

The Magnitude of Menu Costs: A Structural Estimation

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The leading theories on monetary policy non-neutrality require some degree of price rigidity, which is often introduced by assuming fixed costs of price adjustment, also known as menu costs. Empirical evidence on the existence of such menu costs is scarce. Using weekly data on prices, costs and units sold by a supermarket chain, I estimate a discrete-choice dynamic model of a multi-product firm facing menu costs with a moment inequalities approach. This empirical methodology allows me to estimate two types of fixed costs of price adjustment: costs that are independent of the number of items that change prices and costs that are incurred at each item's price change. I find that both types of menu costs exist and are substantial. The total cost from changing prices is estimated to be bounded between 0.22% and 0.59% of revenues and between 11.05% and 29.32% of net margins, depending on the specification. The first type of fixed cost accounts for up to 85% of this expense, pointing at substantial economies of scope in price setting.

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1 Introduction

The leading theories on the monetary policy transmission mechanism require some degree of price rigidity. The most common way to introduce price rigidity in a rigorous way in macroeconomic monetary models involves fixed costs of price adjustment, also known as menu costs. The monetary economics literature makes an extensive use of menu costs¹, but there have been only a few attempts at estimating actual menu costs. The first generation of menu cost models ignored price setting interactions by assuming that each firm sells only one product and was rejected by the empirical evidence.² Midrigan (2011) shows that economies of scope in price setting can help improve the empirical fit of menu cost models and achieve high degrees of monetary non-neutrality. These theoretical results beg the empirical question of whether such price setting interactions exist in reality.

I estimate a dynamic multi-product firm model using supermarket scanner data on weekly sales, prices and costs. Following Sheshinski and Weiss (1992), I model two types of menu costs: a “common menu cost” that is paid independently of how many price changes are made and a “item menu cost” that is proportional to the number of price changes. I find that both types of menu costs are statistically and economically significant. The total cost from changing prices in the period of my analysis is estimated to be bounded between 0.22% and 0.59% of revenues and between 11.05% and 29.32% of net margins, depending on the specification. The “common menu cost” accounts for up to 85% of this expense, pointing at substantial economies of scope in price setting.

I combine a structural model of the dynamic pricing decision of a supermarket with an empirical demand model for differentiated products. On the one hand, I estimate demand following Berry, Levinsohn, and Pakes (1995) with a random coefficients model. On the other hand, I model the pricing decision of the supermarket as a dynamic unconstrained maximization of the discounted stream of profits. A manager is responsible for choosing prices for all the products belonging to the same category in order to maximize the profits of the supermarket.

This paper improves on previous estimates in two dimensions. First, I estimate menu costs using a multi-product firm model, whereas all previous structural estimates were done with single-product firm models. To the best of my knowledge, I am the first to estimate both fixed costs that are independent of the number of items that change prices

¹Barro (1972), Sheshinski and Weiss (1977) and Mankiw (1985) were the first to consider the impact of fixed costs of price adjustment on price stickiness and many recent papers in the macro literature follow their approach. Some examples are Nakamura and Steinsson (2010), Midrigan (2011), Eichenbaum et al. (2011), Kehoe and Midrigan (2011), Gertler and Leahy (2006), Dotsey, King, and Wolman (2009).

²Some notable examples are Golosov and Lucas (2007) and Klenow and Kryvtsov (2008)

and fixed costs that are incurred at each item's price change. The recent theoretical literature shows that economies of scope in price setting are crucial for matching the empirical facts about prices and produce high degrees of monetary non-neutrality.³ If a firm sells many products and faces economies of scope in price setting, once the price of a product is changed the firm can change the price of the other products with small additional costs. This is consistent with the observation of many small individual price changes and a high average price change that is typical of most microdata on individual prices. Additionally Midrigan (2011) shows that with economies of scope in price setting high degrees of monetary non-neutrality can be achieved with menu costs around 0.34% of revenues, which is consistent with my estimates.

Second, I use moment inequalities estimation⁴, which allows me to deal with the dimensionality problem caused by a multi-product firm setting. The choice set of a firm that decides every week whether to change the price of N products contains 2^N possible choices, which makes it computationally infeasible to use traditional discrete choice empirical methods. My estimation procedure is based on the simple assumption that the agent chooses strategies that according to her own expectations will lead to higher profits than feasible alternatives. A supermarket manager will change prices only if the cost of doing so is lower than the increased profits; conversely, she will not change prices if the costs are higher. By estimating a demand model, I am able to predict how sales, and therefore profits, would have changed if the manager had made different pricing decisions and therefore provide bounds for the magnitude of menu costs the manager faces.

My results reveal two interesting features of menu costs. First, the estimated menu costs are substantial and are consistent with the values shown by the theoretical literature to be large enough to produce high degrees of monetary non-neutrality.⁵ This result provides empirical support for the existence of menu costs and therefore for the ability of state dependent pricing models to replicate the main features of the dynamic response of real variables to monetary policy shocks. Second, I find substantial economies of scope in price setting and therefore provide empirical evidence for Midrigan (2011) and more generally for the second-generation of state dependent pricing models, which have been able to revive the interest in menu costs as a possible explanation for the observed monetary non-neutrality.

³Some notable examples are Midrigan (2011) and Alvarez and Lippi (2012)

⁴My empirical strategy draws extensively from Pakes (2010), Pakes et al. (2011) and Morales et al. (2011).

⁵Midrigan (2011) uses menu costs around 0.34% of revenues. In the multi-sector model by Nakamura and Steinsson (2010) menu costs are less than 0.5% in most sectors.

The empirical evidence shows that monetary policy has real effects, at least in the short run⁶, but we still do not completely understand why. The prices collected by the Bureau of Labor and Statistics to compute the CPI have been shown to display significant price rigidity⁷: median price duration is around 3 quarters. A class of models that can produce significant price rigidity is represented by state dependent pricing models; firms face a fixed cost of price adjustment, also known as menu cost, which makes less frequent the adjustment of prices. Caplin and Spulber (1987) show that in state dependent pricing models there is a selection effect: the firms that change prices are those that are far from their optimal price. This selection effect substantially weakens the real effects of monetary policy. Golosov and Lucas (2007) expand on this intuition by calibrating a heterogeneous agents model with firms facing fixed costs of price adjustment using microdata on prices from Klenow and Kryvtsov (2008) and find that monetary non-neutrality cannot be produced by menu cost models calibrated on the US economy.

