

The Roles of Price Points and Menu Costs in Price Rigidity^{*}

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Abstract

Macroeconomic models often generate nominal price rigidity via menu costs. This paper provides empirical evidence that treating menu costs as a structural explanation for sticky prices may be spurious. Using scanner data, I note two empirical facts: (1) price points, embodied in nine-ending prices, account for approximately two-thirds of prices; (2) at the conclusion of sales, post-sale prices return to their pre-sale levels more than three-fourths of the time. I construct a model that nests roles for menu costs and price points and estimate model variants via simulated method of moments. Excluding the two facts yields a statistically and economically significant role for menu costs in generating price rigidity. Incorporating the two facts yields an incentive to set nine-ending prices two orders of magnitude larger than the menu costs in this model. In this setting, the price point model can match the two stylized facts, but menu costs are effectively irrelevant as a source of price rigidity. The choice of a mechanism for price rigidity matters for aggregate dynamics.

Keywords: price rigidity; menu costs; price points; nine-ending prices; simulated method of moments

JEL codes: E31, L11, D40, C15, M31

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Sticky prices are an integral component of most macroeconomic models that generate considerable periods of monetary nonneutrality. Understanding the mechanisms that produce price rigidity is therefore an essential task for building proper micro foundations of these macro models. Following a long tradition, the most commonly modeled structural impediments to price adjustment are menu costs—the costs associated with literally changing the price of an item. In this paper, I provide empirical evidence that menu costs per se are largely irrelevant as a source of price rigidity.

Using multiple scanner price datasets—covering billions of observations, multiple retail venues in grocery stores and drugstores, many retail chains, different time periods, and broad national coverage across the United States—I document and discuss two stylized facts. First, approximately two-thirds of prices end in the digit nine—a highly prominent price point. Second, at the conclusion of sales (i.e., temporary price mark-downs), post-sale prices return to their pre-sale levels more than three-fourths of the time—and nine-ending prices play a nontrivial role in this latter fact as well.

I build a simple state-dependent pricing model that embeds two potential key frictions. First, I allow for a canonical menu cost: when the firm wishes to change its nominal price, it must pay a fixed, nonconvex adjustment cost to do so. Second, I allow a role for price points in the firm's decision problem: the firm may potentially receive a benefit—either real or perceived—from setting prices that end in the digit nine.

This model yields several noteworthy effects. First, depending on the parameterization, it can generate an overreliance on prices that end in the digit nine. Second, the use of these price points can result in both price rigidity—since the firm may be reluctant to change its price away from a nine ending—and relatively large price changes when it does adjust even in response to

small changes in its costs—since it may jump to nearby nine-ending prices. Third, to the extent that price points matter to the firm, they also naturally create an incentive for a firm to return post-sale prices precisely back to their pre-sale levels.

I estimate the model using scanner data from Dominick’s Finer Foods, a grocery store chain. Excluding the above facts and constraining the estimation to assume price points are irrelevant, I estimate a statistically and economically significant menu cost to match commonly cited moments related to price rigidity. However, the model cannot match the two above facts. Jointly estimating the sizes of the menu cost and price point frictions and incorporating the above facts changes the results. The size of the estimated menu cost drops markedly, suggesting that menu cost estimates using grocery store data that do not consider price points—such as Slade (1998), Nakamura and Zerom (2010), and Stella (2013)—suffer from an omitted variable bias that attributes too much stickiness to menu costs as a structural impediment to changing prices. Indeed, the estimated price point sensitivity is roughly two orders of magnitude larger than menu costs in this model. In this setting, the price point model can match the two stylized facts, but menu costs are effectively too small to generate substantial price rigidity. These results suggest that relying on menu costs as a structural explanation for price rigidity—which is arguably their most attractive feature in macro models featuring state-dependent pricing—may be spurious.

Extending the model to illustrate its implied aggregate behavior, I show that the choice of a mechanism for price rigidity matters for macro dynamics. Using the estimated parameters, the price point model generates movements in output distinct from those of the simple menu cost model.

The marketing and retailing literatures have long recognized the importance of price points and price endings, especially the digit nine. Despite the explosion of interest in sticky

prices since Bils and Klenow (2004), the sticky price literature has largely avoided this issue, with the notable exceptions of U.S. empirical work by Kashyap (1995), Blinder et al. (1998), and Levy et al. (2011).¹ While most macro models assume some form of price rigidity, those that model firm optimizing behavior in state-dependent pricing models rely primarily on menu costs to generate price rigidity, as in Golosov and Lucas (2007) among others. The key innovation of this paper is to integrate price points and menu costs into a single framework and jointly estimate the parameters of the model.

