Menu Costs, Strategic Interactions, and Retail Price Movements

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Abstract

This paper examines a state-dependent pricing model in the presence of fixed adjustment costs of prices – menu costs. A model with menu costs has potential to explain an important characteristic of retail price movements: prices discretely jump. This paper shows that the assumption about market structure is crucial in identifying menu costs. Especially, prices in a tight oligopolistic market could be more rigid than those in more competitive market such as monopolistically competitive one. If so, the estimates of menu costs under the assumption of monopolistic competitions in the past studies are potentially biased upwards due to the rigidity from strategic interactions among brands. In addition, the estimate could be biased downwards without controlling for the benefits from unobserved promotional activities.

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Developing and estimating a dynamic discrete-choice model with multiple agents to correct these potential biases, this paper provides empirical evidence that menu costs as well as strategic interactions are important for explaining the observed degree of price rigidity in weekly price movements of typical retail products, graham crackers.
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1 Introduction

In this paper, I develop an economic model in which, faced with fixed adjustment costs of changing their prices, manufacturers play a dynamic game of price competition. Estimating the structural model, this paper draws inferences on a potential source of the discrete movements commonly observed in data of retail prices — menu costs accompanied with firms' price changes. In particular, I estimate menu costs by taking into account a factor that potentially make the estimates of menu costs under the assumption of monopolistic competitions in the past studies biased upwards due to the rigidity from strategic interactions among brands in an oligopolistic market. In addition, I show that the estimate could be biased downwards without controlling for unobserved profit-enhancing promotional activities of manufacturers accompanied with price reduction. Especially, the bias due to strategic interactions on the estimate of menu costs has not been investigated before. Using a scanner data set collected from a large supermarket chain, after correcting these potential biases, I provide empirical evidence that menu costs are statistically significant as well as economically important in explaining the high-frequency, weekly movements of the retail prices in my data set.

This paper defines menu costs as any fixed adjustment costs a manufacturer has to pay whenever changing its price within a period, regardless of the magnitude and direction of the price change.[1] These fixed adjustment costs may include not only the costs of relabelling price tags but also managerial costs and information-gathering costs, which might occur when firms changing their prices. Importantly, several recent papers provide evidence that these menu costs are empirically crucial. On the one hand, 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 a crucial role in the price setting behavior of retail supermarkets. On the other hand, estimating menu costs as structural parameters of single-agent dynamic discrete-choice models in monopolistic competitive markets, Slade (1998) and Aguirregabiria (1999) find that menu costs are statistically significant. This paper also adopts dynamic discrete choice models to estimate menu costs, and introduce oligopolistic competition into my model.[2] This paper argues that

[1]Menu costs can be asymmetric: the fixed adjustment costs can differ across directions of price changes. In this paper, however, I examine only symmetric menu costs.

[2]The definition of menu costs in this paper follows those by Slade (1998) and Aguirregabiria (1999).

the estimates of menu costs are potentially biased when I adopt a monopolistic competition model to an oligopolistic market, and when I do not control for unobserved promotional activities.

As frequently observed in the recent macroeconomic literature, monopolistic competition is the most common market structure maintained by theoretical and empirical studies of price rigidity.[3] This assumption of market structure, however, is problematic if the following two facts are taken into account. First, it is obvious that not all product markets in an economy are monopolistically competitive. If the market of a product is dominated by a small number of firms, the assumption of oligopolistic competition is appropriate for studying the pricing behavior of firms. Second, under oligopolistic competition, if we employ the estimates of menu costs in the past studies under the maintained assumption of monopolistic competition, the estimate might be potentially biased upwards. This is due to possible strategic interactions among firms in an oligopolistic market. For exposition, suppose that there are a few firms in an oligopolistic market, which compete with respect to their prices. While monopolistic competition models create strategic complementarity between each firm's price and the average price of all firms, each firm perceives its own market power so small that the average price is regarded as being exogenous. In contrast, in a tight oligopoly market, each firm takes into account strategic interactions among firms more explicitly. This would lead to stronger strategic complementarity, and firms may prefer less aggressive price competition. Because of their strategic interactions, the equilibrium price of the market might be rigid to some extent, *regardless of the existence of menu costs*. In the literature of empirical industrial organization, for example, Neumark and Sharpe (1992) and Carlton (1989) provide empirical evidence of positive correlation between price rigidity and market concentration. In this case, ignoring the effect of the strategic interactions on price rigidity makes an estimate of menu costs biased upwards. This means that, to derive an inference on menu costs, it is important to take into account the market structure of a product and the strategic interactions among the firms in the market.

[3]For example, Blanchard and Kiyotaki (1987) show that menu costs combined with monopolistic competition may generate large effect of monetary shocks on output. To explain the persistent effects of monetary policy shocks on real aggregate variables observed in aggregate time series data, Yun (1996), Smets and Wouters (2003), and Christiano, Eichenbaum and Evans (2005) introduce the staggered multi-period price setting mechanism of Calvo (1983) into dynamic stochastic general equilibrium models with monopolistically competitive firms.

Although a slew of recent papers study price rigidity using micro data, almost none of them investigates the relationship between the price rigidity of a product and its market structure taking into account the effect of strategic interactions.[4] There are, however, a few exceptions. Dutta and Rustichini (1995) and Lipman and Wang (2000) develop theoretical models in which, being faced with menu costs, firms in a duopoly market play a dynamic game under perfect information.[5] Unfortunately, it is not a straightforward exercise to construct econometric models from their theoretical implications. One alternative approach used by Slade (1999) consists of estimating thresholds of price changes as functions of strategic variables within a reduced-form statistical model. Assuming that firms follow a variant of (s, S) policy, Slade (1999) observes that strategic interactions among firms engaging oligopolistic competition exacerbate price rigidity. This observation suggests possible upward bias of the estimates of menu costs, as discussed above. This paper goes beyond the reduced-form model of Slade (1999) by developing a fully-structural dynamic discrete-choice model with menu costs and strategic interactions. I model oligopolistic competitions and incorporate them directly into an econometric model. Since the effect of oligopolistic interactions on prices is captured by strategies in the model, the rigidity due to menu costs is separately inferred from that caused by strategic interactions.[6] This approach leads to more precise estimates of the magnitude of menu costs if oligopolistic interactions are important in my sample.

Estimated menu costs may also be biased downwards because of unobserved profit-enhancing promotional activities of firms accompanied with price reduction. To explain this potential downward bias, suppose that, given menu costs, promotional activities of firms reduce the prices of their products but, at the same time, increase the firms' profits. The problem is that when researchers cannot observe these promotional activities perfectly, it is not possible to control for the profit-increasing effects of downward price changes. As a result, the estimate of menu costs might be biased downwards because the estimates capture not only menu costs of price changes but also these profit-increasing effects as

[4] Sheshinski and Weiss (1977), Carlton (1986), Cecchetti (1986), Kashyap (1995), and Lach and Tsiddon (1996) are among the earlier studies on price rigidity with micro data.

[5] One source of price rigidity in an oligopolistic market would be collusion. Modelling collusion is, however, beyond the scope of this paper. For a theoretical model, see Athey, Bagwell and Sanchirico (2004).

[6] My econometric model does not impose the assumption that strategic interactions lead to price rigidity. Thus, I may find less or more price rigidity in my oligopoly model than in a monopolistic competition model.

fixed adjustment costs of price changes.[7] To deal with this possible downward bias of the estimates of menu costs due to unobserved promotional activities, I introduce a dummy variable specific to price reductions under the hypothesis that my estimate of menu costs increases when the dummy variable is included into my econometric model.

With the weekly retail price data of graham crackers collected in Dominick's Finer Food, I identify menu costs based on a dynamic discrete-choice model with multiple agents. Since my price data are well characterized by frequent discrete jumps, I exploit fixed adjustment costs to explain these observed discrete price changes, as in the dynamic discrete-choice models with a single agent under monopolistic competition by Slade (1998) and Aguirregabiria (1999). To take into account the effect of strategic interactions among manufacturers on price rigidity, I develop a dynamic discrete-choice model with multiple agents in an oligopolistic market.

I estimate my fully-structural dynamic discrete-choice model exploiting the nested pseudo likelihood algorithm (NPL) developed by Aguirregabiria and Mira (2002, 2004). The NPL includes the conditional choice probability (CCP) estimator of Hotz and Miller (1993) as well as the nested fixed point (NFXP) estimator of Rust (1987) as extreme cases. The major advantage of the NPL over the other two estimators is that the NPL gains efficiency compared to the CCP, while the NPL saves computational costs compared to the NFXP. Aguirregabiria and Mira (2002) develop the NPL for estimating dynamic discrete-choice models with a single agent. Aguirregabiria and Mira (2006) extend their NPL to a multiple agent setting that allows strategic interactions among players. I adopt their estimator to analyze the price-change game in an oligopolistic market.

Firstly, I find that my estimates of menu costs are statistically significant. The size of the estimated menu costs is close to those estimated in the past studies using the data from different markets. Therefore, I conclude that menu costs explain the observed degree of price rigidity, and play an economically important role in the weekly movements of my price data. Secondly, estimating the augmented models with the dummy variable specific to price reductions, I provide evidence that unobserved profit-enhancing promotional activities in fact leads to statistically significant downward bias of the estimate of menu costs.