Midrigan (2011) is the first to consider a multi-product setting in which firms produce and sell many products and face economies of scope in adjusting prices; price setting interactions combined with a fat-tailed distribution of cost shocks substantially weaken the selection effect described by Golosov and Lucas so that monetary policy can have large real effects. Some evidence supporting this new approach of modeling menu costs comes from Klenow and Kryvtsov (2008), who compare the performance of time dependent and first generation state dependent pricing models and find that neither the former nor the latter satisfactorily match the data; they conclude that second generation state dependent models, like Midrigan (2011), are broadly consistent with the empirical facts. In this paper, I provide a formal empirical test for the existence of economies of scope for multi-product firms. I find that menu costs exist and more importantly that economies of scope play an important role in price setting. These results provide empirical support for the second generation of state dependent pricing models that have been so successful in explaining monetary non-neutrality.

The rest of the paper is organized as follows. Section 2 describes the dynamic problem of the retailer and the model of demand. Section 3 explains the estimation procedure; I first estimate a discrete-choice model of demand and then use the moment inequalities approach to estimate the parameters of interest. Section 4 explains how I construct confidence intervals. Section 5 introduces the Dominick's dataset and presents some summary statistics. Section 6 contains the main results of the paper. Finally, in Section 7 I compare

⁶See Christiano et al. (1996), Cochrane (1998), and Romer and Romer (2004)

⁷Some notable examples of studies on microprice data are Hosken et al. (2000), Bils and Klenow (2004), Kackmeister (2007), Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008)

my results with the previous literature and in Section 8, I conclude.

2 Theory

2.1 Pricing Decision

In this section, I present a model of the pricing decision made by supermarket managers. Supermarkets provide an optimal setting for studying price setting interactions as they are a perfect example of multi-product firm. I focus on a product category and model the decision made by the manager responsible for setting prices in order to maximize profits; supermarket profits depend on the prices that are charged for the products sold (the vector \mathbf{p} in my model), the demand for the products (\mathbf{q}) and the wholesale costs (\mathbf{c}) that the supermarket pays for the products. In the next section I explain in detail how I model demand.

Assumption 1 *The supermarket is a local monopolist.*

This assumption is consistent with the evidence that consumers do not shop across stores on a product-by-product basis.⁸ Dreze et al. (1994) run an experiment in a random subsample of stores belonging to the Dominick’s Finer Foods chain by changing prices across 26 product categories for 16 weeks; they find that the price changes had no impact on store traffic after a three months period. Chintagunta et al. (2003) present evidence that stores collect all competitors’ prices only once per year and on a weekly basis they follow competitors’ action in a very limited way.⁹ Since I consider deviations from decisions on prices of a few products at a time, the assumption that pricing decisions do not depend on

⁸Slade (1995) and Chintagunta et al. (2003) provide some anecdotal evidence. Slade (1995), for instance, interviewed grocery-chain marketing managers who claimed that according to their experience less than 10% of households visit several stores within the same week to search for the lowest-priced product.

⁹Chintagunta et al. (2003) report: “We also conducted telephone interviews with Chicago area store managers and our findings were consistent with this claim. Stores do condition on their competitors actions in a limited way by collecting a weekly sample of half a dozen SKUs from the local competitors entire store offerings. However, this behavior seems more consistent with competition on overall offerings rather than on a category-by-category basis. Stores collect a fullbook of about 600 to 1000 prices from local competitors annually. This practice is not likely to generate inter-store competition at the category level and weekly frequency we consider in our analysis”. Slade (1998) also states: “The anecdotal evidence therefore favours a model where competition is among brands within a store. This does not mean, however, that chains fail to compete. Rather it implies that chains compete via their total offerings rather than through individual items such as saltine crackers”

the behavior of competitors seems to be reasonable and simplifies the empirical analysis.¹⁰

Assumption 2 *The category manager decides every week the regular prices of all the products within a category taking as exogenously determined the calendar of promotions and the wholesale prices.*

To model correctly the pricing decision process it is necessary to understand how the supermarket where my data was collected, Dominick's Finer Foods, set prices. It has been well documented by the marketing literature that in the retail industry pricing decisions are made by category managers who are responsible for setting the prices of all the products within a category in order to maximize the firm's profits¹¹; there is plenty of evidence that this is the organizational structure of Dominick's as well.

A striking feature of supermarket pricing is represented by promotions, which happen frequently in every category of products. Chintagunta (2003) and Anderson et al. (2011) report that in the Dominick's supermarket chain promotions are funded almost entirely by manufactures and the timing is determined by the retailer in advance so as to allow the category managers to make the pricing decisions conditional on the promotion calendar. Consequently, category managers have very limited power on the promotional schedule, and simply take it as given when they set regular prices.

Wholesale prices represent the costs that the supermarket pays for the products that it sells, the vector \mathbf{c} in my framework. Villas-Boas (2007) analyzes the vertical relationship in the supermarket industry and finds that manufacturers price at marginal cost, whereas the retailer sets prices with an unconstrained profit maximization.¹² Given this evidence, I assume that the supermarket is a price-taker in its relationship with suppliers and the category manager makes pricing decisions taking the wholesale prices \mathbf{c} as exogenously determined.

When a manager decides to change a regular price, he has to pay a fixed cost. This fixed cost is composed of two components. The first component does not depend on the number of price changes. The classical example is about a restaurant manager who wants to change the price of one or more items in the restaurant menu; new menus will have to be printed and the cost of printing does not depend on how many prices are changed.¹³ The second component of the fixed cost is proportional to the number of price changes

¹⁰Slade (1998), Besanko et al. (1998), Chintagunta et al. (2003), Montgomery (1997) and others make this same modeling assumption and treat the retailer as a local monopolist.

¹¹Some examples are Bolton and Shankar (2003) and Besanko et al. (2005)

¹²Some more evidence on the vertical relationship in the supermarket industry is provided by Sudhir (2001) and Kadiyali et al. (2000).

