepsilon_t\}$ is the conditional expectation operator on the payoff relevant state variables in store s at period t. Since the time horizon is infinite and the problem has a stationary Markov structure, I assume a Markov stationary environment. I drop the time and store subscript from all the variables adopting the notations of $x = x_{st}$ and $x' = x_{st+1}$ for any variable y. I investigate only a Markov perfect equilibrium in which brands follow symmetric pure Markov strategies with imperfect information in this paper.

Let $\sigma = \{\sigma_1, \sigma_2\}$ denote a set of arbitrary strategies of the two brands, where σ_i defines a mapping from the state space of (x, ε_i) into the action space. Denote the one-period profit without private information conditional on choosing j by $\pi_i^{\sigma}(x, j)$. Let $V_i^{\sigma}(x)$ express the value of brand i

when both brands follow the strategy σ and the state is x. Furthermore, let $f(x'|x, j)$ represent the transition probability of the observable state variables conditional on the action of choosing alternative j. When the private information is integrated out, the corresponding Bellman equation is

$$V_i^\sigma(x) = \int \max_{j\in J}\{\pi_i^\sigma(x, j) + \varepsilon_i^j + \beta \sum_{x'} f(x'|x, j)V_i^\sigma(x')\}g_i(\varepsilon_i)d\varepsilon_i, \tag{7}$$

where $\Pi_i^\sigma(x, j)$ is the profit defined by common-knowledge state variables x conditional on brand i's choosing the alternative j given that the rival brand follows strategy σ_2. Then, the conditional choice probability — or the best response probability — for brand i to choose alternative j given the strategy of the other brand that is associated with a set of Markov strategies σ can be written as

$$Pr_i(j|x) = \int I\{j = \arg\max_{j\in J}\{\pi_i^\sigma(x, j) + \varepsilon_i^j + \beta \sum_{x'} f(x'|x, j)V_i^\sigma(x')\}g_i(\varepsilon_i)d\varepsilon_i\}. \tag{8}$$

Aguirregabiria and Mira (2007) show that a Markov perfect equilibrium, associated with the equilibrium strategy $\{\sigma_1^*, \sigma_2^*\}$, is characterized as a set of probability functions $\{Pr_1(x), Pr_2(x)\}$ that solve the coupled-fixed-point problem presented by equations (7) and (8) in its probability space. The representation in the probability space is used to describe the likelihood function for estimation.[12]

The wholesale price is unobservable to a researcher. However, w_{ist} is set taking into account the optimal retail pricing behavior expressed by equation (2). Therefore, solving equations (2) for w_{1st} and w_{2st}, wholesale price w_{ist} is expressed as a function of suggestive price $\mathbf{p}_{ist}$ as follows:

$$\begin{aligned} w_{1st} &= [\lambda_2\lambda_3 + b_0b_3^2(b_0 - b_2)]^{-1}\{\lambda_1\lambda_3\mathbf{p}_{1st} + b_3(b_0 - b_2)\lambda_1\mathbf{p}_{2st} \\ &\quad -(b_0 - b_2)[2\lambda_3 + (2b_1 + b_3)b_3]\tilde{d}_{1st} - [(2b_1 + b_3)\lambda_3 + 2b_0b_3(b_0 - b_2)]\tilde{d}_{2st}\} \end{aligned} \tag{9}$$

and

$$\begin{aligned} w_{2st} &= [\lambda_2\lambda_3 + b_0b_3^2(b_0 - b_2)]^{-1}\{\lambda_1\lambda_2\mathbf{p}_{2st} + b_3b_0\lambda_1\mathbf{p}_{1st} \\ &\quad -[2\lambda_2 - (2b_1 + b_3)b_3]b_0\tilde{d}_{2st} - [(2b_1 + b_3)\lambda_2 - 2b_0b_3(b_0 - b_2)]\tilde{d}_{1st}\}. \end{aligned} \tag{10}$$

The suggestive prices are also unobservable. In the following, I regard the suggestive price as the middle value of observed retail price in the discretized space. The wholesale price backed out from

[12] For the representation in the probability space, see the appendix.

the observed retail price is considered to be in the range of the corresponding suggestive price, and the profit is evaluated at its middle value[13]. For a small price change such that $\mathbf{p}_{ist} = \mathbf{p}_{ist-1}$ but $P_{ist} \neq P_{ist-1}$ observed in the data, I assume that brands did not suggest a price change but the store changed its price due to an unobserved factor captured by the idiosyncratic demand error term. When brands set their suggestive prices and wholesale prices, each brand forms an expectation with respect to the suggestive price of the other brand conditional on the state variables.

The above model maintains several important assumptions. First, the main competition in the model is the one between brands. The previous literature offers supportive evidence on the claim that the main price competitors in a narrowly defined category are brands. For example, analyzing the DFF data, Montgomery (1997) states that weekly deviations of prices from regular prices mainly reflect manufacturers' competitive actions. Slade (1998) assumes brands as price setters with a passive retailer analyzing the brand competition in a saltine-cracker category. According to telephone interviews with supermarket-chain managers, she claims that the competition important in a category is the one among brands. In addition, the stores are modeled as local monopolists so that the competition is in a store, not in a region. Interviewing with the DFF stores, Chintagunta, Dube, and Singh (2003), who also model the stores as local monopolists, confirm the claim also made by Slade (1998) that stores are not competing with other stores or chains on product-by-product basis. Nevertheless, the competition may be affected by location or size of stores. These factors are controlled by store-fixed effects in the estimation.

Second, shelf prices are set by each store. The data shows that pricing decision at DFF is centralized to a certain extent, but stores exhibit some discretional power in price setting. In the case of graham crackers, retail prices of a graham cracker product from one brand are fairly uniform across stores, but the exact price levels and the timings of the price changes are not totally the same. The correlation of the timing of price changes across stores is about 0.8. These facts suggest that pricing decision at the brand level is dominant for the price of the graham crackers, but stores have some discretional power.

[13]Using AAC is another way to measure the wholesale price. However, I do not directly exploit this variable since (1) AAC need not to be the same as the wholesale price if stores hold inventory, and (2) the literature does not agree with the validity of this variable as a measure of wholesale price (Peltzman 2000). The first problem is more serious in a storable goods such as graham crackers.

Third, brands sell products to stores, not a whole chain. According to Peltzman (2000), the wholesale price is uniform across stores implying that it is a chain who negotiates with manufacturers. Peltzman (2000), however, states that manufacturers changed their promotion policy toward DFF during the sample period to prevent stores from exploiting geographical price differentials. It may imply that stores have a certain power in the negotiations with manufacturers.

As I noted before, the monopolisitic-competition model is described in the appendix. The important difference in the monopolistic competition model from the duopoly model in this paper is that, following Slade (1998) and Aguirregabiria (1999), I treat the evolution of rp_{ist} as exogenous in the econometric model. An interpretation of this treatment would be that a brand takes into account its rival's price but treats the effect of its own decision through the rival's reaction in future as trivial. In other words, the observed outcomes are simply those of the static Bayesian-Nash equilibrium. In this sense, the monopolistic-competition model studied in the previous papers lacks dynamic strategic interactions.[14]

Note that, in the duopoly model stated above, no detailed structure to introduce price rigidity due to dynamic strategic interactions such as collusion is imposed. Therefore, the estimates of menu-cost parameters under the assumption of dynamic duopoly can be either smaller or greater than those under that under the assumption of monopolistic competition. The strategy of this paper is to see whether or not the data shows the evidence of such bias.

4. Empirical results

This section describes the empirical results of this paper. The demand equation and the transition processes of exogenous state variables are estimated separately from the menu-cost parameter. I first describe the results of the estimation of the demand equation, second state the discretization of state variables, and, finally, report the estimated menu costs.

4.1. Demand estimation

[14] These two papers, however, feature other aspects of the models that are absent from this paper. Slade (1998) incorporates a stock of goodwill accumulated by consumers due to price reductions into her model. Aguirregabiria (1999) finds a crucial role of inventory held by retail stores in pricing behaviors of retail products.

The demand equation (1) is common to the duopoly model and the monopolistic-competition model. I show the results of 7 specifications: 3 OLS and 4 IV estimations. In all the specifications, the dependent variable is the quantity sold standardized by 10 oz. The independent variables common to all the specifications are own price *price*, rival price *rp*, the weighted average of the prices of non-national brands (Dominick's and Sarelno) with weight being total quantity sold in the sample period *sdp*, a brand dummy variable *br*, which takes one for Nabisco and zero for Keebler, the customer count *cc*, store-dummy variables, and time dummies for month and year. The customer count, which is the average numbers of customers per day who visit the corresponding store within a week, is used to control for the time-varying size of potential purchasers[15]. The independent variables appearing in some of the specifications are a cross term of *price* and *br*, a cross term of *rp* and *br*, a dummy variable of bonus, the duration since the end of the last bonus, and the duration within a period of consecutive bonus. All the monetary variables are per 10 oz and deflated by the CPI of food in the United States.