[7] A promotional activity might be a demand shifter specific to price reduction and has a positive effect on a manufacturer's profit in this case. If a researcher cannot identify this demand shifter from data, the researcher captures the effect of the promotional activity as *negative* fixed adjustment costs of price changes.

Finally, the comparison between the results of my oligopolistic market model with those of a monopolistic competitive market model statistically supports the empirical hypothesis that strategic interactions among manufacturers results in upward bias of the estimator based on the latter model. In summary, the results of this paper not only confirm the inferences drawn by the past studies using the data of another product — fixed adjustment costs of price changes are statistically significant as well as economically important —, but also empirically reveal another potentially crucial source of price rigidity — strategic interactions among firms in oligopolistic markets.

Section 2 introduces a dynamic discrete-choice model with multiple agents under an oligopolistic market. Section 3 describes the empirical model to identify and estimate menu costs. Section 4 discusses the data set and estimates the demand function for graham crackers and transitory probabilities of descritized state variables. After reporting the main results in section 5, I conclude in section 6.

2 The model

This section introduces a structural model in this paper, which leads to identification of menu costs. This model describes a dynamic duopoly game between two manufacturers, who decide whether to change the retail prices of their products in the presence of menu costs.

2.1 The environment

The purpose of the analysis in this paper is to focus on a dynamic brand competition with respect to price changes. To do so, I assume a specific structure of decision making of manufacturers. First, I assume that manufacturers – or brands – are competing with respect to prices. The assumptions on the strategic instruments manufacturers are competing with have potentially critical effect on the hypothesis to test. In this paper, I investigate price competition as I am concerned with how firms adjust their prices facing fixed adjustment costs of prices.

Second, I assume that the competition is among manufactures rather than among retailers. Manufactures sell their branded products through a retailer. They act to maximize the sum of discounted profits and extract all the profits obtained in the retail store. This vertically-integrated structure is a strong assumption, but could be reasonable when a retailer is neutral and acts passively regarding the competition among manufacturers. There is evidence that this assumption could be justified for the data I use in this paper. In this paper, I analyze brand competition of a narrowly defined single product category – graham crackers. When we look at prices in a narrowly defined product with small sales such as graham crackers, the price differentials across brands might reflect the competition among brands rather than that among retailers. For example, conducting an interview with a manager in a supermarket, Slade(1995, 1998, 1999) states that retailers are competing with their overall offering rather than through a single product. Chintagunta, Dubé and Singh (2003) confirm the claim by Slade through an interview with a store manager in Dominick's Finer Food (DFF), the supermarket whose data set I use. In addition, using the DFF data set, Montgomery (1997) state that the price movements across time reflects manufacturers' decision making rather than the retailer's. Besanko, Dubé and Gupta (2005) also show that the pass-through elasticity between retail prices and wholesale prices is as high as 80 percent in the product category of crackers, which is the product analyzed in this paper, in DFF.[8] These description and evidence show that retailers generally act passively in the pricing of a single minor product.

Third, I assume that the manufacturers maximize the profits gained within a store. I define a price-cost margin as the difference between a retail price and a wholesale price, but not that between a retail price and a marginal production cost. This assumption is imposed since I would like to extract the competitive aspect among manufacturers reflected in retail prices.

Finally, the manufacturers decide only whether or not to change their current prices but not exact price levels. A price level is determined by a retailer, who follows a certain pricing rule. This assumption is made to capture the fact that the retailers act passively but it is hard to consider that the manufacturers can control the retail prices perfectly.

These assumptions are strong and abstract actual vertical structure to a great extent. Ideally, the model would include an explicit vertical structure such that the manufacturers

[8] In the analysis of Besanko et al. (2005), the pass-through elasticity of 100 percent means that the retailer acts completely passive in pricing. On one hand, they shows that the pass-through elasticity of beer exceeds 500 percent. This indicates that the retailer tend to discount the product more heavily than manufacturers intend. They confirm that the retailer uses a package of beer as a loss-leader. On the other hand, the pass-through elasticity of toothpaste is as low as 20 percent.

set their wholesale prices constructing expectations with respect to retailers' pricing and other manufacturers' pricing given their own production costs. This straightforward structure of vertical integration is, however, difficult to be incorporated into a dynamic oligopoly model with fixed adjustment costs, which is structurally estimated later.[9] Also, even under the vertically-integrated structure, it might be ideal to assume that manufacturers decide both price changes and the price levels. The extension to this direction requires a model to have both discrete and continuous control variables. Although the extension to this direction would be fruitful, I focus on the most simple structure in this paper.

In the following, I formalize the model under the assumptions stated above.

2.2 The problems of manufacturers

Consider a market in which two manufacturers compete with respect to their prices p_{it} and p_{-it} for periods $t = 1, 2, ..., \infty$. Let $i = \{1, 2\}$ and $-i = \{2, 1\}$ denote the indices of a manufacturer and its rival, respectively. To sell their products, the manufacturers have to put their products on the shelf in a retail store with no cost. For simplicity, I consider a vertically integrated manufacturer-retailer relationship, in which the retailer acts passively: the manufacturers' decisions to change their prices are always implemented by the retailer.

At the beginning of each period, the manufacturers know the wholesale prices of the two products, $\{c_{it}, c_{-it}\}$, and the values of demand conditions in the past period, $\{d_{it-1}, d_{-it-1}\}$. The current demand conditions, $\{d_{it}, d_{-it}\}$, and the consumption, $\{q_{it}, q_{-it}\}$, realize during the period t. The demand function for the product of manufacturer $i = \{1, 2\}$ is

$$q_{it} = d_{it} - b_0 p_{it} + b_1 p_{-it}, \tag{1}$$

where $b_0 \geq 0$, $b_1 \geq 0$, $b_1 < b_0$, and $-i = \{2, 1\}$. q_{it} and p_{it} stand for the quantity sold and the price of the product of manufacturer i, respectively. Let a_{it} denote the discrete action taken by manufacturer i at period t: $a_{it} = 0$ means no price change and $a_{it} = 1$ a price change, respectively. Changing prices incurs fixed price adjustment costs, $\gamma > 0$, i.e., menu costs. In addition, manufacturer i receives private information ε_{it} that affects its profitability. Private information ε_{it} is a vector including ε^0_{it} and ε^1_{it} as its elements, where ε^a_{it} is the private information of manufacturer i when taking action $a = \{0, 1\}$.

[9] For a static model with an explicit vertical structure, see Villas-Boas and Zhao (2005).

Subsequently, the manufacturers simultaneously decide whether to change their prices or not. Once manufacturer i decides to change its prices incurring menu costs, shelf price p_{it} is determined at the optimal level without menu costs. The actual shelf prices are set by the retailer. It is worth noting that this paper does not model the decision making with respect to shelf price levels, but this decision is modelled as a stochastic process that is of common knowledge across the manufacturers.

For any price of manufacturer $-i$, p_{-it}, the one-period profit of manufacturer i at period t is defined as

$$\Pi_{it}(p_{it}, d_{it}, c_{it}, a_{it}, a_{-it}) = (1 - a_{it})\pi_{it}^0 + a_{it}\pi_{it}^1, \tag{2}$$

where

$$\pi_{it}^0 = (p_{it-1} - c_{it})(d_{it} - b_0 p_{it-1} + b_1 p_{-it}) + \varepsilon_{it}^0 \tag{3}$$

and

$$\pi_{it}^1 = (p_{it} - c_{it})(d_{it} - b_0 p_{it} + b_1 p_{-it}) + \varepsilon_{it}^1 - \gamma. \tag{4}$$

The one-period profit of manufacturer i depends on the action its rival takes, a_{-it}, through the rival's retail price p_{-it}. In particular, equation (3) shows the one-period profit for manufacturer i at period t when the manufacturer takes action $a_{it} = 0$, while equation (4) is the profit when manufacturer i decides to change its price.

The demand conditions and wholesale prices, which evolve independently from the actions taken by the manufacturers, follow stationary first-order Markov processes with the density functions $f_i^d(d_{it}|d_{it-1})$ and $f_i^c(c_{it}|c_{it-1})$, respectively.[10] The shelf prices of the products depend on the actions of the manufacturers. Let $f_i^p(p_{it}|d_{it-1}, p_{it-1}, c_{it}, a_{it})$ be the transition density function of the retail price of manufacturer i. Denote the transition density function of the retail price of manufacture i when it takes action $a_{it} = 1$ by $\hat{f}_i^p(p_{it}|d_{it-1}, p_{it-1}, c_{it})$. Then, the transition density function is described as

$$f_i^p(p_{it}|p_{it-1}, d_{it-1}, c_{it}, a_{it}) = \begin{cases} \hat{f}_i^p(p_{it}|d_{it-1}, p_{it-1}, c_{it}) & \text{if } a_{it} = 1, \\ \text{degenerated at} \quad p_{it} = p_{it-1} & \text{if } a_{it} = 0. \end{cases}$$

The state variables in this model consist of commonly and privately observable components. The commonly observable component is denoted by a vector x_t such that $x_t =$

[10] The assumption that the demand conditions are independently distributed implies that there is no interaction between manufacturers and consumers. The processes of the wholesale prices are also assumed to be exogenous because I focus on a price competition in a retail store.