¹³This is how the name "menu cost" originated.

and represents a cost that has to be paid for each price change. In sum, I posit two types of fixed costs of price adjustment: costs that are independent of the number of items that change prices and costs that are incurred at each item’s price change. The period t profits for product category P are therefore given by:

$$\pi_t^P = [\mathbf{p}_t - \mathbf{c}_t] \cdot \mathbf{q}_t - \eta_1 \cdot \mathbf{1}(\exists j : p_{jt} \neq p_{jt-1}) - \sum_{j=1}^J \eta_2 \cdot \mathbf{1}(p_{jt} \neq p_{jt-1}) \quad (1)$$

where \mathbf{q}_t is the vector of quantities sold for the J goods in category P , \mathbf{p}_t is the vector of prices, \mathbf{c}_t is the vector of marginal costs, η_1 is the “common menu cost”, which is independent of the number of price changes and η_2 is the “item menu cost”, which is incurred at each price change. The category manager faces a dynamic optimization problem and decides each period a vector of prices \mathbf{p}_t in order to maximize the discounted sum of profits given his information set in period t , \mathcal{J}_t , and his subjective expectations, \mathcal{E} :

$$\max_{\{\mathbf{p}_t \in \mathcal{B}_t\}} \mathcal{E}_t \left[\sum_{\tau=t}^{\infty} \delta^\tau \pi_\tau^P | \mathcal{J}_t \right] \quad (2)$$

where δ is the discount factor. Each price p_{jt} is chosen among the values in set \mathcal{B}_{jt} . During promotions \mathcal{B}_{jt} is restricted to the predetermined promotional price, whereas when the product is not on promotion the manager can choose any positive real number and \mathcal{B}_{jt} coincides with \mathcal{R}^+ . I will make assumptions on the agent’s expectations \mathcal{E} in Section 3.4.

2.2 Demand

To estimate menu costs with moment inequalities I need to compute counterfactuals. Computing a counterfactual consists in finding out how much the supermarket would have made in profits if it had charged a different price vector. I therefore need to estimate the demand of the products in the categories I choose to analyze. In my notation, I need to estimate \mathbf{q}_t . Once I have a way to forecast demand, I can then compute counterfactuals and moment inequalities.

Estimating demand for differentiated products poses mainly two challenges. First, the demand for a product does not depend only on its own characteristics and price, but also on those of other products that are perceived as substitutes by the consumers. For this reason a simple linear model that relates the market share of a product to its own

characteristics would be too restrictive. On the other hand, we could specify a set of demand equations, one for each product, and have the demand for a product depend on its own price and the price of the other products; the problem with this approach is that if there are many products, the number of parameters to estimate would be too high. Furthermore a simple linear model would not be able to control for the heterogeneity in consumer tastes.

A way to solve the dimensionality problem is to make some functional form assumptions; in the logit demand model, for instance, products are projected onto a space of characteristics and this simplifies the estimation. The drawback is that the functional form assumptions in most cases drive the results of the estimation; in the case of the logit model, the estimated own- and cross-price elasticities depend only on the price and the market share, implying that the lower is the price the lower will be the elasticity and that consumers substitute between different products in proportion to market share, regardless of the characteristics of the products. These properties of the logit model are unrealistic in most cases.

The second challenge in estimating demand is represented by the endogeneity of prices. There are almost always some product characteristics that are hard to measure, but are correlated with prices and if not included in the estimation will bias the price coefficients. Another possible source of endogeneity is the omission of a control for advertisement; manufacturers run national TV ads and supermarkets engage in local advertisement; these marketing efforts must be correlated with the retail prices.

Following the recent empirical IO literature, I use a random-coefficients logit model,¹⁴ which captures the substitution patterns between products in a nontrivial way and whose estimation controls for the endogeneity of prices. I assume static demand, which is reasonable for the data I use in the estimation; I will focus on the beer sales of the Dominick's supermarkets and the industry lore is that the beer product is typically consumed within a few hour of its purchase, so one might worry less about the stockpiling of goods and other dynamic demand issues.¹⁵

I observe $t = 1, \dots, T$ markets, each with $i = 1, \dots, I$ consumers, where a market t is a store-week combination. In this model when a customer visits the supermarket he is allowed to buy and consume only one product within the product category of analysis, but he can also choose not to buy any product in that category. I assume that the indirect

¹⁴My demand model is based on Berry et al. (1995) and Nevo (2001)

¹⁵See Anheuser-Busch Inc. "Beer Shopper Poll" 2005.

utility of consumer i from consuming product j in market t takes a quasi-linear form:

$$u_{ijt} = \alpha_i(y_i - p_{jt}) + x_{jt}\beta_i + \xi_{jt} + \epsilon_{ijt} \quad (3)$$

where y_i is the income of consumer i , p_{jt} is the price of product j , x_{jt} is a vector of observed characteristics, ξ_{jt} captures the unobserved product characteristic and ϵ_{ijt} is a mean zero stochastic term. Consumer preferences are represented by the random coefficients α_i and β_i that can be decomposed in a constant component and an individual unobserved component v_i , which is distributed according to a standard multivariate normal distribution. The matrix of parameters Σ allows each component of v_i to have a different variance.

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma v_i, \quad v_i \sim P_v^*(v)$$

The utility can be then decomposed in three parts: δ_{jt} is the mean utility given by product j at time t , μ_{ijt} is the individual deviation from mean utility and ϵ_{ijt} is distributed according to a Type I extreme-value distribution:

$$u_{ijt} = \alpha_i y_i + \delta_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_1) + \mu_{ijt}(x_{jt}, p_{jt}, v_i; \theta_2) + \epsilon_{ijt} \quad (4)$$

$$\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}$$

$$\mu_{ijt} = [-p_{jt} \quad x_{jt}]\Sigma v_i$$

Finally consumers can choose not to buy any product and consume the outside option; both the mean utility and the individual deviation from mean utility of the outside good are normalized to zero:

$$u_{i0t} = \alpha_i y_i + \epsilon_{i0t}$$

Having derived the utility of purchasing one unit of product j at time t for individual i , it is possible to compute the share of customers who are going to choose product j over all the other products and the outside good. Assuming ties occur with zero probability, the

market share of product j in market t is:

$$s_{jt}(x_{jt}, p_{jt}, \xi_{jt}; \theta_2) = \int_{A_{jt}} dP_\epsilon^*(\epsilon) dP_v^*(v) \quad (5)$$

$$A_{jt} = \{(v_i, \epsilon_{i0t}, \dots, \epsilon_{iJt}) | u_{ijt} \geq u_{ilt} \quad \forall l = 0, 1, \dots, J\}$$

The price elasticities will therefore be:

$$\frac{\partial s_{jt}}{\partial p_{ht}} \frac{p_{ht}}{s_{jt}} = \begin{cases} -\frac{p_{jt}}{s_{jt}} \int \alpha_i s_{ijt} (1 - s_{ijt}) dP_v^*(v) & \text{if } j = h \\ \frac{p_{ht}}{s_{jt}} \int \alpha_i s_{ijt} s_{iht} dP_v^*(v) & \text{if otherwise} \end{cases}$$

Substitutions patterns are not predetermined by the functional form or some other assumption, but depend both on the sensitivity to prices α and on the product and consumer characteristics. Brands with similar characteristics are more substitutable and the degree of substitutability is estimated instead of assumed.