The demand error term, which is e_{ist}, is assumed to include the unobserved store-brand term that affects demand and possibly correlates with price variables. Having included a brand dummy variable and time dummies, ξ_{ist} may include unobserved promotional activity (Nevo and Hatzitaskos 2006) and weekly in-store valuation affected by shelf space and display (Chintagunta, Dube, and Singh 2003). To control for these endogeneity, I need an effective promotional variable or the instruments that is correlated with price but uncorrelated with weekly store-brand demand error term. First, I include a promotional variable: a bonus indicator provided by the data set. Second, I use AAC as instrumental variables for the price. The correlation between the retail price and AAC is 0.73 in my sample. Chintagunta, Dube, and Singh (2003) use a measure of wholesale cost created from AAC and its lags as instruments. Having controlled for display and feature, they argue that the wholesale price, which is uniform across stores, is independent of current store-brand demand. Nevo and Hatzitaskos (2006), who study both category and product demand over a chain, use AAC as the instrument of price in one of their estimations[16]. They note the potential endogeneity of AAC since, regarding it as a wholesale price, it may be correlated with unobserved promotion captured in the error term. They note that AAC is not the current wholesale price but

[15]The unit of customer count is 1,000.

[16]The corresponding estimation result is shown in their appendix. They use the result from OLS to derive their main result.

the weighted average of past and current ones, and therefore the problem will be less serious. I also assume that rival price and the prices of Salerno and Dominick's as endogenous, and use the corresponding AAC and their lags as instruments.

Table 4 shows the results of the demand estimations. The first column shows the names of the variables. From the second to the last columns show the results of the different specifications. OLS 1 includes the following variables: *price*, *rp*, *sdp*, *cc*, *br*, and constant. The store-fixed effects, time dummies, and a dummy variable to control for outliers are also included but their coefficients are not shown[17]. The sign of the coefficients are those expected. The own demand elasticity evaluated at mean is -2.8. The own elasticities evaluated at brand-specific means are -4.34 for Keebler and -2.04 for Nabisco. The elasticity, which is calculated as $\frac{\partial q_{ist}}{\partial p_{ist}}/\frac{\bar{q}_i}{\bar{p}_i}$ where $\bar{q}_i$ and $\bar{p}_i$ are the means of price and quantity of brand i respectively, is greater for Keebler since $\frac{\bar{q}_i}{\bar{p}_i}$ is much smaller for Keebler. From the fourth to the fifth column, OLS2, show the estimated coefficients of the specification allowing asymmetric coefficients on own price and rival price across brands. While the coefficients on the asymmetricity are statistically significant, the brand-specific elasticities are similar to those calculated in OLS1. The specification OLS3 includes the following variables: *bonus*, which is the dummy variable that takes one when bonus-buy takes place and zero otherwise; *bonus duration*, which is the number of weeks elapsed since the end of last bonus; and *bonus duration 2*, which is the number of weeks elapsed since the beginning of the bonus[18]. The coefficient on *bonus* shows the positive effect as expected. The coefficient on *bonus duration* is negative but it is not statistically significant. Sometimes, bonus takes place for consecutive multiple periods. If most consumers buy products at the first week of bonus, the demand from the second week may decline. To capture such a dynamics, I include the variable *bonus duration 2*. This variable takes one at the second week of bonus, two at the third week, and so on. The estimated coefficient on *bonus duration 2* is negative showing that, continuing bonus does not increase demand as much as in the first week. Importantly, in OLS3, the estimated coefficients on *price* and the other price variables are not affected much by including the variables of bonus. The estimated coefficient on *price* is slightly lower than that of OLS2, but the bonus does not absorb the price variation much. The estimated elasticities for both brands evaluated at the brand-specific means are -3.99 and -2.37,

[17] The dummy variable to control for outliers takes one when the quantity sold exceeds 500 oz. Such events occur 2.84 % of the whole sample.

[18] I divide the variables *bonus duration* and *bonus duration 2* by 10.

respectively.

From the eighth column to the last column are the results of the estimations with instrumental variables. IV1 shows the estimated values of coefficients with AAC, lagged AAC, rival AAC, lagged rival AAC, the AAC of Salerno and Dominick's as instruments dealing with *price*, *rp*, and *sdp* as endogenous variables. Compared to OLS1, the size of own price coefficient increases by almost 20 %. IV2 includes $br \times price$ and $br \times rp$ with additional instruments of the cross terms of AAC and *br*, and rival price and *br*. While the size of the own and rival price coefficients does not change much between IV1 and IV2. The coefficient on the cross term between own price and brand is now insignificant. IV3 includes*bonus*, *duration*, and *bonus duration 2*, which are assumed to be exogenous. The properties of the estimated coefficients are the similar as those in OLS3 except that the cross term on own price is insignificant. IV4 treat the bonus-related variables as endogenous ones. The mean-elasticities are around -3.4, and the brand-specific elasticities are about -5.3 for Keebler, and -2.3 for Nabisco. The overidentifiaction test is not rejected in all the estimation showing empirical support on the validity of the instruments.

The results of the above demand estimations show that the own-price elasticity is about -2.5 in OLS and -3.5 in the IV estimations using store-level AAC as the instruments. While the main claim of this paper regarding relative size of the menu costs between monopolistic competition model and duopoly model will not be affected by the size of the demand elasticity, the estimated size will be affected. I try the estimation of the menu costs using both results from OLS and IV.

One problem in the data set is that prices have little weekly variations across stores. This lack of cross-sectional variations of prices might be problematic in estimating pricing behaviors because using the observations from all the stores results in spuriously small standard errors of the estimates of menu costs without much difference in their values[19]. Therefore, in the exercise below, I provide the result from the five stores, which has the least missing observations. The number of observations is now 3694.

4.2. State variables

From the estimated demand equation, I next construct demand condition d_{ist}. The demand condition is computed from the estimated coefficients on *cc*, *sdp*,*bonus*, *duration*, and *duration*

[19] I owe this point to the helpful comments from seminar participants at Queen's University.

bonus 2, store and time dummy variables, outlier, and constant in the demand equation. The state variables consist of $x_i = \{p_1, p_2, d_1, d_2, c, br\}$ in the duopoly model and $x_i = \{price, rp, d, rd, c, br\}$ in the monopolistic competition model. Table 5 shows the means and the standard deviations of the state variables before discretization. The third column reports that price has a moderate degree of variance; the demand condition has a relatively large variance; and, the production cost varies little. I discretize the state variables in vector x_i as follows. In the main exercise, the size of the state space for each model is 1800: $np = 5$, $nd = 6$, $nc = 1$, and $nbr = 2$. I set the lower and upper bounds of the state space to the 5 % and 95% tiles of the samples. The number of grids of each variable are relatively small compared to the recent applications of dynamic discrete choice models[20]. This size of the discretization is, however, appropriate in the current application. This is because the range of the choice variable, real price, is small. The 10 % quartile of real price is 2.08 and the 90 % quartile is 2.46 per box. Thus, dividing it into 5 grids creates small bins. The last variable in the vector of the state variables, br, is a fixed state variable that takes one for Nabisco ($i = 2$) and zero for Keebler ($i = 1$). In addition, the coarseness of the state space does not affect the estimated size of menu cost. I tried estimations with various size of state space in the exercise below. I find no systematic relationship between the coarseness of the state space and the estimated size of menu cost as shown later.

The state space is discretized according to a uniform grid in the space of the empirical probability distribution of each variable. I apply the same state space to all the price variables, p_1 and p_2 for the duopoly model as well as p and rp for monopolistic competition model. In addition, d_1 and d_2 are also discretized so that they have the same support. This is because I want to make sure that the estimation results do not depend on the difference in the state space construction. Therefore, a potential difference in the estimates of the menu cost parameter γ between the duopoly model and the monopolistic competition model is solely due to the specification about interactions between the brands.

The transition probabilities of the demand condition and the rival price are estimated following the method by Tauchen (1986). This method generates more smooth transition processes

[20]For example, the size of the state space in Collard-Wexeler (2010) is 1.4 million in his study of the U.S. concrete industry. On the other hand, the studies such as Slade(1998) and Aguirregabiria(1999), with whose results I compare the results of this paper, use a smaller state space.

than the alternative method such as counting the number of the samples that fall into each cell of the state space. To evaluate the representative value in each cell of the state space, I use the middle point of the range of each cell.

4.3. Wholesale prices The profit functions of the brands contain wholesale price, which is recovered

from the observed retail price according to equations (9) and (10). To identify the wholesale price, I assume one-to-one correspondence between wholesale price and retail price when retail prices experiences a 'large' price change. In addition, when the recovered wholesale price exceeds the retail price, I scale down the directly recovered wholesale price so that the wholesale price is equivalent to the mean of AAC although this is an ad-hoc way to construct the wholesale price. Table 7 shows the mean value of the derived wholesale prices and the frequency of wholesale-price changes. On average, both brands change their wholesale price for 26 % of time while Keebler changes slightly more frequently.