$\{p_{it-1}, p_{-it-1}, d_{it-1}, d_{-it-1}, c_{it}, c_{-it}\}$. Private information ε_{it} is observable only for manufacture i, and is independently and identically distributed with a known density function $g(\varepsilon_{it})$ across actions, manufacturers, and time. Manufacturer i observes $\{x_t, \varepsilon_{it}\}$, while a researcher observes only x_t. Throughout this paper, I assume that the state space of x_t, X, has a finite discrete support of dimension M.

The assumption of i.i.d. private information is admittedly strong. This assumption would be, however, acceptable in a well-defined model. My model defines the observable components of the profit gained by brands in a store as precise as possible based on the economic theory. In addition, my empirical model controls for dynamics and strategic interactions, which could be very important in the actual decision making of price changes, by directly incorporating theoretical counterparts into the empirical model. In addition, this assumption is necessary to implement an empirical method for a dynamic discrete choice model with multiple agents. For example, if the private information is correlated across manufacturers, each player can infer the private information of the other manufacturers based on its own private information. This requires a researcher to take additional integration with respect to private information. [11] Moreover, without the assumption of serially uncorrelated private information, manufacturers infer the current private information of the others based on the past state variables. Then, the size of state space expands exponentially in the number of the size of state space, and therefore too large to be dealt with even for the problem with the small number of grids per state variable.

Given the vector of the state variables and the expected sequence of its rival's action, manufacturer i maximizes the following objective function

$$E\{\sum_{s=t}^{\infty} \beta^{s-t} \Pi_{is}(p_{is}, d_{is}, c_{is}, a_{is}, a_{-is}) \mid x_t, \varepsilon_{it}\}, \tag{5}$$

where $\beta \in (0\ 1)$ is the discount factor, and $E\{\cdot \mid x_t, \varepsilon_{it}\}$ is the mathematical expectation operator conditional on the payoff relevant state variables at period t. The action of manufacturer $-i$, a_{-is}, affects the current profit of manufacturer i through p_{-is}.

Since the time horizon is infinite and the problem has Markov structure, I assume Markov stationary environment in the following.

[11] Moreover, relaxing this assumption makes some part of the empirical method employed in this paper infeasible.

2.3 Markov strategy, Bellman equation, and equilibria

The manufacturers solve the stationary Markov problem and play Markov strategies.[12] Since the problem is stationary with infinite time horizon, I drop time-subscript t from the rest of the analysis. Instead, I use $x' = (p'_i, p'_{-i}, d'_i, d'_{-i}, c'_i, c'_{-i})$ and $\varepsilon' = (\varepsilon'_i, \varepsilon'_{-i})$ to denote the state variables at the next period.[13]

The realization of one-period profit depends on the demand conditions and shelf prices at the end of a period, which are the state variables in the next period.[14] When the manufacturers $i = \{1, 2\}$ decide whether to change their prices at the beginning of period t, the profits are random because the manufacturers do not determine the levels of their shelf prices, which are stochastic with the density function f_i^p. Therefore, the manufacturers have to form expectation with respect to the levels of the shelf prices at the time of decision making. In addition, I assume that demand conditions realize after the manufacturers made their decision abut price changes. Therefore, the manufacturers form their expectation with respect to demand conditions as well. Let $d_{it} = d_{-it} = d_t$ so that demand conditions are symmetric across manufacturers.

Let $\sigma = \{\sigma_i, \sigma_{-i}\}$ be a set of arbitrary strategies of the manufacturers, where σ_i defines a mapping from the state space of (x, ε_i) into the action space; that is, $\sigma_i : M \times R^2 \rightarrow \{0, 1\}$. Given σ, the *conditional choice probability* for manufacturer i to choose action a, $P_i^\sigma(a_i = a|x)$, is defined as

$$\begin{aligned} P_i^\sigma(a_i = a|x) &= Prob[\sigma_i(x, \varepsilon_i) = a|x] \\ &= \int I\{\sigma_i(x, \varepsilon_i) = a\} g(\varepsilon_i) d\varepsilon_i. \end{aligned} \tag{6}$$

Manufacturer i forms expectation about the action of its rival according to the conditional choice probability, $P_{-i}^\sigma(a_{-i} = a|x)$.

[12] If $\{x_{it}, \varepsilon_{it}\} = \{x_{is}, \varepsilon_{is}\}$, then manufacturer i's decision at period t and s are the same ($a_{it} = a_{is}$).

[13] The following description about strategies, the Bellman equation, and the equilibria is based on Aguirregabiria and Mira (2006), who characterize a dynamic game structure with discrete choices and space. Aguirregabiria and Mira (2006) analyze an entry-and-exit game as an example of the application of their basic model structure.

[14] Puterman (1994) shows that I can set up a problem with a one-period payoff depending on the state in the next period.

Define the expected one-period profit for manufacturer i conditional on $a_i = a$ and x as

$$\Pi_i^\sigma(a,x) = \sum_{a_{-i}\in\{0,1\}} P_{-i}^\sigma(a_{-i}|x) \sum_{p'_{-i}} f_i^p(p'_{-i}|p_{-i}, c_{-i}, a_{-i}) \sum_{p'_i} f_i^p(p'_i|p_i, c_i, a_i) \sum_{d'} f^d(d' \mid d)\Pi_i(p'_i, c_i, d', a_i, a_{-i}). \quad (7)$$

The *ex ante* one-period profit depends on the transition probability of prices and manufacturers' actions. When making its decision, manufacturers i forms expectation with respect to d' and p'_i, given the choice probabilities of manufacturer $-i$.

Given state x, private information ε_i, and strategy σ, let $\tilde{V}_i^\sigma(x, \varepsilon_i)$ be the value function of manufacturer i associated with an optimal choice a. Then, the Bellman equation of manufacturer i is

$$\tilde{V}_i^\sigma(x,\varepsilon_i) = \max_{a\in\{0,1\}}\{\Pi_i^\sigma(a,x) + \varepsilon_i^a + \beta \sum_{x'\in X} f(x'|x, a_i) \int \tilde{V}_i^\sigma(x', \varepsilon'_i) g(\varepsilon'_i) d\varepsilon_i\}, \quad (8)$$

where $f(x'|x, a_i) = \sum_{a_{-i}} P_{-i}^\sigma(a_{-i}, x) f(x'|x, a_i, a_{-i})$. Integrating out private information ε_i, I can rewrite the above Bellman equation (8) in terms of commonly observable state variables x. Let $V_i^\sigma(x)$ be the *integrated value function* of manufacturer i facing state x given strategy σ, $V_i^\sigma(x) = \int \tilde{V}_i^\sigma(x, \varepsilon_i) g(\varepsilon_i) d\varepsilon_i$. With the integrated value function, the Bellman equation (8) is rewritten as

$$V_i^\sigma(x) = \int \max_{a\in\{0,1\}}\{\Pi_i^\sigma(a,x) + \varepsilon_i^a + \beta \sum_{x'\in X} f(x'|x, a_i) V_i^\sigma(x')\} g_i(\varepsilon_i) d\varepsilon_i. \quad (9)$$

The right hand side of equation (9) defines a contraction mapping in the space of the integrated value functions. For each manufacturer, there exists a unique value function V_i^σ that solves the functional equation (9), given an arbitrary strategy σ.

For $i = \{1, 2\}$ and any (x, ε_i), the *best response function* for manufacturer i is defined as strategy σ_i such that

$$\sigma_i(x, \varepsilon_i) = \arg\max_{a\in\{0,1\}}\{\Pi_i^\sigma(a,x) + \varepsilon_i^a + \beta \sum_{x'} f(x'|x, a) V_i^\sigma(x')\}. \quad (10)$$

The pair of the best response functions, $\{\sigma^*(x_i, \varepsilon_i), \sigma^*(x_{-i}, \varepsilon_{-i})\}$, which defines the best responses of the manufacturers to their rival's best response functions, characterizes a Markov perfect equilibrium in this game.

Following Milgrom and Weber (1985), a Markov perfect equilibrium can be represented in a probability space. Note that the functions, $\Pi_i^\sigma(a, x)$, $f(x'|x, a)$, and $V_i^\sigma(x')$, depend on the strategies of the manufacturers through the conditional choice probabilities P associated with an arbitrary strategy σ. The equilibrium *best response probabilities*, which is integrated smoothed best response function, associated with a set of Markov perfect equilibrium strategy σ^*, is the fixed point of the following mapping:

$$\begin{aligned} P_i^*(a|x) &= \int I[a = \sigma_i^*(x, \varepsilon_i)] g_i(\varepsilon_i) d\varepsilon_i \\ &= \int I\{a = \arg\max_{a \in \{0,1\}} \{\Pi_i^{\sigma^*}(a, x) + \varepsilon_i^a + \beta \sum_{x'} f(x'|x, a) V_i^{\sigma^*}(x')\} g_i(\varepsilon_i) d\varepsilon_i \} \end{aligned} \quad (11)$$

Let P^* be the best response probabilities in matrix form. The right hand side of equation (11) can be represented with a mapping operator from probability space to probability space, $\Lambda(P)$. Since this mapping is continuous in choice probabilities P, by Brower's fixed point theorem, there exist the best response probabilities P^* that satisfy $P^* = \Lambda(P^*)$. [15]

A Markov perfect equilibrium is, then, characterized by a solution to the coupled fixed point problem consisting of equations (9) and (11) due to the interdependence between the value functions and the conditional choice probabilities. Given the conditional choice probabilities, I solve the dynamic programming problems of equation (9) for manufacturers $i = \{1, 2\}$. Given these value functions, the best response probabilities are obtained from equation (11).