3 Estimation Procedure

3.1 First Stage: Demand Estimation

In order to estimate the random coefficients demand model I follow Berry et al. (1995) and Nevo (2001). First, for a given set of parameters θ , I solve for the system of equations:

$$s_{jt}(\delta_t; \theta_2) = S_t \quad t = 1, \dots, T \quad (6)$$

where $s(\cdot)$ is defined as (5) and S_t are the observed market shares. Products' market shares are calculated with respect to the potential market which is defined as the number of customers who visit the store in a period.¹⁶ I approximate the integral in (5) with a

¹⁶I observe the number of customers that enter the supermarket every week and I assume that each customer can choose whether to buy one beer product or not. The market size is therefore the number of customers who visit the store in a period.

smooth simulator; given a set of draws from $P(v)$ the approximation is:

$$s_{jt} = \frac{1}{I} \sum_{i=1}^I \frac{\exp[\delta_{jt} + \sum_{k=1}^K x_{jt}^k \sigma_k v_i^k]}{1 + \sum_{m=1}^J \exp[\delta_{mt} + \sum_{k=1}^K x_{jt}^k \sigma_k v_i^k]}$$

Once I obtain the estimates for δ_t from (6), I can compute the unobserved characteristic ξ_t :

$$\xi_{jt} = \delta_{jt}(S_t; \theta_2) - (x_{jt}\beta + \alpha p_{jt}) = \omega_{jt}$$

Given a set of instruments Z such that:

$$E[Z_m \omega(\theta)] = 0 \quad m = 1, \dots, M$$

I employ two-step GMM estimation and therefore the estimate is

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \omega(\theta)' Z \Phi^{-1} Z' \omega(\theta)$$

Product and time fixed effects are included in the observed characteristics of the products and therefore the unobserved characteristic ξ_{jt} reduces to a week-store specific deviation from the mean valuation of the product. In order to estimate jointly the constant preference parameters α and β and the product fixed effects I follow the procedure described by Nevo (2001). Let's define d the set of product dummy coefficients and ζ the unobserved product characteristics, then from (3):

$$d = x\beta + \zeta$$

If we assume that $E[\zeta|x] = 0$, then we can estimate β and ζ using a minimum distance estimator:

$$\hat{\beta} = (x'V_d^{-1}x)^{-1}x'V_d^{-1}\hat{d}, \quad \hat{\zeta} = \hat{d} - x\hat{\beta}$$

Where \hat{d} is estimated with the full model and V_d is the covariance matrix of these estimates

3.2 Instruments for Demand Estimation

In the estimation of demand we cannot assume that prices are exogenous to the unobserved factors; it is impossible to measure all the attributes of the products and therefore there will be some unobserved attributes that influence prices and are omitted from the model. Furthermore supermarkets engage in local marketing efforts, like fliers and street ads; some products are also advertised at the national level through magazines and TV commercials. Unfortunately, I do not have a measure of these marketing efforts, which are most probably correlated with price. For these reasons price is endogenous and we need exogenous instruments for it.

Following Goldberg and Hellerstein, I use as instruments the interaction of hourly wages in the beverage industry with weekly bilateral exchange rates for foreign brands. It is reasonable to assume that these factor prices are uncorrelated with the unobserved attributes of products and the marketing efforts of the supermarket. In order to allow labor to enter the production function of each product differently, the factor prices are interacted with brand dummies to generate the instrumental variables I use in the demand estimation.¹⁷

3.3 Bounding Menu Costs

I explain here how the moment inequality approach is applied to the estimation of menu costs. If I were to estimate menu costs using the traditional discrete choice approach, I would have to deal with a very complicated dynamic problem. Using moment inequalities I can sidestep finding a solution to the dynamic problem and estimate the menu costs using a revealed preference approach. Following Morales et al. (2011), I want to apply the Euler's perturbation method and consider a one period deviation from the observed decisions of the supermarket. Each week the manager has to decide whether to keep the prices unchanged or change them; let's call $d^T = \{d_t, d_{t+1}, \dots\}$ the sequence of binary decisions by the manager to change or not the prices, (d equals 0 if there is no price change and 1 if there is a price change). Let's consider a one period deviation from the strategy adopted at time t , $d_a^T = \{d_{a,t}, d_{t+1}, \dots\}$. Since the manager chose the observed and not the alternative strategy, it must be that according to his expectations the former would

¹⁷Villas-Boas (2007) is the first to propose and use this type of instruments

deliver a higher expected discounted stream of profits than the latter:

$$\mathcal{E}_t[\pi(d^T, p^T)] \geq \mathcal{E}_t[\pi(d_a^T, p_a^T)]$$

where p^T and p_a^T are respectively the observed and the alternative price sequences and \mathcal{E} the agent's expectation operator. The estimation relies on the observation that in the counterfactual the manager makes a different pricing decision and therefore has to pay a different menu cost; in some deviations the counterfactual profits contain more fixed costs of price adjustment than the actual profits, whereas in other deviations the opposite is true. The difference between actual and counterfactual profits can be used to provide upper and lower bounds for the two types of menu costs.

In the empirical analysis I use four types of moment inequalities, which I describe here through four examples. In the first example, the price of product j is changed at time t from p to p' , kept the same for a period and changed again in $t + 2$ to p'' . A one period deviation consists in not changing the price at time t and then following the observed strategy, which is to keep it unchanged at time $t + 1$ and change it at time $t + 2$ to p'' . In the alternative scenario the manager does not pay the menu costs at time t , whereas in reality he did. This example generates the first type of inequality:

$$\eta_1 + \eta_2 \leq \mathcal{E}_t[\tilde{\pi}(d^T, p^T) - \tilde{\pi}(d_a^T, p_a^T)]$$

where $\tilde{\pi}$ is equal to π minus the menu costs paid at time t and η_1 and η_2 are the two types of menu costs.