4.4. Estimation of menu costs

This section describes the estimated results of menu costs. To estimate menu cost parameter γ, I exploit the nested pseudo-likelihood (NPL) estimator developed by Aguirregabiria and Mira (2002, 2007). The advantage to use the NPL estimator over a full-solution method is a computational one: I do not need to solve a dynamic-programming problem for each iteration of the maximum-likelihood estimation of the structural parameters of the model. Moreover, the method is useful in the current application since it allows me to estimate all the parameters in the demand equation and the transition process separately from the dynamic one, which is a menu-cost parameter in this paper. The value function is recovered from data by exploiting the infinite-horizon Markov-stationary structure of the model. I left the details of the estimation procedure in the appendix.

Table 8 presents the results of the structural estimation of γ both for the duopoly model and the monopolistic-competition model using the result of IV4 in the demand estimation. The size of the estimate of γ is 4.53 for the monopolistic-competition model and 1.96 for the duopoly model. While the two estimates are statistically significant at the 1 % level, the duopoly model results in a higher likelihood, which means a better fit to the data. The estimated γ in the duopoly model is much smaller than that of the monopolistic-competition model. From the difference in the estimated γ between the two models, this upward bias is due to the specification of the monopolistic-competition model.

The above result depends on the specification of a demand equation and a specific size of state space. To see how robust the above result is, I estimate the duopoly model by (1) different specifications of the demand equation and (2) the different size of the state space. First, Table 9 shows the results across different specifications of the demand estimation. From the second column to the fifth column are the estimated menu costs under the assumption of duopoly model using the results from all the specifications. While the results using the IV estimations are slightly higher than those using OLS, the difference among the results is small. Thus, the result is robust in the difference with respect to which demand estimation result is employed. Second, Table 10 shows the estimates by different coarseness of the state space. The rows show the number of the grids of the demand condition nd, and the columns take the number of the grids of the price np. For example, $nd = 2$ and $np = 2$ means that price and demand condition are divided into two grids for each. This implies that the size of the state space is 32. As stated in the section of the state space, there is no systematic relationship between the size of the state space and the estimated size of the menu cost. On average, the size of menu cost is around 1.85, which is close to the main result reported in Table 7.

4.5. Price rigidity and the state space

The above estimation result has shown that price rigidity due to not only menu cost but due to the dynamic duopolistic interactions plays an important role to explain price rigidity observed. To examine the properties of the price rigidity due to the duopolistic interactions, I next examine the property of the conditional choice probability of no-price change.

Figure 2 shows the contour plot of the predicted choice probabilities of no-price change in the monopolistic-competition model and the duopoly model assuming that the menu cost is 1.96, which is the result of the duopoly model in Table 7. The results are based on the estimation using IV4 with the number of grids being $np = 5$ and $nd = 6$. Figure 2-(a) shows the predicted choice probabilities of no-price change of Keebler in the duopoly model;Figure 2-(b) those of Keebler in the monopolistic-competition model; Figure 2-(c) those of Nabisco in the duopoly model; Figure 2-(d) those of Nabisco in the monopolistic-competition model. The horizontal axis shows the own past price in the state space, p_{t-1}, and the vertical axis shows rp_{t-1}: 1 corresponds to the lowest previous price level, p^1 for p_{t-1} and rp^1 for rp_{t-1}, and so on. The choice probabilities for the duopoly model are those estimated to derive the main result in Table 7, but the choice probabilities for the monopolistic competition model are the counter-factual one. The plots show in gray scale: the lighter the color is, the probability of no-price change is higher. The values choice probabilities are on the contour lines.

The figures highlight the three important aspects of the estimated conditional choice probabilities. First, the difference between the monopolistic competition and the duopoly model is apparent: the monopolistic competition model predicts lower probabilities of no-price changes than the duopoly model for both brands: 0.11 vs. 0.39 for Keebler and 0.39 vs. 0.60 % for Nabisco, on average. As noted before, the duopoly model in this paper does not specify any deep theoretical structure to generate a higher price rigidity in the presence of dynamic duopolistic interactions. This result suggests that the rigidity in the duopoly model is generated from tighter interactions between the two national brands than that in the monopolistic-competition model. Such a stronger strategic interaction observed in the duopoly model is a primary source for upward bias in the estimates of menu costs if the underlying data-generating process is specified as the monopolistic-competition model. Second, the table highlights asymmetry between brands. In both of the monopolistic competition model and the duopoly model, Keebler tends to change its price more frequently than Nabisco. This property is consistent with the observed data. Third, the price rigidity is sensitive to the level of own state variable. The price rigidity dramatically increases as the own state gets lower, and the tendency is more strong in the duopoly model. The price rigidity is, however, not sensitive to the rival state variable. This feature seems to make the importance of strategic interactions obscure. In addition, the above figures does not answer to the question how the strategic interactions in the duopoly model leads to more price rigidities compared to the monopolistic competition model. For example, as stated in the introduction, Slade(1999) suggests that price rigidities will be stronger as previous price level is higher due to strategic complementarity. If the dynamic duopolistic competition exacerbates such strategic complementarity, it can be the source of stronger price rigidity in the duopoly model. Such observation is, however, not seen in the figures discussed above. To examine this issue further, I next examine the relationship between the level of the state variables and strategic complementarity.

To see how strategic complementarity affects the price rigidity, I examine how price rigidities change as the coefficients of price and rival price in the demand estimation vary conducting a counter-factual exercise. The key parameter in the exercise are the coefficient on *rp*, but the one on *price* is also crucial. Then, I first examine how the coefficient on *price* relates to price rigidity.

From Figure 3 - (a) to Figure 3 - (f) are the contour plots of the predicted choice probabilities under the different size of coefficient on *price* and the mode of competition. In this exercise, I keep the degree of asymmetricity between brands low: the coefficients on $price \times br$, $rp \times br$, and br are set to be 1. The size of menu cost is set to be 2.0. To highlight the impact of own price coefficient, the coefficient on *rp* is set to be 1, with which strategic complementarity is fairly weak. The figures on the top show the relationship between price rigidity and state variables of prices when the coefficient on *price* is as large as -30 implying relatively high own demand elasticity on average. This value is close to the one in the main result. With such high demand elasticity on average, price rigidity is higher at the lower state of own past price. However, the relationship reverses as the own price coefficient becomes smaller. When the size of price coefficient is -20, price rigidity is higher as the own state is higher. This is quite natural since when the demand elasticity is lower on average, a price setter will not lose much by keeping its price high.

From Figure 4 - (a) to Figure 4 - (f) are the results of a similar exercise as those in Figure 3, but now the coefficient on *rp* is changed keeping *price* at -30. The value of the other variables are the same as in Figure 3. The top-left figure, (a), which is also appears as Figure 3-(e), shows the price rigidity when the price complementarity is fairly weak. The middle-left figure, 4-(c), shows that, as price complementarity gets stronger, the price rigidity at the higher level of own state gets higher. In addition, price rigidities are more sensitive to rival state. The bottom-left figure 4 - (e) shows the choice probabilities when the coefficient on *rp* is 15. With such a relatively strong price complementarity, the contour plot is more complex. First, now the area with highest price rigidities is the one with the highest prices for both own and rival prices. It implies that if prices of both brands are high, brands are likely to stay at the high state. This is along the line with the intuition of Slade (1999) discussed above. Second, brands are more likely to change its price as the discrepancy between own price level and rival price level in the state space is greater. This suggests the strong tendency to try to catch-up the rival in the environment with high strategic complementarities. Third, the right-hand side are the figures of monopolistic-competition model.

Comparing these two sets of figures makes it clear that the choice probabilities of the duopoly model is more responsive to the past rival's price than that in the monopolistic competition. This comparison shows that strategic complementarity is more likely to lead to price rigidity with the dynamic duopolistic interactions. Since the exercise in Figure 4 are conditional on a fairly high own demand elasticity on average, the tendency discussed may be stronger if the demand is less elastic.

The next question is how dynamics play a role in the above result discussed. Figure 5 compares the price rigidity under the assumption of myopic agents and that under the dynamic model. Figure 5-(a) and Figure 5-(b) are the same plot of the bottom ones in the Figure 4. In these plots, the discount factor is set to be 0.99. On the other hand, Figure 5-(c) and Figure 5-(d) are the contour plots of the choice probabilities when the discount factor is set to be 0 keeping the other conditions the same as in Figure 4-(e) and Figure 4-(f). First, comparing Figure 5-(a) and 5-(c) reveals how the presence of dynamics is important for strategic interactions to impact price rigidities. In Figure 5-(a), choice probabilities vary along the different states of rival prices in a great degree. This implies own current action also influences future actions of the rival, and each brand takes into account such dynamic interactions. On the other hand, such interactions are almost absent in Figure 5-(c) where brands act myopically. Second, the monopolistic competition model lacks clear reactions to rival price both in Figure 5-(b) and 5-(d), which show the predicted choice probabilities in the monopolistic competition model with $beta$=0.99 and $beta$=0, respectively.