3 The estimation procedure

In this paper, estimating menu costs γ includes the following two steps. First, I construct demand conditions by estimating a demand equation, and then estimate the transition probabilities of the state variables after discretizing these variables. Second, using the results of the first step, I estimate menu costs γ with the NPL estimator developed by Aguirregabiria and Mira (2002).

The NPL estimator includes the Conditional Choice Probability (CCP) estimator by Hotz and Miller (1993) and the Nested Fixed Point (NFXP) estimator by Rust (1987) as extreme cases. The NPL estimator gains efficiency compared to the CCP estimator while it saves computational costs compared to the NFXP estimator.[16] Recent developments for

[15] In general, the uniqueness of equilibrium is not guaranteed.

[16] The applications of the NPL estimator to dynamic discrete choice games include Aguirregabiria and Mira (2006) for an entry and exit game in a local retail market in Chile, Zhang-Foutz and Kadiyali (2003) for a game of release date preannouncements of movies, and Collard-Wexler (2005) for an entry-exit game in the

estimating dynamic discrete choice games provide several alternative estimators such as in Jofre-Bonet and Pesendorfer (2003), Bajari, Benkard and Levin (2005), Pakes, Ostrovsky and Berry (2005), and Pesendorfer and Schmidt-Dengler(2003,2004). Although several studies examine small sample properties in their proposed estimators, so far no consensus has been reached about which estimator performs better than others, in particular, for my problem. Aguirregabiria and Mira (2006) conduct the Monte Carlo experiments based on an entry and exit game. Comparing the NPL estimator and the two-stage pseudo maximum likelihood estimator, they show NPL performs better especially when strategic interactions are strong.[17]

3.1 Estimating demand equation and transition probabilities

To estimate the demand function (1), I specify the following empirical demand equation:

$$\begin{aligned}\ln(q_{it}) &= d_t + b_0 \ln(p_{it}) + b_1 \ln(p_{-it}) + \epsilon_{it} \\ &= \{\alpha_0 + D_t\alpha\} + b_0 \ln(p_{it}) + b_1 \ln(p_{-it}) + \epsilon_{it}, \end{aligned} \tag{12}$$

where α_0 is a constant term, D_{it} is a vector of demand shifting variables, α is a vector of coefficients on the demand shifting variables, and ϵ is a demand error. I estimate equation (12) by two-stage least squares (2SLS). With the estimated coefficients $\{\hat{\alpha_0}, \hat{\alpha}\}$, demand conditions d_{it} are constructed as $\{d_t = \hat{\alpha_0} + D_t\hat{\alpha}\}$. Estimated demand coefficients $\hat{b_0}$ and $\hat{b_1}$ are used to construct the one-period profits of the manufacturers.

I then discretize the demand conditions, wholesale prices, and shelf prices. Using the discretized variables, I estimate transition probability density functions f^d , f_i^c, and f_i^p, using the method by Tauchen (1986). The construction of f_i^p needs some additional procedure since f_i^p is conditional on not only own past value and the current choice but on the values of demand conditions and costs.[18]

Theoretically, the initial values of conditional choice probabilities should not matter as the consistency of NPL estimator does not require the consistency of initial choice proa-

ready-mix concrete industry. The code of NPL for a single agent model by Victor Aguirregabiria is available at http://people.bu.edu/vaguirre/. The code I use in this paper both for a single agent model and a multiple agent model is based on his code. I thank him for making his program available.

[17]The two-stage pseudo maximum likelihood estimator corresponds to the NPL estimator at K=1, where K is the number of iteration in the nested algorithm.

[18]For the details of estimations of transition probabilities and initial choice probabilities, see Appendix A.1.

bilities. In this paper, I construct the initial values of conditional choice probabilities the results of a probit estimation in the following manner. First, I estimate a reduced-form probit model, in which the dependent variable is an index function $I\{\Delta p \neq 0\}$ in the case of binary choice problem, and the explanatory variables include constant, d_{t-1}, p_{it-1}, $p_{-i(1)t-1}$, $p_{-i(2)t-1}$, c_{it}, $c_{-i(1)t}$, $c_{-i(2)t}$, where the subscripts $-i(1)$ and $-i(2)$ present rival firms. The estimation is conducted using the discretised variables. Then, I obtain the conditional choice probabilities for each value of state space by evaluating the predicted probabilities at each bin of state space.

3.2 Estimating menu costs

This section derives the pseudo-likelihood function to estimate menu costs. For convenience, define the following notations: the rival's expected price under its conditional choice probability P, $p^P_{-it} = \sum_{a_{-i}\in\{0,1\}} P(a_{-i} \mid x_t) \sum_{p_{-it}} p_{-it} f^p_{-i}(p_{-it} \mid x_t, a_{-i})$ for a given x_t ; manufacturer i's expected price associated with action a, $p^a_{it} = \sum_{p_{it}} p_{it} f^p_i(p_{it} \mid p_{it-1}, c_{it}, d_t, a_{it} = a)$ for a given p_{it-1}. Given the estimated coefficients of the demand equation (12), $\hat{b}_0$ and $\hat{b}_1$, and the constructed demand conditions d_t, I set up the expected one-period profit associated with action a as

$$\widehat{\Pi}^P_i(a, x_t) = (p^a_{it} - c_{it}) \exp(d_t - \widehat{b_0} \ln(p^a_{it}) + \widehat{b_1} \ln(p^P_{-it})) - \gamma I\{a = 1\}.$$

For exposition, denote $\widehat{\Pi}^P_i(a, x_t) = z^P_{it}\theta$, where $z^{aP}_{it} = \{(p^a_{it} - c_{it}) \exp(d_t - \hat{b_0} \ln(p^a_{it}) + \hat{b_1} \ln(p^P_{-it})), -I\{a = 1\}\}$ 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 $e^{P^*}_i(a)$ be the vector of the expectation of ε^a_i conditional on x.[19]

The empirical counterparts of the value functions (9) and the best response probabilities (11) are derived according to the mapping expression by Aguirregabiria and Mira (2006). Let $\Gamma_i(P)$ denote the mapping operator of the value functions (9) in vector form given conditional choice probabilities P, and $\Psi(a \mid x)$ be the operator representing the best response probabilities given $\Gamma_i(P)$. [20] $\Gamma_i(P)$ can be written as $\Gamma_i(P) = Z^P_i\theta + \lambda^P_i$, where $Z^P_i = (I - \beta F^P)^{-1} \sum_{a\in\{0,1\}} P^*_i(a)\Pi_i(a)$ and $\lambda^P_i = (I - \beta F^P)^{-1} \sum_{a\in\{0,1\}} e^{P^*}_i(a)$, where

[19] $F^P = \sum_{a_i} \sum_{a_{-i}} P(a_i) * P(a_{-i}) * (F^p_i \otimes F^p_{-i} \otimes F^d \otimes F^c_i \otimes F^c_{-i})$, 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.

[20] For the details of the derivation, see Appendix A.2.

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.[21] Then, $e_i^P(a) = \text{Euler's constant} - \ln(P_i^a)$, where Euler's constant is about 0.577. The mapping of the best response probabilities Ψ_i given P is

$$\Psi_i(a) = \frac{\exp\{z_{it}^a\theta + \beta F^a(Z_i^P\theta + \lambda_i^P)\}}{\sum_a \exp\{z_{it}^a\theta + \beta F^a(Z_i^P\theta + \lambda_i^P)\}}. \tag{13}$$

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

$$\sum_{i=1}^{2}\sum_{t=1}^{\infty}\sum_{a\in\{0,1\}} I\{a_{it}=a\}\ln\Psi_i(a \mid x_t; P^o, \theta^o), \tag{14}$$

where $\Psi_i(a \mid x; P^o, \theta^o)$ 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. First, I conduct the pseudo-maximum likelihood estimation of θ given P_0 (initial values of P), and then obtain the updated $\hat{P}_1$ using $\hat{\theta}_1$ according to the mapping Ψ. Second, I iterate this procedure for $K \geq 1$ stages. In the estimation, the K-stage pseudo-log-likelihood is constructed as:

$$\sum_{i=1}^{2}\sum_{t=1}^{T}\sum_{a\in\{0,1\}} I\{a_{it}=a\}\ln\Psi_i(a \mid x_t; \hat{P}^{K-1}, \theta). \tag{15}$$

Letting $\hat{\theta}$ denote the structural parameter that maximizes equation (15), I can obtain the K-stage estimator of conditional choice probabilities:

$$\hat{P}^K = \Psi(\hat{P}^{K-1}; \hat{\theta}^K). \tag{16}$$

This estimator is also known as a quasi-generalized M-estimator. 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.[22]

[21] The cumulative distribution function of the type I extreme distribution is $G(\varepsilon) = \exp(-e^{(-\varepsilon)})$.