In the second example, the manager changes at time t the prices of products j and h ; the cost of price adjustment equals $(\eta_1 + 2\eta_2)$. In the counterfactual, the manager changes only the price of product h , which entails menu costs equal to $(\eta_1 + \eta_2)$. In reality and in the counterfactual the firm is paying the “common menu cost”, but in reality the firm is paying more “item menu cost” than in the counterfactual and therefore I can derive an upper bound for the “item menu cost”, the second type of inequality:

$$\eta_2 \leq \mathcal{E}_t[\tilde{\pi}(d^T, p^T) - \tilde{\pi}(d_a^T, p_a^T)]$$

Another possible deviation is to change the price when the manager decided not to. In the third example the manager changes the prices of products h and k at time t , but the

price of product j remains unchanged at p until $t + 2$, when it is changed to p'' . In the counterfactual the price of j is changed at time t to p' and kept at p' until $t + 2$, when it is changed to p'' . In reality the menu cost is $(\eta_1 + 2\eta_2)$, but in the counterfactual one more additional price is changed and therefore the menu costs are higher and equal to $(\eta_1 + 3\eta_2)$. This example generates the third type of inequality, which provides a lower bound for the “item menu cost”:

$$\eta_2 \geq \mathcal{E}_t[\tilde{\pi}(d_a^T, p_a^T) - \tilde{\pi}(d^T, p^T)]$$

In the fourth and last example, at time t the manager does not change any price and therefore does not pay any menu cost. In the counterfactual, the manager changes one price at time t and then follows the observed strategy from period $t + 1$ onwards; in the counterfactual the firm pays menu costs equal to $(\eta_1 + \eta_2)$. I can then derive the fourth and last inequality, which provides a lower bound for the sum of the two types of menu costs:

$$\eta_1 + \eta_2 \geq \mathcal{E}_t[\tilde{\pi}(d_a^T, p_a^T) - \tilde{\pi}(d^T, p^T)]$$

3.4 Linear Moment Inequality Approach

We can write N inequalities, where each inequality represents a deviation from what the supermarket actually did:

$$\mathcal{E}\Delta\tilde{\pi}_a \geq \eta_1 \cdot S_{a,1} + \eta_2 \cdot S_{a,2} \quad S_{a,1}, S_{a,2} \in \mathbb{Z}, \quad a \in \{1, \dots, N\}, \quad \eta_1, \eta_2 \in \bar{\Theta}^C \subseteq \mathbb{R} \quad (7)$$

where $\tilde{\pi} = [\mathbf{p}_t - \mathbf{c}_t] \cdot \mathbf{q}_t$,¹⁸ a indexes a deviation from the actual price decision chosen by the supermarket manager, the expectation \mathcal{E} is conditional on the agent’s information set, but to make the notation easier to read from here on I will omit the conditioning on the agent’s information set, $S_{a,1}$ can take three values $\{-1 \ 0 \ 1\}$ depending on whether there are price changes in both the actual and the alternative scenario, $S_{a,2}$ is equal to the difference between the number of price changes, η_1 is the “common menu cost” and η_2 is the “item menu cost”. At the true parameter $(\eta_1, \eta_2) = (\eta_1^0, \eta_2^0)$ equation (7) holds for all

¹⁸In other words, $\tilde{\pi}$ is profits minus the menu costs

the deviations a .

Following Pakes (2010), we need an assumption on the agent's expectations of profits and on the difference between the profit measure that the agent uses and the one that the econometrician uses. I assume rational expectations, which implies that the supermarket managers make the right choices on average; the average is computed across choices made by different managers in multiple periods and with respect to multiple counterfactuals. From here on, the agent's subjective expectations \mathcal{E} are going to be rational expectations, denoted by E . Let's call r the function I use to estimate the profits and π the agent's profit function:

$$r = \pi + \nu$$

The relevant difference is between r and $E[\pi]$, so we can rewrite:

$$\begin{aligned} r &= E[\pi] + \nu_1 \\ \nu_1 &= \{\pi - E[\pi]\} + \nu \end{aligned}$$

The first component of ν_1 is the expectational error by the agent and is due to uncertainty. The second component is mean independent of the information set known by the agent before making the decision; in my setting I have some simulation error due to the approximation of the integral in (5) via simulation.

Let $\{z_{a,k}, k = 1, \dots, K\}$ be a set of nonnegative K instruments for each a . At the true parameters we can write:

$$E z_{a,k} \Delta \tilde{\pi}_a \geq z_{a,k} S_{a,1} \eta_1^0 + z_{a,k} S_{a,2} \eta_2^0 \quad \text{for all } k \text{ and } a \quad (8)$$

Since I assume that the econometrician profit function r is equal to the agent's profit function π plus some simulation error ν , I can say that the difference between the econometrician's and the agent's profit functions is exogenous to the instruments of the moment inequalities estimation, $E(\nu|z_{a,k}) = 0$. I can then write down K moment inequalities that are satisfied at the true parameter:

$$m_k(\eta_1^0, \eta_2^0) \geq 0 \quad \forall k \in \{1, 2, \dots, K\} \quad (9)$$

where m_k is equal to:

$$m_k(\eta_1^0, \eta_2^0) = E[z_{a,k} \Delta \tilde{r}_a] - z_{a,k} S_{a,1} \eta_1 - z_{a,k} S_{a,2} \eta_2$$

The identified set Θ^C is the subset of points that satisfy the K linear constraints in equation (9). If I define $Q(\theta)$ as :

$$Q(\eta) = \sum_{k=1}^K (\min\{0, m_k(\eta)\})^2 \quad (10)$$

then the identified set is the set of points $\eta \in \Theta^C$ solving:

$$0 = \min_{\eta \in \Theta^C} Q(\eta) \quad (11)$$

The empirical counterparts of (9) and (10) are:

$$\hat{m}_k(\eta_1, \eta_2) = \sum_{a=1}^N \frac{z_{a,k} \Delta \tilde{r}_a}{N} - \sum_{a=1}^N \frac{z_{a,k} S_{a,1}}{N} \eta_1 - \sum_{a=1}^N \frac{z_{a,k} S_{a,2}}{N} \eta_2 \quad (12)$$

$$\hat{Q}(\eta_1, \eta_2) = \sum_{k=1}^K (\min\{0, \hat{m}_k(\eta)\})^2 \quad (13)$$

and I can find the estimate of the identified set by solving:

$$\hat{\Theta} = \arg \min_{\eta \in \Theta^C} \hat{Q}(\eta) \quad (14)$$

In my application, K is equal to 4 and the instruments $z_{a,k}$ are indicator variables for the four types of moment inequalities described in Section 3.3. The first two types of moment inequalities provide me with upper bounds and the remaining two with lower bounds. When I need to reset the price optimally in a counterfactual, I change the price of a product by the amount that prices of that product are usually changed, in most cases 10 cents.