The discussion about Figure 2 - 5 has shown several important properties of the model. First, the overall price rigidity in the duopoly model is more strong than in the monopolisitic-competition model. Second, the size of own-price elasticity and cross-price elasticities are crucial in determining how price rigidity relates to the level of own and rival price in the state space. As the strategic complementarity is stronger, price tends to be more rigid as the past price levels of the both brands are higher. Third, the dynamics also plays an important role for strategic complementarity to impact price rigidity. Taking into account future reactions leads to more complex reactions to rival's state variable comparing to a myopic model under the assumption of the duopoly competition.

4.6. Comparison with previous studies

Table 11 compares the results of this paper with those of the previous studies. Due to the specific structure of this model, the estimated menu costs may not be directly comparable to the ones in the previous studies. It will be, however, valuable to examine what factor can contribute to the difference and the similarity of the results. The first row of the table shows the result of the duopoly model. Its point estimate of the menu cost parameter, 1.96, is greater than the result by Aguirregabiria (1999), 1.45, and that by Lévy et al.(1997), 0.52 while it is smaller than that in Slade(1998)[21] It is not surprising that the estimate of this paper is greater than the direct measure of menu costs calculated by Lévy et al.(1997), 0.52, because the estimate could capture any costs associated with price changes, whereas the reported number by Lévy et al.(1997) includes only physical and labor costs of price changes.

The size of menu costs in terms of the percentage of revenue is 18 % in this paper. This number is much greater than those reported in most of the previous studies, while it is closer to that found from the estimates by Slade (1998).[22] Note that Aguirregabiria (1999) estimates menu costs using various products, while Slade (1998) examines a single product as in this paper. This difference implies that menu costs might be relatively uniform across products in retail stores, and that the large estimate of menu costs as the percentage of revenues this paper observes might simply reflect the small revenues generated by graham crackers.

The bottom row of Table 11 shows the estimated value of menu costs from a recent study by Nakamura and Zerom (2009) using a dynamic oligopolistic model. Their estimate of menu costs as the percentage of revenue is much smaller than the one I obtain.[23] One reason may be that, when they estimate menu costs at the level of wholesale markets, their menu costs may not include an important part of price changes at retail markets such as the costs to print and deliver price tags. Another reason may be the difference in the specification of the market structure between this study and theirs. Since this paper assumes a duopolistic model abstracting potential strategic

[21]The result of Aguirregabiria (1999), 1.45, is calculated from the reported values of asymmetric menu costs using reported shares in revenue as weights from Table 6. He also reports the results of the specification with symmetric menu costs, whose estimated results are also close to this value (for example, 1.12 in the specification 2 in Table 5).

[22]Slade (1989) does not report the estimate of menu costs as the percentage in revenue. The revenue is calculated as the weighted average across brands using the information provided in her paper.

[23] Their estimate of the absolute magnitude of menu costs is not comparable because their menu cost is for a price change within the entire U.S. market.

interactions with the other two brands, the estimate of menu costs in this paper might be still biased upwards.

Although the estimated size of menu costs in this paper is from the single product, it is informative to compare the size of menu costs this paper finds and that calibrated commonly in past studies in macroeconomics. For example, under a general equilibrium model with monopolistic competitions and menu costs, Blanchard and Kiyotaki (1987) calculate the size of menu costs that suffices to prevent firms from adjusting their prices. The calculated size of menu costs is 0.08 % of the total revenue. The subsequent studies in macroeconomics need the size of 0.5 % - 0.7 % of the total revenue to fit the models to selected sample moments and to affect aggregate price dynamics. The empirical results from graham crackers this paper studies show that the estimated size of menu costs is large enough to have significant effects on aggregate price adjustments. Therefore, I conclude that menu costs have significant implications for price adjustment behaviors economically as well as statistically. This paper shows that dynamic strategic interactions could induce a significant degree of price rigidity. This result implies an important message of this paper: not only menu costs but also dynamic strategic interactions among brands are important for explaining the observed degree of price rigidity.

5. Conclusion

This paper studies weekly price movements of a typical product sold in retail stores, graham crackers. As observed commonly in retail price data, the price movements of the product are well characterized by frequent discrete jumps. To explain the discreteness of price changes, I employ a dynamic discrete-choice model with menu costs as the hypothesized data-generating process. Since the market of graham crackers is dominated by a few brands and the pricing behaviors of two national brands are similar to each other, I further take into account duopolistic interactions between the two national brands to examine possible effects of dynamic strategic interactions on the discrete behavior of the prices. I estimate this dynamic discrete-choice model with duopolistic competition by exploiting a recent development in the estimation of dynamic discrete choice games, the NPL estimator. The results show that menu costs are important statistically and economically. In addition, I claim that adopting a monopolistic-competition model in explaining the price data could lead to a possible bias in the estimate of menu costs. If dynamic strategic interactions among firms affect the pricing behavior in the sample, the estimated menu costs with a monopolistic-competition model are biased upwards because strategic interactions in an duoplolistic competition potentially create price rigidity. The results show that the estimate of menu costs under a dynamic-duopoly market is smaller than and statistically different from that under monopolistic competition. This means that dynamic-duopoly competitions explain some part of price rigidity, which is captured by menu costs unless a researcher incorporates dynamic-duopoly interactions in the data. Thus, at least in the sample of this paper, I conclude that dynamic strategic interactions could be an important source of price rigidity and the assumption about market structure is important to identify menu costs.

A caveat should be mentioned on the whole exercise of this paper. As mentioned before, this paper does not specify any theoretical structure in strategic interactions between brands that leads to price rigidity *a priori*. An extension of this paper will be to incorporate a structure that can cause price rigidity due to dynamic strategic interactions more explicitly such as an implicit collusion. Rotemberg and Saloner (1990), Rotemberg and Woodford (1992), and Athey, Bagwell, and Sanchirico (2004) theoretically show that strategies with rigid prices can be supported as results of collusion in duopolistic and oligopolistic environment. Using the entry-and-exit model, Fershtman and Pakes(2000) numerically analyze a dynamic game allowing collusion. I leave developing a dynamic pricing model by incorporating the implications of these studies as an important future research.

Appendix

1 Construction of Production Cost

This section explains the construction of the production cost. According to the package of graham crackers, the main ingredients consist of enriched flour (wheat flour and fortification ingredients such as iron), whole grain wheat flour, sugar, oil, salt, corn syrup, salt, baking soda, cornstarch and artificial flavor. In addition, according to the Input-Output table, wage and paper also consist of significant portion of cost. In the 1992 benchmark for cookies and crackers industry (industry number 141802), the top components in production costs are the value added (35 %), compensation to employees(21%), paperboard containers and boxes(4.9%), flour and other grain mill products (4.3%), wholesale trade (3.3%), sugar (2.8%), edible fats and oil (2.8%). These components account for about 70 % of the output value.

I use monthly PPI of these main components to create a measure of production cost combining the information of the wholesale price[1]. First, PPI matching major components in the IO table are collected from the BLS web-site. They are the PPI of wheat flour (series id: WPU02120301), fats and oils(WPU027), sugar(WPU0253), wholesale trade(CEU4142000035), and paper boxes and containers (WPU091503). I also obtained the wage index of hourly earnings of non-durable manufacturer(CEU3200000008) as a measure of wage. Since the PPI of whole grain flour was not available, that of plain flour was used instead.

Having obtained these PPI, I create a measure of cost in the following steps:

1. Normalize the each series by the values of September 1989, which is the first sample period, so that the value in the starting period is 1.
2. Calculate the average wholesale price of a graham cracker in the starting period. I use the average of AAC per box of three brands except the private brand in September 1989 and October 1989 from DFF data set. I omit the private brand since AAC of the private brand is very low, and may not include the margin in the same manner as the other brands. AAC of October 1989 is included because of small sample number in September 1989.
3. Set the cost of flour in September 1989 as 4.3 % of the above average wholesale price, and calculate the dollar value, which yields $ 0.07. Calculate the costs of the other variables in the same manner.
4. Calculate the costs from October 1989 and thereafter by adopting the growth of PPI series. For example, the cost of flour in October 1989 ($0.07) is the cost in September 1989 ($0.07) times the PPI of flour in the same period (0.99).
5. Then, sum the costs of wheat flour, fats, sugar, wholesale trade, and wage. The average of the implied costs from September 1989 to the end period May 1998 is $0.71 per box.