This paper also contributes to the sticky price literature and the debate about the importance of sales. Klenow and Kryvtsov (2008), Nakamura and Steinsson (2008), and Kehoe and Midrigan (2008, 2015) show that including or excluding sales has a dramatic impact on estimated average durations between price changes, which in turn affects the results of macro models calibrated to one or the other duration.² The fact that most sales are “undone”—in that the firm’s post-sale price returns to its pre-sale level—lends some support to the view that sales should be treated as special or as a nuisance to abstract from in macro models. Instead, I argue that the behavior of prices around sales is as an important test of structural price-setting models. Ultimately, this behavior is more supportive of price point models than canonical menu costs.

An additional drawback of menu cost models is their inability to generate small price changes: the presence of a menu cost that is sufficiently large to deter too-frequent adjustment also prevents many small price changes. As noted by Midrigan (2011), while the average absolute size of price changes tends to be relatively large in the empirical data, there are also many small changes in absolute value. While not a part of the estimation, the price point model

¹ For example, recent surveys by Klenow and Malin (2011) and Nakamura and Steinsson (2013) omit references to price points as a source of price rigidity.

² Coibion et al. (2015) focus on the cyclical behavior of sales, which is beyond the scope of this paper.

closely matches the frequency of very small price changes (less than 2.5 percent and less than 1 percent in absolute value) in the Dominick’s data.

Price points can help rationalize the inertia that Eichenbaum et al. (2011) find in reference prices—i.e., the most commonly used prices within a quarter. Intuitively, price points help to channel firms’ prices to certain nominal levels. In this framework, there is no longer a need to assume that firms are restricted to choosing from a small set of prices prescribed by a “price plan” that is costly to adjust, as in Eichenbaum et al. (2011).

Section I discusses the data used in this paper and the stylized facts of interest. Section II presents a model that allows a role for price points and menu costs in a firm’s price-setting problem, and Section III sets out the estimation strategy. Parameter estimates are presented in Section IV. Section V discusses the results in the context of the literature. Section VI considers the aggregate implications of the models, and Section VII concludes.

I. Stylized Facts on Price Endings and Sales in Retail Scanner Datasets

Scanner datasets from retail chains enable studying price dynamics using massive numbers of observations across many goods, stores, and even retail chains. This paper uses data from two such datasets which have been widely studied in the price rigidity literature.

The first is the scanner dataset of prices for Dominick’s Finer Foods, a Chicago-area supermarket chain, which contains more than 3,500 items with UPC labels. The data are available at a weekly frequency, beginning in September 1989 and running for 400 weeks through May 1997. The dataset contains nearly 99 million observations and is publicly available through the James M. Kilts Center at the University of Chicago Booth School of Business.

The second dataset is from IRI and is documented in Bronnenberg et al. (2008). The data are available at a weekly frequency, beginning in January 2001 and ending December 2011. I use the store sales data covering the complete set of UPC codes in 30 product categories. This dataset has more than 2.3 billion observations from grocery stores; it also has nearly 164 million observations from drugstores in the same categories. The IRI data come from more than 100 different chains and 47 of IRI's 64 markets, implying broad national coverage of retail chain pricing behavior.

This paper focuses on several facts related to price endings, price behavior around sales, and the interaction between them. The first fact is that prices ending in the digit nine dominate these retail scanner datasets. Figure 1 shows that approximately two-thirds of retail scanner prices end in the digit nine: 63.6% of Dominick's prices, 63.7% of the IRI grocery store prices, and 75.0% of the IRI drugstore prices have a nine in the final cents digit.³ These frequencies of nine-ending prices are incredibly far from the 10% that would occur if price endings were chosen at random and uniformly distributed.

Because Dominick's is a single chain while the IRI data contain many grocery store and drugstore chains, Figure 2 shows the distribution of the frequency of nine-ending prices across chains. In these scanner datasets, 86.9% of grocery store chains and drugstore chains set more than half of their prices to nine-endings; the vast majority set between 50% and 80% of their prices to nine-endings. With few exceptions, most retail chains' price-setting behaviors produce a frequency of nine-ending prices similar to Dominick's.

³ Price is generated in these datasets by dividing weekly revenue by quantity, producing an average weekly price. Restricting attention only to the prices of goods for which quantity sold equals 1 in a given week—so that revenue equals exact price—yields frequencies of nine-ending prices of 64.4% at Dominick's, 78.2% in IRI grocery stores, and 85.6% in IRI drugstores. While this procedure guards against erroneously rounding prices to nine-endings because of mid-week price changes or selling x goods for price y , it overweights products with low volumes. The fraction of observations with quantity equal to 1 varies greatly by scanner dataset, covering 98.7% of Dominick's observations, 21.7% of IRI grocery store observations, and 45.6% of IRI drugstore observations.