[22] See Gourieroux and Monfort (1995) for the asymptotic characterizations of a quasi-generalized M-estimator. For the asymptotic characterization of the NPL estimator, see Aguirregabiria and Mira (2002, 2004).

3.3 Estimation with potential multiplicity of equilibria

The parameter of menu costs might not be point-identified because the model potentially could have multiple equilibria. Without knowing the selection mechanism of the game, it is not possible to construct the likelihood functions. As in Aguirregabiria and Mira (2006) and the other studies who propose alternative estimators such as Pesendorfer and Schmidt-Dengler (2003), and Pakes et al. (2005), I assume that the observed data are generated from one equilibrium. This assumption implies that, given a vector of observable state variables, a certain strategy is chosen with probability one in the data. Therefore, this assumption avoids the problem of unknown selection mechanism. This assumption is not, unfortunately, testable, and whether this assumption is satisfied or not is the problem and data specific. In the context of entry-exit game with cross-sectional data with short time periods, Aguirregabiria and Mira emphasize the importance of the condition where players are the same across markets. Similarly, Pesendorfer and Schmidt-Dengler(2003, 2005) argue that this assumption is more likely to be satisfied in a single market with the same players than multiple markets with different players. In my model, the players are fixed for the entire periods, and they play in the same market. Therefore, it is not likely that the players switch the equilibrium they play. Moreover, as I will discuss the property of my data below, the markets are similar to each other as they are in the same city.

4 Data, demand estimation, and transition probabilities

I analyze the empirical model stated above choosing one product, graham crackers, sold in a large supermarket chain in the United States. This section first describes the property of the data. Second, I report the empirical results to prepare for the estimation of menu costs: the estimated demand equation and transition probabilities of the state variables.

4.1 The data

The data in this paper are from the weekly scanner data set collected in the branch stores of Dominick's Finer Food, the second largest supermarket chain in metropolitan Chicago during my sample period from September 1989 to May 1997.[23] The data set contains

[23] The data set is available at http://gsbwww.uchicago.edu/kilts/research/db/dominicks/.

information such as shelf prices, quantities sold, and importantly a proxy variable of wholesale prices (average acquisition costs) by stores as well as by Universal Product Codes, which distinguish products. The products in the data set are priced on weekly basis, which matches my sample frequency.

My sample contains 21 stores out of the total 84 stores in the supermarket chain. These stores are chosen based on the availability of transaction records.[24]

I choose graham crackers as the product to be analyzed because (i) a small number of manufacturers dominate the market; (ii) there is only one similar size of package; (iii) graham crackers are minor products so that I can avoid the possibility that pricing is affected by loss-leader motivation of the retailer. There are three national brands (Sarelno, Keebler, and Nabisco), and one private brand of Dominick's. The sizes of packages are 15 oz or 16 oz. [25]

Table 1 shows the market shares of the manufacturers in the total sales of graham crackers in these 21 stores. The market share of the four brands is about 97 percent of the total sales of graham crackers. Among them, the three national brands have the market share of 72.24 percent. I analyze the competition among these national brands.[26] Figure 3.1 plots the shelf prices of three national brands in a representative store. The figure shows two important aspects of the data. First, the shelf prices discretely jump both upwards and downwards. Second, most of downward price changes are followed by upward price changes almost the same magnitude within a quite short period. In particular, I can interpret the second aspect as promotional activities with "temporary discounts". In total, I have an unbalanced panel data with 21978 observations (7326 observations for three brands). The number of weeks available in a particular store ranges from 328 to 362 depending on the numbers of missing data.

Tables 2 and 3 report the summary statistics of the prices, quantity sold, and costs in

[24] I omit the stores with too many missing data from the sample. For the details of choice of the stores, see Appendix A.3.

[25] In addition, the data set provides a code that show whether DFF buys a product is directly from manufacturers or through wholesalers. According the code, DFF buys graham crackers directly from manufacturers.

[26] I assume that the private brand, Dominick's, does not join the game among the national brands, and treat the price of Dominick's as being exogenous.

the sample, and the descriptive statistics associated with price changes.[27] All the monetary values are in nominal. Price changes are conducted for 32.6 percent in the all weeks. The magnitudes of downward price changes and upward price changes are similar to each other with 0.28 dollars and 0.27 dollars on average, respectively.

In the estimation of dynamic discrete choice game, using the data set with a long sample period has an advantage over short panel data sets often used for an entry-exit game. In my sample, I can observe the actions of each player and transitions of state variables repeatedly. This feature leads to more precise estimate of conditional choice probabilities and transition probability matrices.

4.2 Demand estimation and state variables

I estimate the demand equation (12) by 2SLS. The dependent variable is the log of quantity sold. The explanatory variables include the following variables. First, price variables are *p* (the log of prices), *rp*(the log of simple average of rivals' prices), *dp* (the log of prices of Dominick's, store brand). The effect of promotional activity is controlled by a dummy variable *bonus*, which takes one when the deal code indicates that "bonus" takes place. Bonus is a promotional activity, which is typically a price reduction associated with a shelf-tag announcing promotion.[28] Once in a while, DFF bundles multiple units into one package. To capture this effect, *bundle* is created which shows additional units bundled. In addition, variables that capture persistent effects of the promotional activity and pricing are created: *durd* (the duration since the last discount more than five percent) and *durb* (the number of weeks in the duration of bonus). [29] Also, *cc* (the log of customer count, which is the number of customers who purchased at least one item in the store) controls for the effect of store traffic on the demand of graham crackers. A unit of customer count is 100. [30] Holiday dummy variables are also created to capture seasonality in demand if there is any. Chevalier, Kashyap and Rossi (2003) report that the demand of several goods exhibits some

[27] I use average acquisition costs (AACs) as the measure of wholesale prices. For the differences of average acquisition cost from the wholesale price, see Appendix A.3.

[28] Unfortunately, the variable of bonus does not capture all the promotional activities. According to the description of the DFF data set, there could be promotional activities even when there is no record in the data set.

[29] For the construction of these variables when the data point is missing, see the Appendix A.3.

[30] Customer counts in the original data set are recorded daily. The daily averages of customer counts in each week are used in the analysis.

degree of seasonality using the data of various goods from Dominck's. According to the week coding in the original data set, I create dummy variables that take one in the week which include any holiday and in its previous week. [31] In addition to these variables, the estimated demand equation includes *constant*, brand dummy variables, and store dummy variables.

To take into account possible endogeneity causing correlations among the current prices of three national brands, p_{it} and p_{-it}, and the demand error term, I use instrumental variables. The instruments include wholesale price, c_{it}, and the average of rivals' wholesale prices, c_{-it}, and a variable constructed by multiplying the wholesale prices by a variable *income*.[32] Since the variation of wholesale prices c_{it} and c_{-it} across stores is small, then the variable created by multiplying c_{it} by income is used to control the variation of prices across stores as well as weeks. In this estimation, the price of Dominick's and promotional variable are regarded as exogenous since, as stated above, the price of Dominick's has weak correlation with the prices of three national brands. Also, bonus is assumed to be exogenous. In the estimation of demand system using the data from DFF, Chintagunta et al. (2003) assume that variables related to promotional activity, which include bonus, are exogenous. They justify this assumption since the schedule of promotional activity is generally determined in advance. Thus, according to their claim, bonus is a pre-determined variable.

Table 4 reports the results of the demand estimation. Most of the coefficients appearing in the table are statistically different form zero at the 5 % significance level while *dp*, *bonus*, and *bundle* are insignificant.

To construct demand conditions, I use the estimates of parameters and variables of a constant, the shelf prices of Dominick's, and customer count. The constructed demand conditions are the same across manufacturers: $d_t = d_{it} = d_{-it}$. Since the customer count and Dominick's prices are not known by manufacturers at the time of decision making, I assume that manufacturers form their expectations with respect to these variables. The *ex ante* one-period profit includes expected demand conditions $\sum_{d_{t+1}} d_{t+1} f^d(d_{t+1} \mid d_t)$ for a

[31] Alternatively, including monthly dummy variables is also considered. However, the results were similar and the results with holiday dummy variables are reported.

[32] The variable *income* is the log of the median of incomes from U.S. Census-data in 1990. Income differs by ZIP codes, and so by stores.

given d_t, where d_t consists of customer count and Dominick's price in the previous period as well as the constant.

The NPL estimator require the state variables to be discretized. Each state variable is divided into two regions according to its empirical distribution so that each cell of a variable has probability 0.5 to be visited. Variables consisting of state variables are evaluated at the lower bound of each grid of each state variables — the values at one percentile and 51 percentile. Table 5 presents the descriptive statistics of the discretized variables. The total number of grids in the discretized state space is 128. Using the discretized variables, I construct the transition probability matrices and the initial values of conditional choice probabilities.[33]

5 Results

5.1 Estimated size of menu costs

Table 6 reports the estimate of menu costs γ. The estimate is 1.009 and statistically different from zero at any conventional significance levels based on the standard error 0.025.[34] This point estimate implies that the marginal cost of a price change is 1.009 U.S. dollars. This amount of menu costs is 3.54 percent of average weekly graham cracker sales per store in a week.