4 Confidence Intervals

I follow Pakes et al. (2011) approach to inference and I construct confidence intervals for the identified set. This section draws extensively from Holmes (2010) and Morales et al. (2011). Let K be the number of moment inequalities and \tilde{w}_a be a $3K \times 1$ vector that contains the moment inequality variables for deviation a , where the first K elements contain $z_{a,k}\Delta r_a$, the second K elements contain $S_{a,1}\eta_1$ and the third K elements contain $S_{a,2}\eta_2$. The sample mean of \tilde{w}_a over the N observed deviations is:

$$\bar{w}_a = \sum_{a=1}^N \frac{\tilde{w}_a}{N}$$

and it has variance-covariance matrix equal to Σ/N , where Σ is the variance-covariance matrix of the distribution of \tilde{w}_a . Pakes et al. (2011) explain how to simulate inner and outer confidence intervals for the identified set by calculating sample analogs of the identified set for simulated moments. Let's start from the inner confidence interval. We construct S simulations of the moment inequalities, drawing a random column vector w_s with $3K$ elements from the normal distribution with mean \bar{w} and variance covariance $\hat{\Sigma}/N$. Then we can derive moment inequalities from w_s by decomposing it in three components of K elements each and rearranging the vectors as in equation (7):

$$w_{1,s} \geq w_{2,s}\eta_1 + w_{3,s}\eta_2 \tag{15}$$

Define \tilde{Q}^{inner} as in (13) and calculate bounds for the parameters η_1 and η_2 . The inner confidence interval for each bound consists in the $\alpha/2$ and $1 - \alpha/2$ percentiles of the distribution of the simulated bounds. In order to compute the outer confidence intervals I'll follow the same procedure, but instead of (15) we have:

$$w_{1,s} \geq w_{2,s}\eta_1 + w_{3,s}\eta_2 + \kappa \tag{16}$$

where κ is evaluated at the actual data and at the estimated bounds and represents the “slack” in the nonbinding moment inequalities:

$$\kappa = \max\left\{0, \sum_{a=1}^N \frac{z_{a,k} \Delta r_a}{N} - \sum_{a=1}^N \frac{z_{a,k} S_{a,1}}{N} \hat{\eta}_1 - \sum_{a=1}^N \frac{z_{a,k} S_{a,2}}{N} \hat{\eta}_2\right\}$$

The deviations I use in the estimations are not statistically independent, because they are derived from $M = 808$ store-week observations. In order to control for this interdependence I follow the subsampling procedure described by Holmes (2010). Let’s draw a store-week subsample of size $b = M/3$ from the $M = 808$ store-week observations and then let’s define the deviation subsample as the set of observations that belong to the store-week subsample. I repeat this procedure and calculate each time the mean \bar{w}_b . Using the different subsample we can estimate the variance covariance matrix of \bar{w}_b and then we can use:

$$\text{Var}(\bar{w}_M) = \frac{b}{M} \text{Var}(\bar{w}_b)$$

as an estimate of the variance-covariance matrix of the distribution of \bar{w}_a .

5 Data Description

5.1 Dominick’s Finer Foods

To implement my estimation strategy, I need data on quantities, prices and costs of the products sold by a multi-product firm over some period of time. Following Goldberg and Hellerstein (2013), I use the dataset collected by the Kilts Center of Marketing at Chicago Booth on the supermarket chain Dominick’s Finer Foods. The data consists in weekly observations of quantities, prices and costs of 37 upc-level beer products sold by the supermarket chain in the Chicago area from 6 June, 1991 to 6 June, 1995. The dataset contains data on around 100 stores in the Chicago area, but prices are not different in each store; stores were divided by the management into 4 price groups, within which prices charged were the same. Data on product characteristics come from a *Consumer Reports* study conducted in 1996.

5.2 Preliminary evidence on economies of scope

Table 1: Median Frequencies of Regular Price Changes

	Probability	Duration in quarters
Unconditional	0.025	3.1
Conditional on at least one price change for other products	0.11	0.7

In the next section, I will show that the moment inequalities estimation uncovers significant economies of scope in price setting, but I would like here to present some preliminary evidence of it. Table 1 describes the frequency of price changes in my dataset by reporting the median frequency of regular price changes. The unconditional median price duration is around 3 quarters, the same reported by Eichenbaum et al. (2010) for their measure of reference prices and also very similar to the price duration in the BLS microdata, as Nakamura and Steinsson (2008) show. Table 1 shows also the median frequency of price changes conditional on existence of at least one price change in the category of products: the probability of a price change for product j increases if I condition on the existence of at least one price change in the category, excluding product j .

Table 2: Economies of Scope

Own markup gap	0.13*** [0.02]
Average markup gap of other goods	1.43*** [0.11]
Product FE	X
Quarter FE	X
Observations	20,941
Pseudo- R^2	0.25

The coefficients reported are marginal effects.

*** p<0.01, ** p<0.05, * p<0.1

Following Midrigan (2011), I estimate a probit model where the dependent variable is a dummy variable equal to 1 if there is a regular price change and equal to 0 otherwise. The

independent variables are the own markup gap and the average markup gap of the other products in the category; the markup gap is computed as the absolute value of the log difference between the last regular markup and the average markup for the product over the time period of the analysis. As shown in Table 2, the higher the own markup gap the higher the probability of a price change. Some reduced form evidence of economies of scope in price setting is given by the positive, large and statistically significant coefficient on the average markup gap of the other goods in the category: if the markup of other products is out of line, the probability of a price change for a product in the same category increases. In the probit regressions I include both time and product fixed effects as controls.