Price endings correlate with typical measures of interest in the price rigidity literature. For example, the top part of Table 1 shows that the unconditional frequency of a price change is 25.2% in the Dominick’s data. The conditional frequency of a price change at time t is lower if the previous period’s price, $p(i,t-1)$, ended in a nine (22.1%) than if it ended in any other digit (30.2%). Levy et al. (2011) present more detailed empirical analysis relating to nine endings in the Dominick’s data but do not explore the relationship between nine endings and memory around sales.⁴ The IRI data for grocery stores and drugstores show the same pattern: nine-ending prices change less frequently than other price endings. Indeed, a non-nine-ending price is more than twice as likely to change as a nine-ending price in the IRI data. The middle of Table 1 shows that the same patterns hold if we exclude prices that were part of a sale at time $t-1$ and time t .

Considerable attention has recently focused on the behavior of prices around sales and implications for the study of price rigidity. Sales, or temporary price markdowns, feature prominently in these retail scanner datasets: as documented below, conditional on an item not being on sale in the previous period, the frequency of beginning a sale is approximately double the frequency of a non-sale price change in each dataset. Because sales involve not only a price decrease but also a price increase, they comprise the majority of all price adjustments.⁵

Furthermore, prices exhibit considerable memory around sales. The bottom part of Table 1 shows that, at the conclusion of a sale, prices return precisely to their level from immediately prior to the sale more than three-fourths of the time across retail scanner datasets. Similar

⁴ Studies of micro data underlying consumer price indices from the Eurosystem’s Inflation Persistence Network also find a statistically significant role for “attractive prices”—i.e., price points, including nine endings—in regressions on the frequency of price changes; see Dhyne et al. (2006) for a review of this evidence.

⁵ The Dominick’s data contain a variable indicating whether a good was on sale for the week or not, but the sale codes were not applied in a consistent manner and thus are not used in this analysis. Sale flags are available in the IRI data. However, for consistency across scanner datasets and in the model simulations below, the Appendix provides details on the sales filter used to determine the start and end dates of sales. It is worth noting here that the sales filter does not require that post-sale prices return to their pre-sale level.

findings have been documented by Levy et al. (2002), Eichenbaum et al. (2011), Guimaraes and Sheedy (2011), and Kehoe and Midrigan (2015). Such a finding is not unique to supermarkets. Using data underlying computation of the U.S. consumer price index, Klenow and Kryvtsov (2008) and Nakamura and Steinsson (2008) find broadly similar patterns.

What is unique to this study is that memory around sales is related to price endings: the frequency with which post-sale prices return to their pre-sale levels differs depending on the pre-sale price ending. Across grocery stores and drugstores, memory around sales is far stronger when the last pre-sale price ended in a nine than when it ended in any other digit. Table 1 shows that the frequency of a post-sale price differing from its pre-sale level is three times larger in all the retail scanner datasets if the pre-sale price ended in a non-nine digit than it is when the pre-sale price ended in a nine. Abstracting from nine-ending prices would generate far less memory around sales than what is observed in the data—primarily because so many prices at the conclusion of a sale return to their pre-sale, nine-ending level.

At a high level, these statistics suggest that, across multiple retail chains and different time periods, retail firms treat the digit nine differently from other digits in setting or adjusting prices. This paper considers a model in which prices that end in the digit nine are “price points” with special properties and estimates the size of this friction vis-à-vis the more traditional menu cost friction that impacts firm price-setting.

II. A Model of Price Points and Menu Costs

The model I consider has the following features. Within a given period, the firm determines the nominal price p it would like to charge for an item. As in the canonical Dixit-Stiglitz

framework, in a frictionless world the firm would always wish to set p equal to a desired markup μ over its nominal marginal cost, denoted mc .

The firm potentially faces two consequential frictions, the size of which require estimation. The first friction allows for the possibility that price changes are costly: there is a menu cost to changing a price, due to the physical costs of literally adjusting the price of an item.⁶ Each price change reduces profits by a fixed amount, $\Phi \geq 0$. The same menu cost is paid for every price change, whether it is expected to be “permanent” or “temporary.”⁷ Such nonconvex adjustment costs follow in a long tradition in the sticky price literature.

The second friction comes from the possibility that price points may factor into the firm’s pricing problem. Price points may vary by firm; using microlevel price data underlying the Israeli consumer price index, Knotek et al. (2014) document differences across establishment types in terms of their favored price endings, with establishments carrying many goods—such as the retail chains in the scanner datasets—favoring nine-ending prices while establishments that carry few items favor round prices. Focusing on the retail chain sector, as in the empirics above, the marketing and retailing literatures have proposed a number of mechanisms through which nine-ending price points may provide a benefit to sellers. Typically, these mechanisms involve a departure from pure rationality by consumers, who may (erroneously) associate price points with sales or who truncate or underestimate nine-ending prices, potentially due to rational inattention

⁶ Some interpretations of “menu costs” subsume a variety of frictions that make price adjustment less frequent; e.g., Gorodnichenko and Weber (2016) use a broad definition of menu costs when studying individual prices underlying the U.S. producer price index.