The estimate of menu costs in the above benchmark specification, however, might be biased downwards by unobservable promotional activities. To explain this potential downward bias, suppose that, given menu costs, there is an unobservable factor that increases the profit of the manufacturer *only when the manufacturer reduces its price.* If the econometric model does not control this profit-enhancing factor specific to downward price changes, the estimate of menu costs is biased downwards because the coefficient γ captures not only fixed adjustment costs of price changes but the profit-increasing effect in this case.[35] The most likely interpretation of this profit-increasing factor is promotional activities due to

[33]For the construction of transition matrices and initial choice probabilities, see the appendix A.1.

[34]The standard error is calculated by 10000 non-parametric bootstrapping resamples.

[35]For exposition, consider the following simple one-period profit of a manufacture $(p-c)q + \lambda I[\Delta p < 0] - \gamma$ where $\lambda > 0$ is the profit-increasing factor specific to downward price changes . If I do not observe and control λ, I estimate menu costs as $\lambda I[\Delta p < 0] - \gamma$, which leads to a downward bias of the estimate of fixed adjustment costs of price changes γ.

the following two reasons. First, a promotional activity for a product usually takes place with not only reducing the price of the product temporarily but also conducting demand-enhancing activities such as advertisements and in-store displays. Second, a promotional activity might decrease the marginal costs the retailers have to pay when the prices are temporarily discounted.[36] Through these two possible effects, the unobserved promotional activities of the manufactures might lead to downward bias of the estimate of menu costs. In fact, I find that the shelf prices in the sample are characterized by frequent downward price changes followed by immediate increases in the prices back to the "regular" price levels. This important characteristic of my price data suggests that promotional activities accompanied with temporary price discounts frequently occur in the sample.

To correct this potential downward bias of the estimate of menu costs γ in the benchmark specification, I create a dummy variable specific to downward price changes, λ. More specifically, I consider the following specification: $z_{it} = \{\pi_{it}(a), -I\{\Delta p_{it} \neq 0\}, I\{\Delta p_{it} < 0\}\}$ and $\theta = \{1, \gamma, \lambda\}$. If the profit-increasing factor specific to downward price changes is important in the sample, I should observe that (i) the sign of λ is positive and (ii) the estimate of coefficient γ is greater than that in the benchmark specification.[37]

Table 7(a) shows the results of the estimation with the augmented specification. As expected, the sign of point estimate of the coefficient on the dummy variable specific to downward price changes, λ, is positive with the value 2.840 and statistically different from zero at any conventional significance levels with nonparametric bootstrapping standard error 0.028. This implies that the unobservable profit-increasing factor specific to downward price changes is crucial in explaining the behavior of the price data in this paper. The identified downward-price-change specific factor λ would include both the demand-shifting factors and the effect reducing in-store-cost. After controlling the profit-enhancing effect, the point estimate of menu costs γ turns out to be 2.578, which is greater than that in the benchmark model. The standard t-statistic rejects the null that the point estimate

[36] For example, with a single agent dynamic discrete choice model with a sample different from ours, Aguirregabiria (1999) observes that menu costs of downward price changes are significantly much lower than those of upwards price changes. He argues that this is because the retailer does not pay for the costs associated with the profit-increasing promotional discounts.

[37] While I emphasize the importance of controlling possible promotional activities, I assume that these activities are exogenously given. These activities can, however, be endogenous and strategic. Incorporating multi-strategic instruments into the model is left to be a future research.

2.578 is equal to that of the benchmark model, 1.009, at any conventional significance level (t-statistic = 60.35). Therefore, the downward bias of the benchmark specification is significant statistically as well as economically.

The most important advantage of the dynamic discrete-choice model with an oligopolistic market in this paper over the standard monopolistic competition model, which is employed by previous studies to estimate menu costs, is that this model takes into account the potential effect of strategic interactions among manufacturers on price rigidity. For example, Slade (1999) shows that prices of oligopolistic firms, which follow a variant of (s,S) strategy, are stickier than those with monopolistically competitive firms because the thresholds of price changes widen as price level goes up. If the effect of strategic interactions among firms on price rigidity is crucial in the observed price behavior, the estimate of menu costs γ with a monopolistic competitive market might be biased upwards. This is because, with a monopolistic competition model that does not identify any strategic interaction, menu costs γ capture not only fixed adjustment costs of price changes but also the price rigidity due to strategic interactions among firms.

To examine the above conjecture, I next estimate menu costs γ under a monopolistic competition model with the dummy variable specific to downward price changes. In the monopolistic competition model, the decision rule of price changes does not depend on the conditional probabilities of the other firms. Therefore, a manufacturer constructs her expectation over only the evolution of exogenous state variables, the future values of the unobservable state variable, and her own future actions. The model contains the three state variables of the demand condition, the wholesale price, and the past price. Since a firm regards the prices of her rival brands as being exogenous, I include the rivals' price as a part of the demand conditions, which is exogenously evolved. Then I compare the estimate of menu costs under the second specification with that under my monopolistic competition model. The oligopolistic model corrects the upward bias in the monopolistic competition model if the strategic interactions among the manufacturers are important in the sample.

Table 7(b) reports the results of the monopolistic competition model.[38] First, the

[38] The estimation of a monopolistic competition model is conducted using the framework of a single-agent dynamic discrete choice model in Aguirregabiria and Mira (2002). Rivals' prices are assumed to evolve exogenously, and included in the demand condition. In addition, the manufacturers do not take into account the conditional choice probabilities of other manufacturers.

coefficient of the dummy variable specific to downward price changes has a positive sign with the magnitude of 3.870, and is statistically different from zero at 1 percent significance level with its standard error 0.04. Thus, the profit-enhancing factor is important regardless of the assumption about the competition among the manufacturers in the sample. Second, the estimated coefficient on menu costs γ under the assumption of monopolistic competition model is 3.443 and significantly different from zero with its standard error of 0.037. This estimated size of menu cost, 3.443, is greater than the counterpart in my oligopolistic model, 2.578. The standard t-statistic rejects the null that these two point estimates are equal at any conventional significance level (t-statistic = -23.38). The difference between the estimated sizes of menu costs reveals the upward bias associated with the identification under the assumption of the monopolistic competition model. Moreover, this result implies that oligopolistic strategic interactions explain some part of price rigidity, which would be captured by menu costs if a researcher estimates the model under monopolistic competition model.

Table 8 compares the results of this paper with those of the previous studies. The first row of the table shows the result of my benchmark specification with binary choice and oligopolistic competitions, but without controlling for downward bias due to unobserved promotional activities. My point estimate of menu costs, 1.009, is close to the result under the assumption of symmetric menu costs by Aguirregabiria (1999), 1.117, but much smaller than that of Slade (1998), 2.55.[39] 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 anything associated with price changes, whereas that reported by Lévy et al. (1997) includes only physical and labor costs of price changes.

The second row shows the estimate of menu cost based on the oligopoly model in this paper, which is close to the estimated size by Slade (1998). The estimated size is also close to the one obtained by Aguirregabiria (1999) with asymmetric menu costs. As before, the estimated menu cost is much greater than that of Lévy et al. (1997). This comparison suggests that dynamic discrete choice models yield similar results in identification of the size of menu costs. My result, 7.56 percent, is, however, much greater than that by Aguirregabiria (1999) in terms of the percentage of menu costs in revenues while it is closer to that by Slade (1998). Note that Aguirregabiria (1999) estimates menu costs using 534

[39] The result of Aguirregabiria (1999) 1.117 is calculated from the estimated value of menu costs, 72.62, in the specification (2) in Table 5 and the number of stores in a supermarket chain, 62, in Aguirregabiria (1999).

brands in various products while Slade (1998) examines a single product as in this paper. This comparison suggests that the menu costs might be relatively uniform across products, and that the large percentage of my estimate in terms of revenues simply reflects the small revenues generated by graham crackers. Therefore, across different products, menu costs might be more comparable in magnitude under the same currency unit rather than in terms of percentage in revenues.

The estimated size of menu costs is also significant in comparison with previous theoretical studies. Although I do not emphasize the implication of the estimated size of menu costs from the single product, the comparison between my estimate and the size of menu costs appearing in the past theoretical studies in macroeconomics would help highlight the importance of the estimated size of menu costs. 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 percent of revenue. The subsequent studies in macroeconomics consider the size of 0.5 - 0.7 percent of revenue to be reasonable, and to have significant impact on price adjustments. For example, using a monopolistically competitive model, Ball and Romer (1990) show that the cost needed to prevent price adjustment to a monetary shock is 0.7 percent of revenue under the reasonable values of mark-up and labor supply elasticity.[40] Golosov and Lucas (2006) use the value of menu costs of 0.5 percent of revenues in their calibration showing their state-dependent model explains the observed correlation between inflation rates and frequency of price changes in past studies well. My estimate, more than 7 percent in revenue, is considerably greater than the values appearing in these theoretical studies. It is, however, worth noting that the estimate in Aguirregabiria (1999), which is similar to my estimate in terms of a nominal value, is just 0.7 percent in revenue. As mentioned before, the large menu costs in my estimate in revenue could result from small sales in graham crackers. Therefore, if we conduct the analysis using various products, the estimated size in terms of revenue could be smaller than the result using only graham crackers. In order to verify this statement, it is, however, necessary to conduct the analysis with various products. At this stage, I left the empirical exercise using other products as a future study.