2 Monopolistic-Competition Model

This section describes the monopolistic-competition model with a menu cost. The difference from the duopoly model in the main text is that, following the monopolistic competition models in Slade(1998) and Aguirregabiria(1999), a brand regards the evolution of rp_t as exogenous. The problem of retail stores is the

[1] To create a measure of production cost, it is ideal to obtain wholesale prices of main ingredients and ratio to combine to create a box of graham crackers. However, the wholesale prices per pound are available for only wheat flour and cane sugar, and the recipe of the graham cracker by the brands analyzed is not obtainable.

same as in the duopoly model. In the problem of brands, the linear demand is the same as in the duopolistic one but comes without a brand-specific subscript,

$$q_{st} = d_{st} - b_0 p_{st} + b_1 rp_{st} + (b_2 p_{st} + b_3 rp_{st}) \times br + e_{st}, \tag{A1-1}$$

The one-period profit at period t conditional on choosing an alternative j is defined as

$$\Pi^j_{st}(x_{st}) = (w^j_{st} - c_t)E_t[q_{st}] + \varepsilon^j_{st} - \gamma I(\mathbf{p}_{st} \neq \mathbf{p}_{st-1})I(P_{st} \neq P_{st-1}), \tag{A1-2}$$

where E_t stands for the conditional expectation operator on the realization of d_{ist} conditional on the current realization of the state variable x_{st}. A brand takes into account rp_t but regards its evolution as exogenous. The timing of the game is as described in the duopoly model. First, brand observes the state variable $(p_{t-1}, rp_{t-1}, d_{t-1}, dr_{t-1}, c_t, br)$. The assumptions about the evolution of demand condition and production cost are the same as before. Brand also receives private information ε_t that affects its profitability. The private information consists of $J = L + 1$ randomly drawn unobserved profit components, which distribute i.i.d. across time and alternatives. Then, the brand chooses whether or not to suggest price change and, conditional on changing the price, at which level to set wholesale price. Considering a stationary Markov environment, I denote the state space as $\{xs, \varepsilon\} = \{p, rp, d, rd, c, br, \varepsilon\}$.

Let Π be the expected one-period profit conditional on choosing an alternative j and xs, and $V(xs')$ be the value with the private information being integrated out. Given state xs and private information ε, the Bellman equation conditional on choosing j after integrating out private information is

$$V^j(xs) = \int \max_{j \in J} \{\Pi(xs, j) + \varepsilon^j + \beta \sum_{xs} f(xs'|xs, j)V(xs')\} g(\varepsilon) d\varepsilon, \tag{A1-3}$$

where $\Pi(xs, j)$ is the profit defined by a set of state variables xs conditional on player i choosing the alternative j. The conditional choice probability to choose an alternative j is

$$Pr(j|xs) = \int I\{\max_{j \in J} \{\Pi(xs, j) + \varepsilon^j + \beta \sum_{xs' \in xs} f(xs'|xs, j)V(xs')\} g(\varepsilon) d\varepsilon. \tag{A1-4}$$

The right hand side of equation (A1-3) defines a contraction mapping in the space of the integrated value functions. There exists a unique value function V_i that solves the functional equation (A1-3).

3 Estimation Procedure

This paper exploits the Nested-Pseudo Likelihood Algorithm developed by Aguirregabiria and Mira (2002, 2007). Below, I describe some details of the estimation procedure in this paper. The estimation consists of the following steps:

1. Estimation of the demand equation
2. Construction of the state space:
    - construction of the demand conditions using the result of the demand equation.
    - the discretization of the state variables
3. Estimation of the initial choice probabilities
4. Estimation of the laws of the evolutions of the state variables, and .
5. Estimation of the dynamic parameter

The details of the estimation from 1 to 4 are discussed in the main text. I talk about the step 5 and 6. In the actual practice, I modified the procedure described in Aguirregabiria(2001) "A Gauss Program for the estimation of discrete choice dynamic programming models using a Nested Pseudo Likelihood Algorithm."

Step 5: The estimation of transition probability matrices of the state variables

I construct the transition probability matrices for $f^d(d_{it}|d_{it-1})$ and $f^{rp}(rp_t|rp_{t-1})$ as follows. The transition probability matrix for rp is used in the monopolistic competition model. For example, the stochastic process of the demand condition for brand i is specified as follows:

$$\mathbf{d}_{it} = \delta_{d0} + \delta_{d1}\mathbf{d}_{it-1} + \epsilon^d_{it} \quad \text{(A3-1)}$$

where $\mathbf{d}_{it}$ and $\mathbf{d}_{it-1}$ are continuous demand conditions; δ_{d0} and δ_{d1} are the coefficients; and ϵ^d_{it} follows an *iid* distribution function $f_{\epsilon^d_{it}}$. The process of the rival price is specified in the analogous manner. The coefficients of the above process are estimated using OLS. Then, using the Kernel density estimation, I derive the distribution of the residual non-parametrically. I construct the transition probability matrix of d_t counting the frequency of the realization of each pair of d_{it} and d_{it-1}.

Step 6: The estimation of the menu-cost parameter

According to Aguirregabiria and Mira(2007), I derive an alternative presentation of value functions and conditional choice probabilities, which are used in the pseudo-likelihood estimation of a menu-cost parameter.

Let P^* be a matrix of equilibrium probabilities, which are best response probabilities, and $V_i^{P^*}$ be the corresponding value functions of brand i. Using P^* and $V_i^{P^*}$, I can rewrite the Bellman equation (7) as

$$V_i^{P^*}(x) = \sum_{j \in J} P_i^*(j \mid x)[\Pi_i^{P^*}(j,x) + e_i^{P^*}(j)] + \beta \sum_{x' \in X} f^{P^*}(x'|x) V_i^{P^*}(x'), \quad \text{(A3-2)}$$

where $f^{P^*}(x'|x)$ is the transition probability induced by P^*, and $e_i^{P^*}(j)$ is the expectation of ε_i^j conditional on x. [2] In vector form, equation (A3-2) is

$$V_i^{P^*} = \sum_{j \in J} P_i^*(j)[\Pi_i^{P^*}(j) + e_i^{P^*}(j)] + \beta \sum_{x' \in X} F^{P^*} V_i^{P^*}, \quad \text{(A3-3)}$$

where $V_i^{P^*}$, $P_i^*(j)$, $\Pi_i^{P^*}$, and $e_i^{P^*}(j)$ are the vectors of the corresponding elements in equation (A3-2) with dimension M, which is the size of the state space. F^{P^*} is a matrix of transition probabilities of $f^{P^*}(x'|x)$.

Under the condition $\beta < 1$, the value function given P^* can be obtained as the solution of the following linear equation:

$$(I - \beta F^{P^*})V_i^{P^*} = \sum_{j \in J} P_i^*(j)[\Pi_i^{P^*}(j) + e_i^{P^*}(j)], \quad \text{(A3-4)}$$

where I is an identity matrix with dimension M. Denote the mapping for the solution of equation (A3-4) as $\Gamma_i(x; P^*)$. For an arbitrary set of probabilities P, the mapping operator $\Gamma_i(x; P)$ gives the values for brand i when all the brands behave according to P. Note that this mapping is constructed given the conditional choice probabilities of brand i as well as those of its rival brand. Using this mapping Γ, instead of V_i^P in equation (A3-4), I define a mapping Ψ to calculate the expected value for brand i to choose action a_i for P:

$$\Psi_i(j|x) = \int I\{j = \arg\max_{j \in J}[\Pi_i^P(j,x) + \varepsilon_i^j + \beta \sum_{x'} f(x'|x,j)\Gamma_i^P(x')]\} g_i(\varepsilon_i) d\varepsilon_i, \quad \text{(A3-5)}$$

I use the two mappings $\Gamma_i(x; P)$ and $\Psi_i(j \mid x)$ to estimate menu costs, γ.

[2] That is, $f^{P^*}(x' \mid x) = \sum_{j_i} \sum_{j_{-i}} P_i^*(j_i \mid x) P_{-i}^*(j_{-i} \mid x) f(x' \mid x, j_i, j_{-i})$.