6 Results

6.1 First Stage

Table 3: Logit Model

	(1) OLS	(2) IV
price	-0.554*** [0.009]	-1.190*** [0.110]
time FE	X	X
product FE	X	X
Observations	29,896	29,896
R^2	0.844	0.803

First Stage

R^2 0.9864

F-statistic 38.57

Robust standard errors in brackets

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3 reports the estimated parameters for the logit model. The simple logit model is estimated by regressing $\ln(s_j) - \ln(s_0)$ on price and product characteristics. I estimate both a simple OLS regression and then I instrument price to control for endogeneity with the instruments described above. The coefficients on price are negative and statistically significant. In the regression, I include as controls product and time fixed effects, brand dummies and product characteristics. Finally, the F-test on the joint significance of the

excluded instruments are significantly higher than the threshold used commonly in the literature of 10. Table 4 reports the results from the full model. The coefficients on price are negative and statistically significant, as expected.¹⁹ Table 5 contains the median own- and cross-price elasticities of five products;²⁰ own-price elasticities are all as expected negative and lower than -1, whereas the cross-price elasticities are positive and vary depending on the degree of substitution between the two products as estimated from the data.

Table 4: Full Model

	(1) mean	(2) std dev
price	-5.425*** [1.780]	2.056*** [0.0781]
alcohol	-0.010 [0.008]	0.703* [0.421]
time FE	X	
product FE	X	
Observations	20,856	
MD weighted R^2	0.14	

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Median Own and Cross Elasticities

-66.56	2.43	0.78	1.47	1.94
0.94	-93.33	0.38	4.30	0.21
1.74	2.19	-70.72	1.80	2.13
1.39	10.99	0.79	-113.16	0.18
0.53	0.15	0.26	0.04	-30.34

6.2 The Size of Menu Costs

In Table 6, I summarize the results of the moment inequalities estimation of the menu costs. Section 3.3 describes the four types of moment inequalities I use to estimate bounds for the menu costs. There are 136 price deviations for the first type of inequality, 537,625,521 for the second, 692 for the third and 105 for the fourth. Since there are too many alternative

¹⁹A constant is included in the estimation, but not shown.

²⁰The full table of the elasticities for all the 37 products is available upon request.

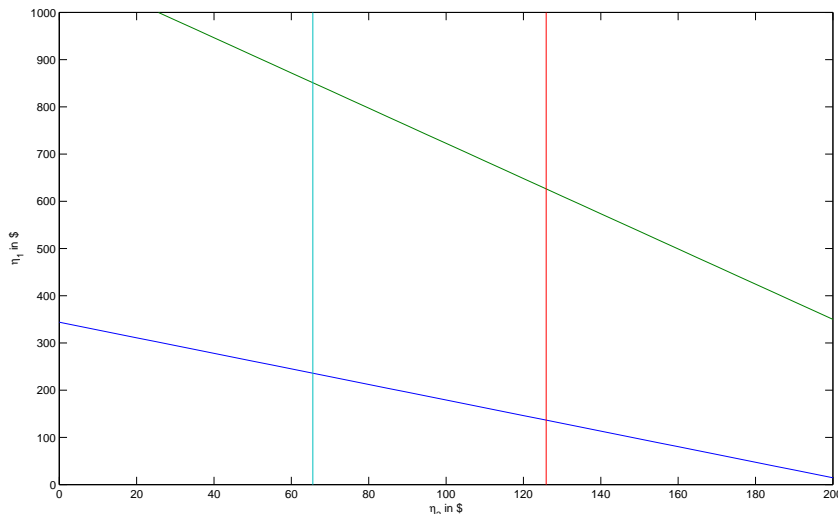
scenarios for the second type of moment inequality, I will need to restrict the sample to make the estimation computationally feasible.

Table 6: Estimated Bounds in \$

	Specification I		Specification II		Specification III	
	Lower	Upper	Lower	Upper	Lower	Upper
Common Menu Cost (η_1)	0	880.70	136.49	851.25	283.72	957.75
Item Menu Cost (η_2)	65.55	375.50	65.55	125.88	36.70	36.70

I estimate three specifications. In “Specification I”, I sample from the pool of possible price deviations for the second inequality.²¹ In the second and third specifications, I restrict my sample of deviations to those that should give me tighter bounds for the estimated parameters. The smaller the change in the cost of a product, the smaller the loss in profits if the price of the product is not changed; focusing on observations of a price change with a small cost change should give me tighter bounds. In “Specification II”, I restrict the sample only to those deviations with a non-zero change in cost in absolute value smaller than 5%. In “Specification III”, I restrict the sample to those deviations with no change in the costs; you would expect very small “item menu cost” if the manger changes the prices of products when their costs do not change.²²

Figure 1: Bounds in Specification II



²¹I resampled a few times to make sure that the results were robust

²²However, the price change could also be dictated by previous cost changes or by some change in the demand for the product.

As shown in Tables 6 and 7, “Specification I” delivers bounds that are too wide and include zero for the “common menu cost”. The other two specifications deliver tighter bounds and show the importance of the “common menu cost”; in “Specification III”, there is no value of the “item menu cost” that verifies all constraints, therefore the moment inequalities estimation provides a point estimate, which is not surprisingly the smallest estimates for the “item menu cost”. Figure 1 visually displays the results from “Specification II”; the first type of inequality delivers the green line in the figure, the second type delivers the red line, the third type delivers the dark blue line and finally the fourth type delivers the light blue line.

In order to understand the relevance of the estimated menu costs, it is useful to relate them to revenues and profits; in Table 7, I report that the expenditure due to menu costs represent, in “Specification II”, between 0.26% and 0.59% of revenues or between 2.84% and 6.36% of gross margin or between 13.08% and 29.32% of net margins; very similar results come from “Specification III”.²³ Table 7 also shows how much each type of menu cost contribute to the total amount paid to change prices; the “common menu cost” η_1 has an important role in both “Specification II” and “Specification III”.

Table 7: Estimated Bounds as a percentage of Revenues and Profits

	Specification II		Specification III	
	Lower	Upper	Lower	Upper
Revenues	0.26%	0.59%	0.22%	0.55%
Gross Margin	2.84%	6.36%	2.40%	6.01%
Net Margin	13.08%	29.32%	11.05%	27.71%
Contribution of η_1	20%	74%	64%	85%
Contribution of η_2	26%	80%	15%	37%

Finally, I computed the confidence intervals as described in Section 4; as Table 8 shows, the confidence intervals are close to the estimated bounds and are bounded away from zero. Unfortunately, it would be computationally unfeasible to compute confidence intervals that include the first stage uncertainty, but given how tight the second stage confidence intervals are, I am less concerned that it would make a difference.