The results from graham crackers show that the size of estimated size of menu costs is

[40]The mark-up is 15 percent of revenue, and the labor elasticity is 0.15.

great enough to have significant effects on price adjustments. Therefore, I conclude that menu costs have significant implication for price adjustment behavior economically as well as statistically. In addition, this paper has shown that strategic interactions could induce rigidity in a tight oligopolistic market. This result implies an important conclusion in this paper: not only menu costs but strategic interactions among manufacturers are important for explaining the observed degree of price rigidity.

6 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 are dominated by a few manufactures, I further assume oligopolistic competition to reflect this market structure, and examine possible effects of oligopolistic strategic interactions among manufacturers on the discrete behavior of the prices. I estimate this dynamic discrete-choice model with oligopolistic 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. However, I claim that adopting the conventional estimators in explaining my price data could lead to two possible biases in the estimate of menu costs. The first bias is downward and due to unobserved promotional activities. If a promotional activity is profit-enhancing, the estimates without controlling this factor result in a downward bias. The results of this paper show that correcting this bias is important for a precise inference on menu costs. The second source of a bias in conventional estimators is the assumption of monopolistic competition. If strategic interactions among manufacturers affect the pricing behavior in the sample, the estimated menu costs with a monopolistic competition model is biased upwards because strategic interactions in an oligopolistic competition potentially create price rigidity, the estimate in the conventional estimator is biased upwards. The results show that the estimate of menu costs under oligopolistic market is smaller than and statistically different from that under monopolistic competition. This means that oligopolistic competitions explain some part of price rigidity, which is captured by menu costs unless a researcher incorporates oligopolistic strategic interactions. Thus, at least in the sample of this paper, I conclude that oligopolistic strategic interactions could be an important source of price rigidity.

Appendix

A.1. Constructing transition probability matrices

Using the discretized variables, I construct the matrices for transition probability: $f_i^d(d_t|d_{t-1})$, $f_i^c(c_{it}|c_{it-1})$, and $f_i^p(p_{it}|d_{it}, p_{it-1}, c_{it}, a_{it})$. To do that, I first specify stochastic processes of p_{it}, d_t, and c_{it}, as follows:

$$\begin{cases} p_{it} = \delta_{pi0} + \delta_{pi1} p_{it-1} + \delta_{pi2} d_t + \delta_{pi3} c_{it} + \epsilon_{it}^p & p_{it} \neq p_{it-1}, \\ p_{it} = p_{it-1} & \text{otherwise,} \end{cases}$$

where if ϵ_{it}^p follows some distribution $f_{\epsilon_{it}^p}$. The demand conditions and costs are distributed independently from other state variables and the decisions of manufacturers:

$$d_t = \delta_{di0} + \delta_{di1} d_{t-1} + \epsilon_t^d$$

and

$$c_{it} = \delta_{ci0} + \delta_{ci1} c_{it-1} + \epsilon_{it}^c,$$

where ϵ_t^d and ϵ_{it}^c follow some distribution function $f_{\epsilon_t^d}$ and $f_{\epsilon_{it}^c}$.

To construct the transition probability matrices, I use the method by Tauchen (1986). Based on the estimations of the density of residuals and the transition processes, the transition probability matrices are constructed. This is done by matching the values of residuals of the process evaluated at discretised space to those of evaluated points used for Kernel density estimation.

A.2. Derivation of alternative presentation of value functions and best response probabilities

According to Aguirregabiria and Mira (2006), 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 manufacturer i. Using P^* and $V_i^{P^*}$, I can rewrite the Bellman equation (9) as

$$V_i^{P^*}(x) = \sum_{a \in \{0,1\}} P_i^*(a \mid x)[\Pi_i^{P^*}(a, x) + e_i^{P^*}(a)] + \beta \sum_{x' \in X} f^{P^*}(x'|x) V_i^{P^*}(x'), \qquad \text{(A2-1)}$$

where $f^{P^*}(x'|x)$ is the transition probability induced by P^*, and $e_i^{P^*}(a)$ is the expectation of ε_i^a conditional on x. [41] In vector form, equation (A2-1) is

$$V_i^{P^*} = \sum_{a\in\{0,1\}} P_i^*(a)[\Pi_i^{P^*}(a) + e_i^{P^*}(a)] + \beta \sum_{x'\in X} F^{P^*} V_i^{P^*},$$

where $V_i^{P^*}$, $P_i^*(a)$, $\Pi_i^{P^*}$, and $e_i^{P^*}(a)$ are the vectors of the corresponding elements in equation (A2-1) with dimension M. 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:

$$(I - \beta F^{P^*})V_i^{P^*} = \sum_{a\in\{0,1\}} P_i^*(a)[\Pi_i^{P^*}(a) + e_i^{P^*}(a)], \tag{A2-2}$$

where I is an identity matrix with dimension M. Denote the mapping for the solution of equation (A2-2) as $\Gamma_i(x; P^*)$. For an arbitrary set of probabilities P, the mapping operator $\Gamma_i(x; P)$ gives the values for manufacturer i when all the manufacturers behave according to P. Note that this mapping is constructed given the conditional choice probabilities of manufacturer i as well as those of its rival manufacturer. Using this mapping Γ, instead of V_i^P in equation (9), I define a mapping Ψ to calculate the expected value for manufacturer i to choose action a_i for P:

$$\Psi_i(a|x) = \int I\{a = \arg\max_{a\in\{0,1\}} [\Pi_i^P(a,x) + \varepsilon_i^a + \beta \sum_{x'} f(x'|x,a)\Gamma_i^P(x')]\} g_i(\varepsilon_i) d\varepsilon_i, \tag{A2-3}$$

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

A.3. The data

This section describes the details about the construction of the two variables, a measure of wholesale prices and promotional code, the choice of stores, and the problem of missing data.

A.3.1. The variables used in the analysis

The analysis in this paper uses the following variables in the original data set: UPC, store code, week code, price, move(quantity sold), profit rate, the code for promotion, bundling (the number of units bundled together), OK (a code to show whether data points are reliable or not), customer count (the number of customers who purchased at least a single good), income (the median of income), each in the original name in the original data set.

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

A.3.2. Recovering a measure of wholesale prices

As stated in the main content, one of the advantages to use the DFF data set is that I could observe a good measure of wholesale prices. The data set contains a variable "profit rate", which presents gross margin of the retailer in terms of percentage in the revenue: $\frac{p_{it}-AAC_{it}}{AAC_{it}} * 100$. Using profit rates and prices, I can recover average acquisition costs (AAC)". AAC is a moving average of wholesale prices of existing inventory

$$\begin{aligned} AAC_t &= [(\text{Quantity bought at the end of t-1}) \\ &\quad *(\text{wholesale price paid at t-1}) \\ &\quad +(\text{Quantity in stock at the end of t-2}) * AAC_{t-1}]/ \\ &\quad (\text{Quantity in stock at the end of t-1}). \end{aligned}$$

AAC are different from the current period wholesale price if the store carries any inventory bought at different prices in any previous periods. As mentioned in other studies for example, Chevalier et al. (2003), the policy of DFF is such that wholesale prices are reflected to acquisition cost fast.

A.3.3. The code of promotional activities

In the DFF data, the code for promotion records three activities of bonus, simple, and in-store coupons. In the analysis, I use only bonus as a measure of promotional activity creating a dummy variable when bonus is recorded. I do not use simple and coupons because of the following reasons. First, bonus is the most frequently used. As stated in the main contents, bonus is typically price reduction with an announcement tag on shelves. Bonus is recorded about 20 percent of the entire period while simple and coupons are recorded only 2 percent and 0 percent, respectively. Second, according to the file description of the DFF data set, simple is described as "simple price reduction". However, the effects of mere price reductions are captured by prices in the demand estimation. In addition, the record for simple is somewhat suspicious in the record of graham crackers. There are several data points that simple is associated with price increases, not price reductions. Finally, coupons are never used in graham crackers. It should be noted that bonus does not perfectly record the promotional activities in the DFF. First, the data set does not contain the information of whether or not bonus is associated with advertisement or in-store display. Second, as stated in the description of the DFF data set, the record of this variable is somewhat inconsistent with the actual implementation of promotional activities. That is, the promotional activities may take place even when bonus and simple are not recorded.

A.3.4. Missing data, the choice of stores, and the data sample

An unfortunate but inevitable characteristic of the DFF data is that there are missing data. This is simply because retail prices and profit margins in the DFF data are recorded only when product items are purchased: there is no record of transaction of a product item when there is no purchase or when the product item is stocked out. If the data points are missing for relatively long time, the reason could be because the store does not carry the product on regular basis or because the store is not operating.

The problem of missing data is quite common among researches using scanner data.[42] As a common practice in studies using scanner data, the missing retail prices could be imputed or simply omitted (list-wise deletion). The imputation of the missing retail prices could potentially create false pricing patterns. Therefore, in this chapter, I employ the list-wise deletion: I omit the data points unless prices both in current and previous periods are available.