⁷ This notably differs from Midrigan and Kehoe (2015), where a firm pays a fixed cost (κ in their terminology) to change the list or permanent price, and a different fixed cost (ϕ in their terminology) to charge a different price—e.g., a sale or temporary price—for only one period. I discuss the difference in more detail below. Midrigan (2011) explores economies of scale in changing prices, which are beyond the scope of this paper.

or the desire to simplify price comparisons across items by mentally coding using left-to-right, digit-by-digit comparisons until the first difference is noted.⁸

As a result, price points can result in kinks, discontinuities, or nonconvexities in the demand curve that are present in the firm's profit function as well—with the effect that the price points are local profit maxima. For example, suppose consumers truncate the final cents' digit. This would transform an otherwise linear (log-linear, etc.) demand curve into a step function.⁹ Because demand would be identical for a price of \$1.50 and \$1.59, the firm would earn higher revenues and profits from setting the \$1.59 price. Moving from \$1.59 to \$1.60 would result in a disproportionate decline in demand and, under general circumstances, a lower level of profits. For the sake of tractability and estimation feasibility, and to remain agnostic on the precise mechanism at play, this paper posits that firms may benefit directly from the use of price points ending in the digit nine via $\kappa \geq 0$, which captures the profit implications of setting a price point.¹⁰

The above concepts can be parsimoniously represented as affecting a firm's profits for good i at time t through a quadratic loss function

$$(1) \quad \Pi(p, mc, \mu) = \chi - \left(\frac{p}{mc} - \mu \right)^2 + \kappa [I(p \in \{\text{price points}\})].$$

In the absence of any frictions ($\kappa=0$ and $\Phi=0$), the firm would set its price p equal to its desired markup over marginal cost, earning some level of profits χ .

⁸ There is an extensive literature on consumer underestimation, truncation, and mental coding processes; see, e.g., Georgoff (1970), Brenner and Brenner (1982), Schindler and Kirby (1997), Schindler and Kibarian (1993), and Thomas and Morwitz (2005). Schindler (1991) provides one example of the association between nine-ending prices and sales.

⁹ Nonlinearities in demand related to nine-ending prices may take other, more complicated forms as well; e.g., Schindler and Kibarian (1996) and Anderson and Simester (2003) provide evidence that demand is higher for nine-ending prices than for proximate non-nine-endings.

¹⁰ Gedenk and Sattler (1999) show that firms may set nine-ending prices when faced with uncertainty over whether a threshold exists between nine-ending prices and round prices. Thus, firms in the model may perceive a benefit κ from setting nine-ending prices whether it truly exists or not.

In the presence of frictions, deviations of the actual price p from its frictionless optimal level (equal to $mc \times \mu$) entail a reduction in profits via the curvature of the profit function. These deviations can arise in the presence of a menu cost $\Phi > 0$ that must be paid when changing the price of good i , because in this case the firm may not always pay the menu cost in order to keep its price at its desired markup over marginal cost. They can also arise when $\kappa > 0$, because in this case a firm's profits will depend on whether p is a nine-ending price point—and hence the indicator variable $I(p \in \{\text{price points}\}) = 1$ —or not. As a result, under some circumstances profits may be higher from setting a nine-ending price point than from setting $p = mc \times \mu$.

Within a given period t , the firm observes its contemporaneous marginal cost mc and desired markup μ —both of which evolve exogenously to the firm—and decides whether to keep its price p or change it. The firm discounts the future at rate β . The value to the firm of keeping its price p is

$$(2) \quad V^K(p, mc, \mu) = \Pi(p, mc, \mu) + \beta EV(p, mc', \mu'),$$

with E the expectations operator over future unknown values of marginal costs and desired markups. The value to the firm of changing its price is

$$(3) \quad V^C(p, mc, \mu) = \max_{\tilde{p}} \Pi(\tilde{p}, mc, \mu) - \Phi + \beta EV(\tilde{p}, mc', \mu'),$$

which captures the menu cost Φ needed to change the price to $\tilde{p}$. Thus, the firm decides whether to change its price or not based on

$$(4) \quad V(p, mc, \mu) = \max\{V^K(p, mc, \mu), V^C(p, mc, \mu)\}.$$

Intuitively, menu costs generate price rigidity by creating a range of inaction around the most recently set price. In response to small shocks, a firm facing a menu cost will wish to maintain the previous price. Once the shocks push the firm outside of this range, it will pay the menu cost and select a new price. By contrast, price points create incentives for the firm to

select from a *set* of prices (in this case, those with nine-endings). This will cause prices from this set to be used disproportionately. In addition, price rigidity will depend on the characteristics of the current price itself (i.e., situational price rigidity). If the current price is a price point, this again generates a range of inaction in response to small shocks and hence price rigidity. But if the current price is not a price point, these prices may appear more flexible.