Next, the pseudo-likelihood function to estimate the menu cost is derived. For convenience, define the following notations: an expected price of a competing brand under its conditional choice probability P, $p^P_{-it} = \sum_{j_{-i}} P(j_{-i} \mid x_t)\mathbf{p}_{-it}$ for given x_t. Given the estimated coefficients of the demand equation and the constructed demand conditions $\hat{d}_{it}$, I set up the expected one-period profit associated with action a as

$$\widehat{\Pi}^P_i(j, x_t) = (w^j_{it} - c_{it})(\hat{d}_{it} - \widehat{b}_0(p^j_{it}) + \widehat{b}_1 \ln(p^P_{-it})) + (\widehat{b_2}p_{ist} + \widehat{b_3}p_{-ist}) \times br - \gamma I\{j = 1\}. \tag{A3-6}$$

For exposition, denote $\widehat{\Pi}^P_i(j, x_t) = z^P_{it}\theta$, where $z^{jP}_{it} = \{(w^j_{it} - c_{it})(d_t - \hat{b_0}(p^j_{it}) + \hat{b_1}(p^P_{-it})(\widehat{b_2}p_{ist} + \widehat{b_3}p_{-ist}) \times br), -I\{j = 1\}\}$ and $\theta = \{1, \gamma\}$. Let F^P be the transition probability matrix representing all the transition processes of the state variables x under the conditional choice probabilities P, and $e^{P^*}_i(j)$ be a vector of the expectation of ε^j_i conditional on x.[3]

The empirical counterparts of the value functions and the best response probabilities are derived according to the mapping expression by Aguirregabiria and Mira(2007). Let $\Gamma_i(P)$ denote the mapping operator of the value function in vector form given conditional choice probabilities P, and $\Psi(j \mid x)$ be the operator representing the best response probabilities given $\Gamma_i(P)$. $\Gamma_i(P)$ can be written as $\Gamma_i(P) = Z^P_i\theta + \tau^P_i$, where $Z^P_i = (I - \beta F^P)^{-1}\sum_j P^*_i(j)\Pi_i(j)$ and $\tau^P_i = (I - \beta F^P)^{-1}\sum_{j\in J} e^{P^*}_i(j)$, where the value of discount factor is assumed to be known *a priori* and fixed at 0.99. Assume that private information follows an i.i.d. Type I Extreme Value distribution.Then, $e^P_i(j) = \text{Euler's constant} - \ln(P^j_i)$, where Euler's constant is about 0.577. The mapping of the best response probabilities Ψ_i given P is

$$\Psi_i(j) = \frac{\exp\{z^j_{it}\theta + \beta F^j(Z^P_i\theta + \tau^P_i)\}}{\sum_j \exp\{z^j_{it}\theta + \beta F^j(Z^P_i\theta + \tau^P_i)\}}. \tag{A3-7}$$

I construct a pseudo-likelihood function to estimate θ treating the conditional choice probability as nuisance parameters. Let P^o and θ^o denote the true conditional choice probabilities and menu costs. Given the true conditional choice probabilities P^o, the corresponding pseudo-log-likelihood function is

$$\sum_{i=1}^{2}\sum_{t=1}^{\infty}\sum_{j\in J} I\{j_{it} = j\} \ln \Psi_i(j \mid x_t; P^o, \theta^o), \tag{A3-8}$$

where $\Psi_i(j \mid x; P^o, \theta^o)$ shows the dependence of Ψ on conditional choice probabilities P^o and menu costs θ^o. The NPL estimator is obtained by the following procedure. I conduct the pseudo-maximum likelihood estimation of θ given a vector of initial values of conditional choice probabilities, P_0, and then obtain the updated $\hat{P}_1$ using $\hat{\theta}_1$ according to the mapping Ψ. I iterate this procedure for $K \geq 1$ stages. In the estimation, the K-stage pseudo-log-likelihood is constructed as:

$$\sum_{i=1}^{2}\sum_{t=1}^{T}\sum_{j} I\{j_{it} = j\} \ln \Psi_i(j \mid x_t; \hat{P}_{K-1}, \theta). \tag{A3-9}$$

Letting $\hat{\theta}_K$ denote the structural parameter that maximizes equation (**??**) in the Kth stage, I can obtain the K-stage estimator of conditional choice probabilities:

$$\hat{P}_K = \Psi(\hat{P}_{K-1}; \hat{\theta}_K). \tag{A3-10}$$

Under standard regularity conditions, it is consistent and asymptotically normal. Moreover, the estimator gains efficiency by repeating for $K > 1$ stages compared to the estimator without the iteration in terms of K. In practice, I conduct the estimation for K stage until $\hat{P}_K = \hat{P}_{K-1}$ or, equivalently, $\hat{\theta}_K = \hat{\theta}_{K-1}$ is obtained. The estimates converge fairly quickly (within 20 iterations). Note that the conditional expected profit except the menu-cost parameter consists of the conditional expected demand times price-cost margin in the U.S. dollars. Since the parameter of menu cost has the same unit as the conditional expected profit as specified in θ, the estimated γ is interpreted in the same unit.

[3] $F^P = \sum_{j_i}\sum_{j_{-i}} P(j_i) * P(j_{-i}) * (F^p_i \otimes F^p_{-i} \otimes F^d_i \otimes F^d_{-i} \otimes F^c_i \otimes F^c_{-i})$, where $*$ represents the element-by-element product, $\otimes$ represents the Kronecker product, and F^p_i represents the matrix of the transition probability f^p_i, respectively.

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Table 1: Summary statistics of brands

Brand	nob	Size of a box	Market share	Mean price	Mean quantity sold
unit		oz	%	$/oz	oz
Keebler	7333	15	18.0	0.17	118
Nabisco	7485	16	34.6	0.16	234
Sarelno	7418	16	16.9	0.15	126
Dominick's	7340	16	30.4	0.12	280

1. Market shares are those of revenue.
2. Prices are nominal.
3. The observations are those with a positive purchase. The statistics are calculated before list-wise deletion for the estimation.

Table 2: Frequency of nominal price changes

Brand	nob	Price Changes	Downward	Upward	Yearly change
unit		%	%	%	times per year
Keebler	7057	31.8	16.2	15.6	16.5
Nabisco	7330	33.9	17	15.6	17.6
Sarelno	7193	22.5	11.4	11.1	11.7
Dominick's	7142	26.8	14.1	12.8	13.9
average (Nabisco & Keebler)		32.85	16.6	15.6	17.05
average (Sarelno & Dominick's)		24.65	12.75	11.95	12.8

1. Yearly change is the average number of price changes per year (52 weeks).
2. The observations are those with a positive purchase and a lagged value. The statistics are calculated before list-wise deletion for the estimation.

Table 3: Summary statistics of bonus

	nob	frequency	mean length
unit		%	week
Keebler	7579	28	2.3
Nabisco	7579	21	2.1

1. The observations are for all the weeks in the sample.

Table 4: Summary statistics of cost ($U.S. per oz)

	mean	std.dev	min	max
cost (nominal)	0.04	0.003	0.04	0.05
cost (real)	0.04	0.001	0.04	0.041

Table 5: Demand Estimation Results : OLS and IV with outliers

Variable	OLS1		OLS2		OLS3		IV1		IV2		IV3		IV4	
price	-32.43	(1.03)	-29.23	(1.62)	-29.82	(1.39)	-39.02	(2.16)	-38.94	(2.70)	-39.72	(3.18)	-39.49	(6.44)
rp	5.78	(1.00)	8.36	(1.82)	8.36	(1.49)	2.97	(1.58)	13.87	(2.43)	14.05	(2.41)	14.12	(3.41)
sdp	0.33	(1.42)	0.38	(1.74)	0.43	(1.42)	18.18	(7.17)	15.05	(7.33)	13.72	(7.67)	5.77	(10.33)
price × *br*			-7.52	(2.41)	-7.84	(2.01)			2.32	(4.96)	1.91	(4.69)	7.39	(7.17)
rp × *br*			-5.21	(2.41)	-4.59	(1.97)			-14.95	(3.32)	-15.47	(3.30)	-13.06	(5.45)
cc	3.67	(0.35)	3.68	(4.65)	3.72	(0.35)	3.65	(0.39)	3.69	(0.38)	3.75	(0.38)	3.65	(0.42)
br	6.79	(0.24)	25.71	(0.91)	25.16	(3.88)	6.62	(0.26)	25.27	(9.54)	26.61	(8.88)	14.39	(17.96)
bonus					1.68	(0.47)					1.51	(0.74)	1.54	(4.25)
bonus duration					-0.043	(0.10)					-0.16	(0.09)	0.73	(1.11)
bonus duration 2					-10.29	(1.72)					-11.18	(1.95)	-6.08	(14.13)
constant	33.35	(3.02)	24.16	(3.55)	25.82	(3.65)	27.51	(9.39)	15.65	(9.63)	20.09	(13.59)	26.85	(23.86)
N	14024		14024		14024		13120		13120		13120		12308	
R^2	0.57		0.57		0.57		0.56		0.56		0.56		0.56	
J-stat (p-value)							3.91 (0.27)		2.67 (0.45)		1.80 (0.61)		6.08(0.11)	
elasticity (average)	-2.80		-2.52		-2.57		-3.37		-3.36		-3.43		-3.41	
elasticity (Keebler)	-4.34		-3.91		-3.99		-5.22		-5.21		-5.31		-5.28	
elasticity (Nabisco)	-2.04		-2.31		-2.37		-2.45		-2.30		-2.38		-2.02	
mean demand condition	53.30		44.23		46.00		46.81		34.46		52.83		52.65	

1. The regressions include a dummy variable for outliers, store-dummy, and time-dummy variables (month and year).
2. Price variables are real-valued. The unit is the U.S. dollars per 10 ounces.
3. The dependant variable is log of quantity sold in 10 ounces.
4. The endogenous variables in IV1 - IV4 are *price*, *rp*, *sdp*, *price* × *br*, and *rp* × *br*. IV4 additionally treats *bonus*, *bonus duration*, *bonus duration 2* as endogenous variables. The excluded instruments are AAC, rival AAC, AAC of Salerno and Dominick's, the lagged variables of these three AAC, the cross term of AAC and brand dummy, the cross term of rival AAC and brand dummy. IV4 includes the second order lagged AAC variables as the excluded instruments as well as the variables used for IV1- IV4.
5. Standard errors are in parenthesis. They are heteroscedasticity and auto-correlation robust.