The construction of the data is as follows. First, I use the data from the stores which are likely to carry the product on regular basis. This is because I need consecutive data series as long as possible. In addition, the stores who do not carry the product regularly might adopt different retail strategies toward the product from those who do. Newly opened stores or closed stores may also adopt different strategies, too. Accordingly, I first omit the stores whose records do not cover the entire sample period. Second, I also omit the stores with too many missing data. At this stage, I take into account the pricing policy of Dominick's that is represented by pricing zone (low, middle, and high) to reflect the variation in prices across stores, and omit the stores if more than 2 percent of data are missing for the stores

[42]For example, Erderm, Keane and Sun (1999) point out that about 80 percent of daily scanner data by Nielsen is also imputed using a complex ad-hoc procedure. Erderm et al. (1999) discuss a potential selection bias due to these missing data. Since the original transaction records and the pricing cycle in DFF are weekly, the percentage of missing data in the entire sample of the DFF data used in this chapter is smaller than those discussed by Erderm et al. (1999). Therefore, the effect of a selection bias due to the missing data on the inferences of this chapter would be also small.

in middle and low pricing zones and 2.5 percent for the stores in high pricing zone.[43] [44] As a result, I select 21 stores.[45]

For my analysis, I need the data points with the following information: a data of a brand in a certain week in a certain store should contain current prices of all the brands including the private brand, and past prices of its own brand. As I employ the list-wise deletion, I simply omit the data points unless all the information is not available. In addition, there is a code called OK, which is attached by University of Chicago to show whether each data point is suspicious or not.[46] These data points are also excluded from the analysis. In total, I have an unbalanced data with 21978 observations (7326 observations for three brands).

The discontinuity of records due to missing data affects the construction of the two variables used in the demand estimation, *durd* and *durb*. *durd* is the number of weeks since last price reduction by more than five percent. *durb* represents the number of weeks since bonus has started. I construct these two variables as follows when encountering missing data. Suppose that the price of a brand is changed more than five percent in the third week but the price in the fourth week is missing. Then, *durd* takes two in the fifth week. In the case *durb*, the value of fifth week simply takes zero unless bonus is held in the fifth week. These duration variables are created before list-wise deletion due to missing information of other brands.

[43] Dominick's assigns 16 pricing zones to each stores based on the competitiveness of outlets with other retailers. University of Chicago arranges these 16 zones into three zones.

[44] There is no stores, of which missing data are less than 2 percent, in the high-price zone.

[45] The store numbers of selected outlets are as follows: 8, 14, 44, 56, 62, 71, 73, 74, 78, 80, 81, 83, 84, 101, 102, 109, 114, 121, 122, 126, 132.

[46] In the total data points of 129516 in the raw data for four brands in all the stores (more than 80 stores) in a chain, two percents of data are labeled as suspicious.

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Figure 1: Shelf Prices of Three National Brands

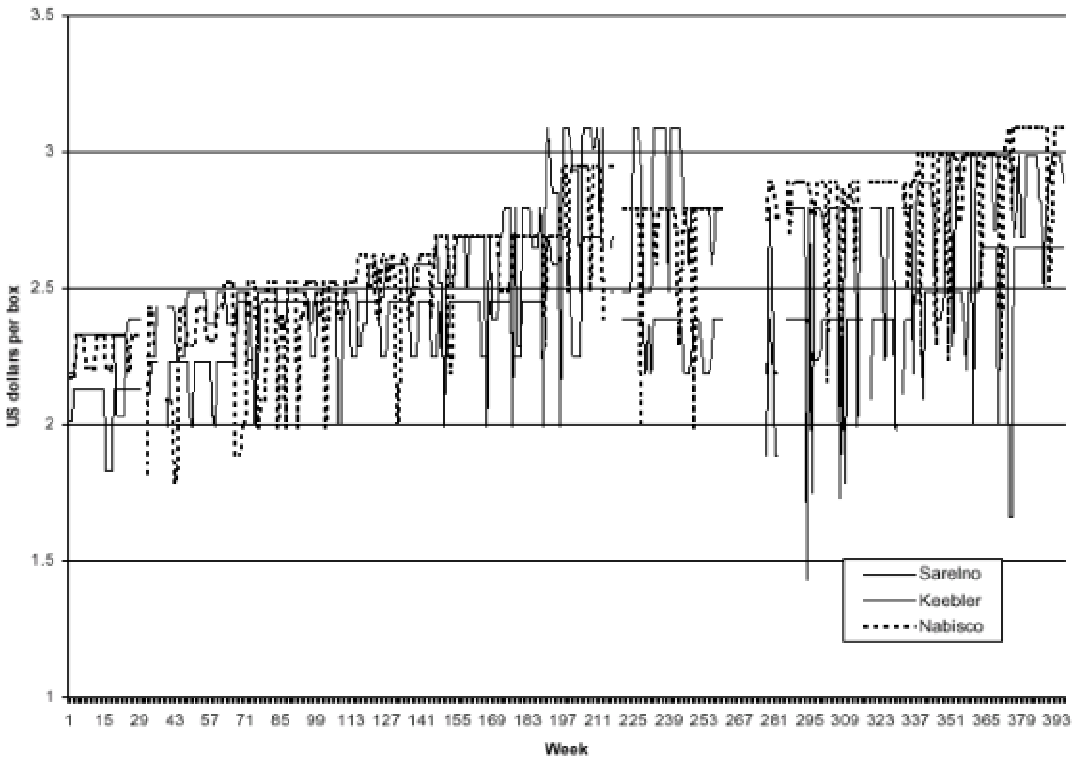

Table 1: Market Shares of Graham Crackers

Manufacturer	size of a box	share in four brands (%)	share in three brands (%)
Sarelno	16 oz	16.78	23.06
Keebler	15 oz	20.24	27.83
Nabisco	16 oz	35.72	49.11
Dominick's	16 oz	27.26	—-

* Shares in total sales in 21 stores.

Table 2: Summary Statistics of Variables

	Mean	Std.Dev.	Min	Max
Quantity (box)	11.29	11.45	1	370
Price ($ U.S.)	2.52	0.28	1.35	3.09
Cost ($ U.S.)	1.8	0.20	1.17	2.21

Table 3: Summary Statistics of Price Changes

	NOB	Mean of $\|\Delta p\|$	Mean of price	Mean of Δq
$\Delta p = 0$	14800 (67.3 %)	0	2.54	0
$\Delta p \neq 0$	7178 (32.6 %)	0.28	2.47	
$\Delta p < 0$	3390 (15.4 %)	0.28	2.33	7.65
$\Delta p > 0$	3788 (17.2 %)	0.27	2.61	-6.29

Table 4: Estimated Demand Equation

Variable*	Coefficient	Standard error**
constant	1.462	0.036
p	-3.782	0.116
rp	0.819	0.106
dp	0.006	0.028
bonus	0.013	0.009
bundle	0.003	0.069
durb	-0.016	0.003
durd	8.52e-6	0.0002
cc	0.836	0.036
brand2 (Keebler)	0.19	0.008
brand3 (Nabisco)	0.471	0.028

* The store-level fixed effects and holiday-dummy variables are also included but not reported.

** White's heteroscedasticity-robust standard errors

Table 5: State Variables (Discretized Values)

Variable	State 1	State 2
d_t	3.015	4.048
$\ln(p_{1t})$	0.2601	0.3784
$\ln(p_{2t})$	0.2765	0.4133
$\ln(p_{3t})$	0.2765	0.4298
$\ln(c_{1t})$	0.1086	0.1893
$\ln(c_{2t})$	0.1475	0.2653
$\ln(c_{3t})$	0.2085	0.2824

Table 6: Estimated Menu Costs

Variable	Estimate	S.E.*
γ	1.009	0.025
Results at $K = 8$		
Log-likelihood = -18780		

*The standard errors are based on 10000 non-parametric bootstrapping re-samples.

Table 7: Estimated Menu Costs and Fixed Costs of Downward Price-Changes

(a) *Oligopoly model*

Variable	Estimate	S.E.
γ	2.578	0.026
λ	2.840	0.028
Results at $K = 30$		
Log-likelihood $= -21910$		

(b) *Monopolistic competition model*

Variable	Estimate	S.E.
γ	3.443	0.037
λ	3.870	0.040
Results at $K = 10$		
Log-likelihood $= -24521$		

*The standard errors are based on 10000 non-parametric bootstrapping re-samples.

Table 8: Menu Costs in Previous Studies

			Menu costs	% in revenues
this study	(1)	$\Delta p \neq 0$	1.009	2.96 %
	(2)	$\Delta p \neq 0$	2.578	7.57 %
Levy et al. (1997)			0.52	0.70 %
			1.33	0.72 %
Slade(1998)		$\Delta p \neq 0$	2.55	(5.11 %) †
Aguirregabiria(1999)	(1)	$\Delta p \neq 0$	(1.117) ‡	
		$\Delta p \neq 0$	(3.06)‡†	0.7 %
		$\Delta p > 0$	2.23	0.31 %
		$\Delta p < 0$	0.83	0.39 %

† The value is calculated from Table IA and VB as the share-weighted average.

‡ The value is calculated from the result of specification (2) in Table 5 and the number of stores.

‡† The value is calculated by the author from Table 6 according to
$I\{\Delta P > 0\} + I\{\Delta P < 0\} = I\{\Delta P \neq 0\}$.