III. Calibration and Estimation Strategy

Central to this paper are the sizes of the menu cost, Φ , and the price point effect, κ , in the firm's profits. Estimating these parameters requires calibrating other parameters where possible and specifying the exogenous processes for marginal costs mc and markups μ .

The data in the retail scanner datasets are weekly, which is the relevant timeframe for the firm's decisions. As such, the discount rate is $\beta=0.96^{1/52}$. Without loss of generality, χ is normalized to ensure the value function is not near zero.

In keeping with the spirit of the sticky price literature, nominal marginal costs for a good have two components: a “price” component P and a “real” component c , such that $mc=P \times c$.¹¹

The price component evolves according to

$$(5) \quad \ln P = \bar{\pi} + \ln P_{-1} + \zeta,$$

with ζ an i.i.d. normal random variable with mean zero and standard deviation σ_{ζ} . The real component of marginal costs evolves according to

$$(6) \quad \ln c = \ln c_{-1} + \varepsilon.$$

¹¹ That is, sticky price models typically use the firm's real price p/P as the relevant state. Since profits in equation (1) depend on p/mc , this interpretation of nominal costs is equivalent to having $(p/P)/c$ in the profit function. The component c then captures the idiosyncratic productivity shocks that have become standard in state-dependent pricing models based on menu costs (see, e.g., Golosov and Lucas 2007), along with other aggregate disturbances.

As in Gertler and Leahy (2008), the shock has two components: $\varepsilon = \gamma \times \eta$. The random variable γ governs the arrival of cost shocks, with $\Pr(\gamma=1)=\lambda$ and $\Pr(\gamma=0)=1-\lambda$. The random variable η determines their size, with η distributed uniformly on $[-\theta, \theta]$.

Taking the model to the scanner data requires a prominent role for sales. While various theories have been proposed to explain sales, this paper models sales as arising in response to time-variation in the firm's exogenous desired markup μ , which follows

$$(7) \quad \mu = \bar{\mu} - \xi.$$

In a New Keynesian framework using Dixit-Stiglitz preferences, exogenous time-variation in the firm's desired markup could arise through time-variation in demand elasticities; see Pesendorfer (2002) and Kehoe and Midrigan (2015). The random variable ξ captures the desired sales state. If $\xi=0$, the firm wishes to set its price equal to its steady-state desired markup $\bar{\mu}$ over marginal cost. If $\xi>0$, the potential for a sale occurs because the firm wishes to set a lower markup and hence a lower price. Whether the firm actually changes its price and has a sale in response to a positive realization of ξ or not depends on its optimization problem. The desired sales state is given by $\xi \in \{0, \xi_s, \xi_b\}$, which affords the opportunity for “big” and “small” sales ($\xi_b > \xi_s > 0$).

The desired sales state follows a Markov process with transition matrix,

	$\xi'=0$	$\xi'=\xi_s$	$\xi'=\xi_b$
$\xi=0$	δ_0	δ_{0s}	$1-\delta_0-\delta_{0s}$
$\xi=\xi_s$	δ_s	$1-\delta_s$	0
$\xi=\xi_b$	δ_b	0	$1-\delta_b$

which rules out the possibility of transitions from one desired sale state to another for simplicity.

To take the model to the scanner data, I select a single retail chain: Dominick's Finer Foods. The Dominick's dataset has among the largest number of observations for a single chain, and while Nakamura et al. (2011) document important heterogeneity in pricing dynamics across

retail chains, the earlier results suggest that Dominick's pricing behaviors with respect to the use of price points and memory around prices are broadly representative. Marginal cost is not well-measured in the Dominick's data and cannot be used to inform the parameters of the cost process in equation (6) (see, e.g., Peltzman 2000); however, I do use the median markup of non-sale prices over average acquisition cost—which can be inferred from the measure of gross profit margins in the Dominick's dataset, and which I assume proxies for marginal cost in steady state—to calibrate the steady-state desired markup $\bar{\mu}$ to 1.42. Converting monthly inflation for the non-seasonally adjusted consumer price index for food and beverages to weekly inflation over the Dominick's sample period yields $\bar{\pi}=5.68 \times 10^{-4}$ and $\sigma_{\pi}=1.73 \times 10^{-3}$.