Table 6: Summary statistics of state variables

	nob	mean	std.dev
price (per 10 ounces)	3678	1.49	0.12
demand condition (IV4)	3694	52.65	4.89
cost (per 10 oz)	3678	0.39	0.01

Table 7: Mean statistics of the Wholesale Price

	Keebler	Nabisco
wholesale price ($U.S. per 10 ounces, deflated)	1.07	1.10
frequency of large price change (%)	27	25
nob	1839	1839

Table 8: Estimated menu costs

	monopolistic competition	duopoly
$\hat{\gamma}$	4.53	1.96
	(0.10)	(0.06)
log-likelihood	-945	-503
nob	3528	3528

1. The estimated results are based on the results of IV 4.
   The size of the state space is 1800 (np=5, nd=6, nc=1, nbr=2).
2. The standard errors are inside parenthesis and
   based on 5000 non-parametric bootstrapping re-samples.

Table 9: Estimated menu costs by different results of the demand estimation

	OLS1	OLS2	OLS3	IV1	IV2	IV3	IV4
$\hat{\gamma}$	1.71	1.64	1.73	1.71	1.66	1.96	1.96
s.e.	(0.05)	(0.05)	(0.05)	(0.12)	(0.10)	(0.06)	(0.06)
log-likelihood	-478	-449	-433	-723	-677	-506	-503
nob	3678	3678	3678	3528	3528	3528	3528

1. The size of the state space is 1800.
2. The standard errors are inside parenthesis and
   based on 5000 non-parametric bootstrapping re-samples.

Table 10: Estimated menu costs and the numbers of grids

$nd\backslash np$	2	3	4	5
2	1.37	2.40	-	-
3	1.62	1.82	2.50	1.78
4	1.73	1.54	1.99	2.43
5	1.80	1.38	1.88	2.12
6	1.83	1.27	1.81	1.96

1. The estimated results are those of the duopoly model. The specification of the demand model is IV4.
2. 'np' stands for the number of grids of *price* and *rp*. 'nd' stands for the number of grids of the demand condition, *d*.
3. No convergence was achieved for -.

Table 11: Comparison of estimated menu costs with previous studies

	size	% in revenues
this study: $\hat{\gamma}$	1.96	18
Levy et al.	0.52	0.7
Slade	2.55	5.11 §
Aguirregabiria	1.45 †	0.7
Nakamura and Zerom	7000	0.23

1. §The value is calculated from Table IA and VB as the share-weighted average.
2. † The value is calculated from Table 6. The reported value in this table is the result from the specification allowing for asymmetric menu costs. The result without asymmetry is close to this value.

Figure 1: Prices of the Four Brands of Standard Graham Crackers

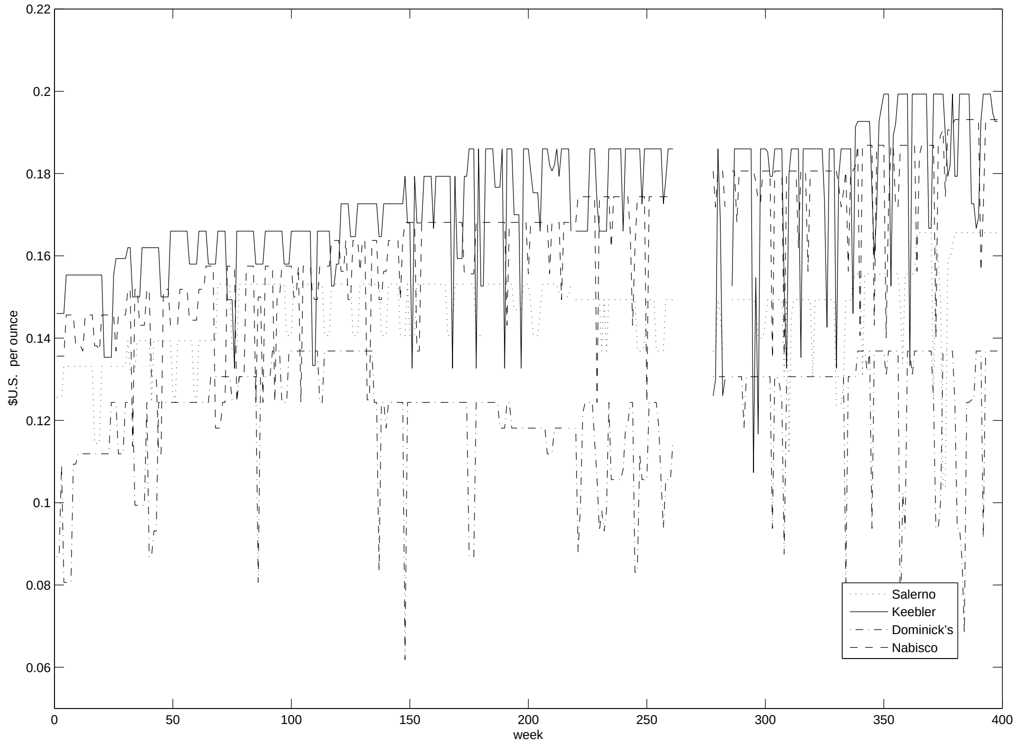
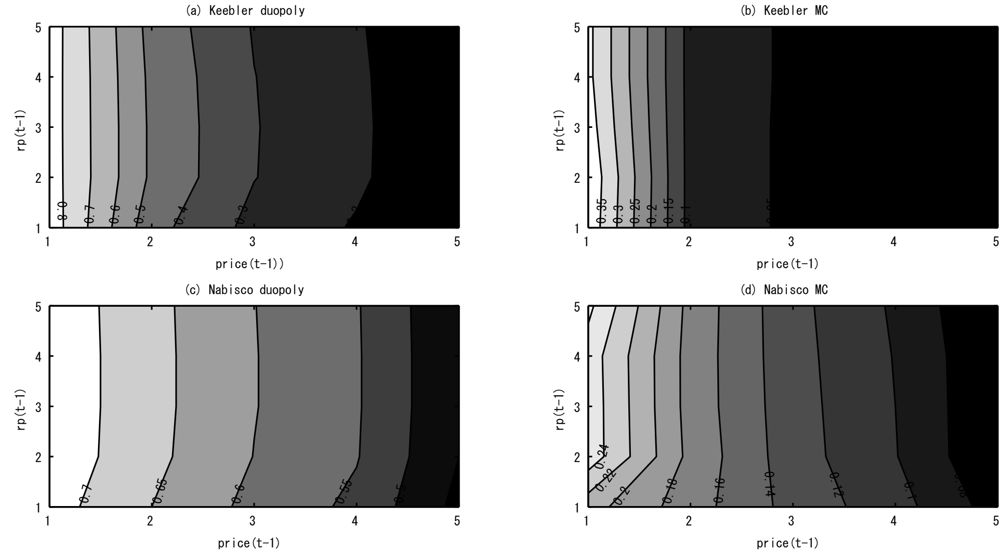
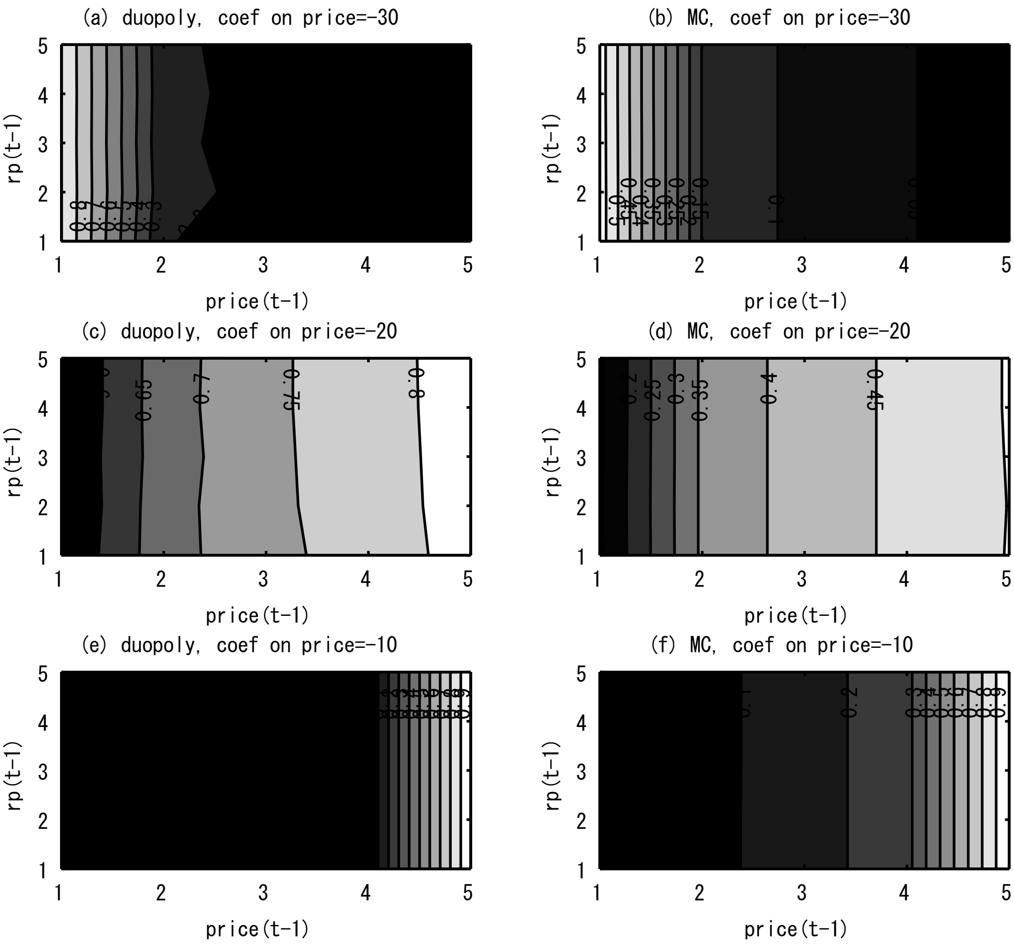