²³Net margins are calculated as 2% of revenues as suggested by Montgomery (1994).

Table 8: Confidence Intervals for Specification II

Confidence Intervals η_1		
PPHI Inner (95 %)	95.01	913.70
PPHI Outer (95 %)	95.01	913.70
Confidence Intervals η_2		
PPHI Inner (95 %)	62.70	127.31
PPHI Outer (95 %)	62.70	127.31
Number of deviations: N=31,114; Number of Markets M=808		

7 Previous Estimates of Menu Costs

The previous literature finds some evidence supporting the existence of menu costs. Most previous estimations have been based on narrative observational evidence, rather than statistical analysis, with the exception of Slade (1998) and Aguirregabiria (1999). Furthermore all previous empirical work, with the exception of Lach and Tsiddon (2007), Bhattarai and Schoenle (2012) and Anderson et al. (2012), was concerned with the price change of a single product and did not consider the interactions of multi-product price setting.

Levy et al. (1997) use store-level data from five multi-store supermarket chains to study the exact process of changing prices. They find that the menu costs average \$105,887 per year per store, which represents 0.7% of revenues or 35.2% of net margins, and amounts to \$0.52 per price change. By interviewing supermarket managers the authors were also able to understand the sources of the menu costs that they estimated: labor costs of changing prices, costs of printing and delivering new price tags, the costs of mistakes made during the price change process, the cost of in-store supervision of the price change process. The main drawback of the Levy et al. paper is that the estimation is based on narrative observational evidence on the physical costs of price adjustment, which is only one component of menu costs. Zbaracki et al. (2004) claim that the physical costs of changing prices are only one component of menu costs and they identify and measure managerial costs and customer costs using data on a industrial firm. They find that both managerial costs and customer costs are more important than the physical costs of price changing. They estimate that menu costs amount to 1.22% of revenues and 20.03% of net margins, or between \$22.52 and \$121.64 per price change.

In order to overcome the limits of direct measurements, a few papers perform a structural estimation of menu costs. Slade (1998) estimates menu costs with GMM by devel-

oping a discrete-choice dynamic programming model that includes both fixed and variable costs of adjusting prices.²⁴ She uses weekly retail prices, factor prices and sales of three brands of saltine crackers sold by four chains of grocery stores in a small US town over the period of two years. It is found that the variable adjustment cost parameter is not statistically significantly different from zero, whereas the fixed cost parameter is estimated with precision. The average cost per price change is \$2.72, of which \$2.55 is fixed. Aguirregabiria (1999) develops a dynamic discrete-choice model, in which the retailer has to decide retail prices and orders to suppliers and faces fixed costs both for adjusting prices and for buying supplies. The retailer has to order supplies before knowing the demand shock, therefore the demand may end up exceeding the retailer’s inventories. This generates a cyclical price behavior with frequent and short lived price reductions, which mimics the frequency of real life sales promotions. Slade (1998) and Aguirregabiria (1999) both use supermarket data. Supermarkets are the stereotypical multi-product firm, but they estimate a single-product firm model because the large dimensions of the choice set in a multi-product setting make the estimation computationally infeasible with the traditional discrete choice methods that they employ. By using moment inequalities, I am able to solve this dimensionality problem and therefore estimate a dynamic multi-product firm model.

Nakamura and Zerom (2010) and Goldberg and Hellerstein (2013) provide estimates of menu cost in their empirical analysis of the puzzle of incomplete exchange rate pass-through, i.e. the incomplete transmission of exchange rate fluctuations to prices for exported and imported goods.²⁵ There are many possible candidate factors that can explain this phenomenon and fixed costs of price adjustment is a leading candidate. Nakamura and Zerom (2010) produce some estimates for menu costs through a calibration exercise and find that menu costs do not explain much of the exchange rate pass-through. On the other hand, Goldberg and Hellerstein (2013) use a revealed preference approach and find that menu costs contribute to explain about a third of the incomplete exchange pass-through in their dataset.

Finally, Lach and Tsiddon (2007), Bhattarai and Schoenle (2012) and Anderson et al. (2012) provide some suggestive evidence for economies of scope in price setting. In all price datasets a substantial fraction of price changes are very small and this observation challenges traditional menu cost models where firms change prices only when their current

²⁴Slade (1998) and Aguirregabiria (1999) use the estimation algorithm developed by Hotz and Miller (1993).

²⁵The incomplete exchange rate pass-through puzzle is well documented by Engel (1999), Parsley and Wei (2001), Goldberg and Campa (2008) and Gopinath et al. (2010)

price is far from the optimal price. Lach and Tsiddon (2007) claim that small price changes are consistent with multi-product firms facing store-specific menu costs that generate economies of scope in price setting. They show that in their dataset of Israeli grocery stores small average price changes are very infrequent and the smaller the individual price change in a store the larger the price change in the remaining products sold by the same store. Bhattarai and Schoenle (2012) analyze microdata on US producer prices and find evidence consistent with the existence of a firm-specific menu cost. They establish three main empirical facts; first, firms that sell more goods adjust prices more frequently, but the price adjustments are smaller on average. Second, firms synchronize the price changes across products. Third, the within firm synchronization of price changes is an increasing function in the number of goods. Anderson et al. (2012) analyze the “uniform pricing” policy that requires all the variants of a product to have the same price and show that prices of products with more variants are more sticky.

8 Conclusion

In menu cost models firms face fixed costs of price adjustment and therefore change prices less frequently than they otherwise would. Klenow and Kryvtsov (2008) and Alvarez et al. (2013) present evidence that menu cost models are overall consistent with the empirical facts on price adjustment. On the other hand, Caplin and Spulber (1987) and Golosov and Lucas (2007) challenge the ability of menu cost models to produce high degrees of monetary non-neutrality. Recently, a new literature in macroeconomics revived the interest in menu cost models by showing that with the introduction of price setting interactions menu cost models are able to match the empirical facts better and to produce real effects of monetary policy. For instance, Midrigan (2011) shows that if firms sell many products and face economies of scope in price setting the selection effect described by Golosov and Lucas (2007) is substantially weakened.

In this paper, I present evidence that menu costs exist and are substantial. I estimate two types of menu costs: costs that are independent of the number of items that change prices and costs that are incurred at each items price change and I find that both menu costs are statistically and economically significant. My findings provide empirical support for second-generation state dependent pricing models and in particular for those models that rely on economies of scope in price setting.

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