Thus, the model has ten parameters to estimate: (1) the sensitivity of profits to nine-ending price points, κ ; (2) the menu cost, Φ ; (3) the probability of a marginal cost shock, λ ; (4) the support of the marginal cost shocks, θ ; (5–6) the “big” and “small” sales states, ξ_b and ξ_s , respectively; and (7–10) four parameters from the transition matrix, δ_0 , δ_{0s} , δ_s , and δ_b . Two moments from the Dominick's data reduce the computational burden and inform δ_{0s} and δ_b . First, 59.8 percent of sales are smaller than average, implying $\delta_{0s}=0.598(1-\delta_0)$. Second, the average duration of a “big” sale is 71.8 percent of the average duration of a “small” sale, implying $\delta_b=1.393\delta_s$. This leaves eight parameters for estimation.

The model is estimated via simulated method of moments (SMM); see McFadden (1989). Let Z denote the vector of parameters to be estimated: $Z=[\kappa, \Phi, \lambda, \theta, \xi_b, \xi_s, \delta_0, \delta_s]'$. The estimates $\hat{Z}$ minimize the weighted difference between a vector of estimated moments from the data, $\hat{\psi}$, and a vector of moments produced via model panel simulations using parameters Z , $\tilde{\psi}(Z)$:

$$(8) \quad \hat{Z} = \arg \min_Z \left[\hat{\psi} - \frac{1}{S} \sum_{s=1}^S \tilde{\psi}_s(Z) \right] \Omega \left[\hat{\psi} - \frac{1}{S} \sum_{s=1}^S \tilde{\psi}_s(Z) \right]',$$

where $S=25$ is the number of replications of the simulated panel dataset over $I=1,000$ items and $T=80$ time periods, which is the approximate average number of observed weeks per item in the Dominick's data. This combination implies that each parameter vector Z is evaluated over a total of 2 million simulated observations. The positive definite weighting matrix Ω comes from bootstrapping the Dominick's data 1,000 times, estimating a new vector of moments $\hat{\psi}_b$, $b=1, \dots, 1000$, and inverting the variance-covariance matrix from those new moments. Estimation of $\hat{Z}$ is conducted via a combination of grid search and simulated annealing (Goffe et al. 1994), with 15 separate simulated annealing estimations performed to ensure $\hat{Z}$ produces the global minimum for equation (8). I report 90% confidence bands around the parameter estimates using a Monte Carlo approach: I reestimate $\hat{Z}$ 500 times, each time drawing a new seed for the shocks underlying my model to account for stochastic simulation variability and a different vector from the set of bootstrapped moments $\{\hat{\psi}_b\}$ to account for sampling variability in the empirical data.

I select moments to identify the model's parameters based on common moments in the sticky price literature reflecting information on the frequency of price changes, their size, and the standard deviation of their size, along with moments related to sales behavior. I consider: (1) the frequency of non-sale price changes; (2) the average absolute size of non-sale price changes; (3) the standard deviation of the size of non-sale price changes; (4) the frequency of beginning a sale, conditional on not having a sale in the previous period; (5) the frequency of ending a sale, conditional on a sale in the previous period; (6) the average size of price changes associated with the start of sales; and (7) the standard deviation of the size of price changes associated with the start of sales. The final two moments are the facts from Section I: (8) the percentage of prices that end in the digit nine; and (9) the frequency with which post-sale prices differ from their pre-sale levels.

The inclusion of price points in the model requires keeping track of nominal prices as a state variable, due to the indicator function $I(p \in \{\text{price points}\})$ in equation (1). Because the time required to solve, simulate, and estimate the model increases exponentially with the number of nodes in each state, I restrict attention to nominal prices in the range of \$0.50 to \$3.00 inclusive.¹² The vast majority of Dominick’s prices—74.6%—are within this range, as shown in Figure 3.¹³ Table 2 shows the moments used in the estimation. The moments from this subset of the Dominick’s dataset are very similar to those from the entire dataset, and they are generally similar to the same moments computed using the IRI datasets as well.

IV. Estimation Results

I estimate two variants of the model. The first is a typical menu cost model omitting price points, as is common in the sticky price literature. Attempts to estimate these types of menu costs in supermarket data include time-use surveys, as in Levy et al (1997), or structural estimations, as in Slade (1998), Nakamura and Zerom (2010), and Stella (2013). Next, I consider the complete model, estimating both the role of price points and menu costs jointly. While the former exercise finds a significant statistical and economic role for menu costs, the latter exercise shows that menu costs are essentially irrelevant as a source of price rigidity after incorporating a role for price points into the analysis.

¹² Estimation of the parameters and confidence intervals below takes approximately 6 months using optimized Fortran code and a high-performance computing cluster.