Figure 2: Choice Probabilities of No-Price Change at γ=1.96



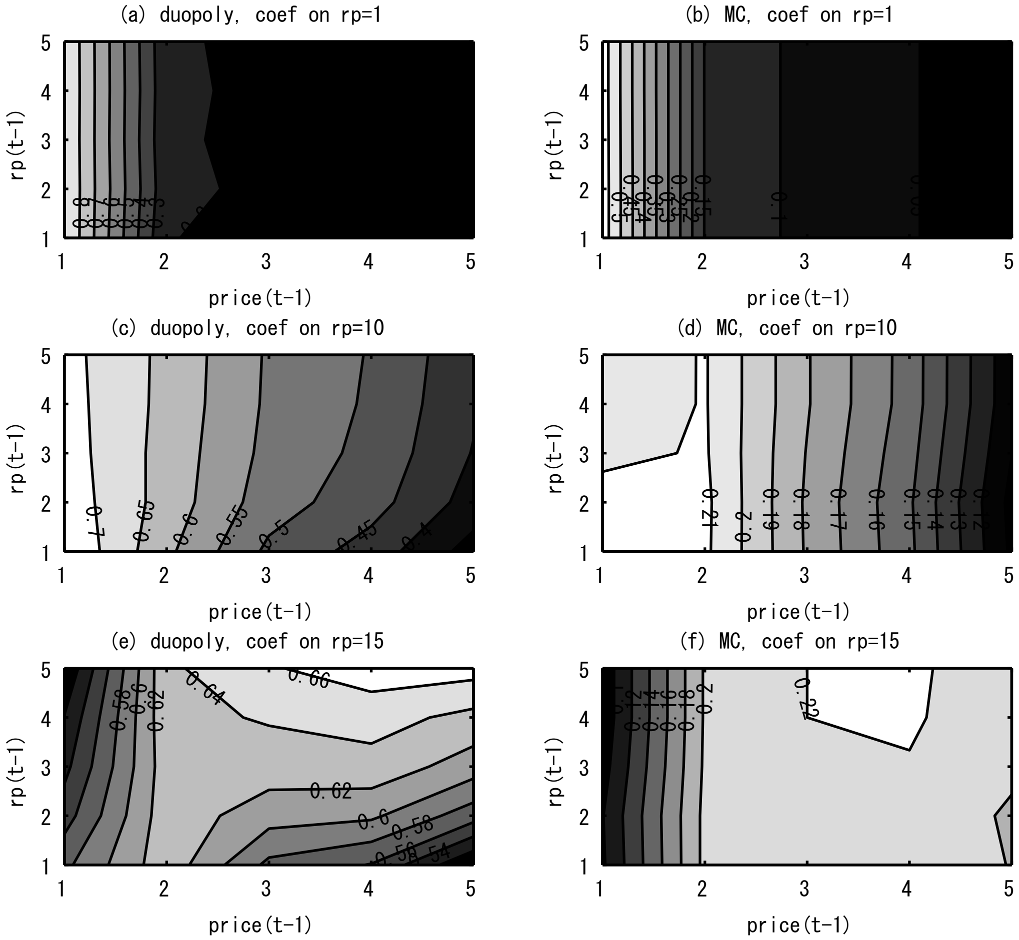
MC stands for the monopolistic-competition model.

Figure 3: Price Rigidity and Own Demand Elasticity



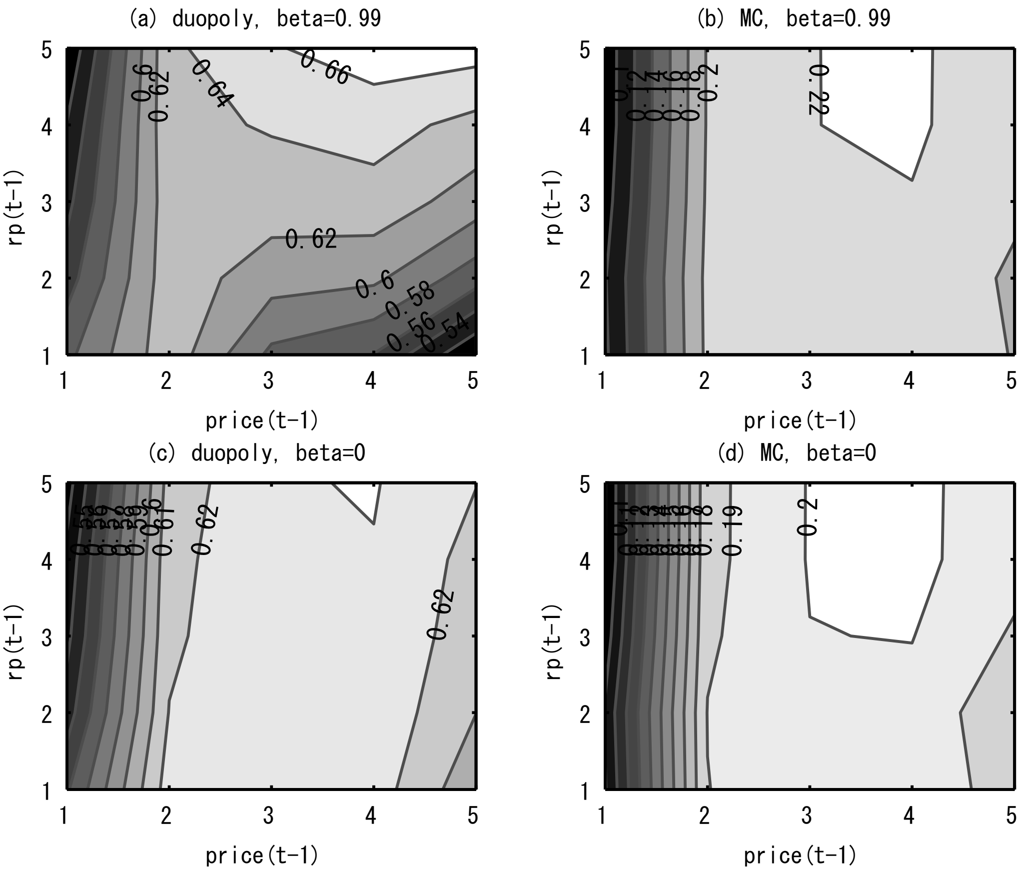
1. MC stands for the monopolistic-competition model.
2. The coefficient on the rival price is set to be 1.

Figure 4: Price Rigidity and Strategic Complementarity



1. MC stands for the monopolistic-competition model.
2. The coefficient on the own price is set to be -30.

Figure 5: Comparison with the model with myopic agents



1. MC stands for the monopolistic-competition model.
2. The coefficient on the own price is -30.
3. The coefficient on the rival price is 1.