¹³ Because of positive trend inflation among many goods categories between the timing of the Dominick’s sample (1989-1997) and the IRI sample (2001-2011), the shares of IRI prices between \$0.50 and \$3.00 are somewhat lower: 55.3% of IRI grocery store observations and 44.9% of IRI drugstore observations.

A Typical Menu Cost Model

To estimate the model with only menu costs (i.e., constrained estimation with $\kappa=0$), I discretize the actual markup state, p/mc , in 0.1 percent intervals over the relevant regions of the markup state space and constrain actions to this grid.¹⁴ With the nine-ending price point effect κ set to zero by assumption, this leaves the menu cost Φ and six other parameters related to the frequency and size of the shocks in the model. Consequently, the model is just-identified by using the first seven moments listed in Table 2.

Table 3 presents the parameter estimates and the corresponding simulated moments.¹⁵ The bottom panel shows that the model closely matches the seven targeted moments at the estimated parameters. The point estimate of the menu cost for this case is 3.99×10^{-3} , with a 90-percent confidence interval from 2.88×10^{-3} to 4.21×10^{-3} . Cost shocks arrive (λ) in approximately 6.7% of periods, and the maximum absolute size of a cost shock (θ) is 9.1%.¹⁶ Matching the large standard deviation of the size of sale-related price changes requires allowing for multiple sales states. Thus, the big sale estimate (ξ_b) implies a desired markup of 0.901, while the desired markup during an estimated small sale (ξ_s) is 1.32. These estimates are consistent with large sales being “loss leaders,” as in Chevalier et al. (2003), which are more transient than other sales.

The final two parameters relate to the transition matrix that governs the evolution of desired markups. The estimate of δ_0 implies approximately a 10% probability that the desired

¹⁴ By the assumptions of the previous section, the other relevant state variable, μ , can take on three values in each of the model variants: $\mu \in \{\bar{\mu}, \bar{\mu} - \xi_s, \bar{\mu} - \xi_b\}$.

¹⁵ The 90% confidence intervals reported in the table were constructed by re-estimating each model 100 times using different underlying draws for the shock processes. In this way, I account for variability arising from the selected set of random draws in the estimation procedure.

¹⁶ The estimates for λ and θ are similar to the calibrations in Kehoe and Midrigan (2008), the working paper version of Kehoe and Midrigan (2015).

markup will switch from its steady-state level to a lower, sale level in any given period. The estimate of δ_s implies that, conditional on the desired markup being $\mu = \bar{\mu} - \xi_s = 1.32$, the desired markup will stay at that level in the next period with a two-thirds probability.

While the menu cost model closely matches the moments used in the estimation, it is incapable of matching the two facts set out in Section I: more than 60 percent of prices end in the digit nine, and post-sale prices return to their pre-sale levels more than three-quarters of the time. The menu cost model produces nine-ending prices approximately 10 percent of the time—the probability of drawing this digit by chance.¹⁷

The inability to match the second fact is because of the forward-looking nature of menu cost models. In a menu cost model in which the adjustment cost is narrowly modeled and interpreted as the cost needed to physically change a price, when a firm decides to pay the fixed cost and adjust its price, the new price it sets should incorporate all relevant information since its last change.¹⁸ This implies that, under even extremely low rates of inflation similar to what Dominick’s experienced, post-sale prices will rarely exhibit memory and return to their pre-sale levels, a pattern clearly illustrated in Figure 4. As the table shows, the menu cost model would predict that post-sale prices differ from their pre-sale levels more than 90% of the time; the Dominick’s data put this figure at 11%, while the IRI data put this figure at no more than 28%.¹⁹

¹⁷ Since p/mc is the relevant state in this model and essentially all menu cost models, the notion of a nominal price is somewhat arbitrary and clearly not constrained to the traditional grid of prices, \$1.00, \$1.01, \$1.02, etc. This figure is found by rounding to two digits.

¹⁸ To the extent that other frictions—e.g., information frictions—are the structural factors behind price rigidity, these factors should be explicitly modeled.

¹⁹ Discretizing the state variables of the menu cost model in successively finer increments would push this moment arbitrarily close to 100 percent, though it would also render impractical the estimation due to time considerations. The state space of the model was finely discretized to conform to standard practice in menu cost models. Conversely, requiring this model to use whole cent nominal price increments would produce a higher incidence of memory around sale prices, but the model would still not be able to match this particular moment.

Price Points and Menu Costs

The second exercise considers the unconstrained estimation of the model by jointly estimating the menu cost parameter and the role of price points. This estimation requires keeping track of nominal prices as a state, due to the indicator function $I(p \in \{\text{price points}\})$ in equation (1). I assume that prices adhere to those feasible under the available monetary denominations.²⁰ To this end, I discretize the nominal price p and nominal marginal cost mc states in one cent increments. The range for the marginal cost process is endogenously determined by the assumption that nominal prices reside in the range of \$0.50 to \$3.00 and the values of the markup process, which are estimated. To estimate the model with prices points and menu costs, I use all nine of the moments set out above.

The estimated model continues to be consistent with the moments commonly associated with the sticky price literature, but it is also now consistent with the two facts from Section I. The estimated nine-ending price point effect is 6.80×10^{-4} , with a 90% confidence interval from 6.49×10^{-4} to 6.87×10^{-4} . Thus, the estimation rejects the nested menu-cost-only specification for the larger set of moments. The estimate of the menu cost falls to 3.29×10^{-6} , with 90% confidence interval 6.5×10^{-7} to 1.98×10^{-5} . That is, when both frictions are estimated jointly, the estimated nine-ending price point effect is roughly two orders of magnitude greater than the estimated menu cost in this model. Even though the menu cost is statistically estimated to be greater than zero, it is effectively irrelevant as a source of price rigidity. For instance, setting the menu cost Φ to zero and keeping the other estimated parameters has a trivial effect: to two decimal places, the resulting moments are unchanged. While other studies have estimated the

²⁰ This rules out pricing in fractions of a cent, or pricing patterns such as two for \$0.99. Less than 1% of prices in the Dominick's database violate this assumption.

size of menu costs in supermarkets for individual products—including Slade (1998), Nakamura and Zerom (2010), and Stella (2013)—those analyses have omitted price points. The results of this paper suggest that omitting price points is likely to upward bias structural estimates of menu costs by a considerable magnitude.

In terms of other parameters, the estimated arrival rate of cost shocks falls to 2.8% from 6.7% in the menu cost model. In spite of this, the frequency of non-sale price changes remains just below 6%, in line with the data. Implicitly, this means that some “sales”—i.e., price changes in response to desired markup shocks—may last longer than the sales window and instead be classified as non-sale price changes, and that some non-sale price changes are caused by drift in the price component of marginal cost. Indeed, sales are slightly more likely to occur under this case than under the menu-cost-only model, as implied by the lower estimate of δ_0 . Regardless, this is not necessarily a drawback to this model, since the Dominick’s data also contain “sales” that last longer than the window used in the sales filter and therefore appear as non-sale price changes. While the sizes of the big and small sales states are comparable, the absolute size of cost shocks is slightly smaller than in the menu-cost-only case as well, at 7.0%.

Interpreting the Menu Cost and Nine-Ending Frictions

Equation (1) does not have a role for revenues or profits per se, which complicates interpretation of the estimated parameters of the model; e.g., Levy et al. (1997) and Dutta et al. (1999) compare menu costs to revenues and profits. However, via equation (1), one can compare the percentage deviation between the actual markup, p/mc , and the steady-state desired markup, $\bar{\mu}$, that is equivalent to the estimated menu cost.

In the model with only a menu cost, paying the menu cost has the same contemporaneous negative effect on profits as allowing the actual markup to differ from the desired markup by 4.34% for one period. In the model that jointly estimates the roles of price points and menu costs, paying the menu cost now has the same contemporaneous negative effect on profits as allowing the actual markup to differ from the desired markup by 0.13%. Fully translating the effects of these frictions on price-setting requires evaluating the complete optimization problem from Section II, but the size of the latter estimate implies that, in isolation, virtually any shock to marginal costs would be big enough to justify a price change based on menu costs alone.

By contrast, the price point effect is equivalent to a 1.81% difference between actual and desired markups. The estimation suggests this is a much bigger impediment to price changes than menu costs.

Ability to Match Additional Moments

Beyond robustness exercises, it is also possible to consider how well the model matches moments not used in the estimation. Table 4 presents additional moments of interest in the Dominick's data and the moments coming from model simulations generated using the estimated parameters from Table 3.

Midrigan (2011) notes that the Dominick's data contain many small price changes. Table 4 shows that more than half of non-sale price changes are smaller than 5% in absolute value, 26.1% are smaller than 2.5%, and 6.7% are smaller than 1%. These facts typically pose a challenge for menu cost models to match, because a menu cost large enough to prevent too-frequent price adjustments also prevents the firm from making many very small price changes;

the value to the firm from making a small price adjustment and paying the menu cost is too often smaller than the value of keeping the old price. This problem is shared by the estimated menu cost model considered in this paper: there are too few small price changes compared with the empirical data. Heterogeneity in menu costs—as in, e.g., Dotsey et al. (1999) and Midrigan (2011)—helps to generate small price changes alongside larger price changes as well, because the firm will make a small adjustment when it is faced with a small menu cost. The model with price points enjoys greater success in generating small price changes, nearly matching the empirical data for non-sale price changes smaller than 2.5% and 1%.

Section I documented that the frequency of price changes in the Dominick’s data varies depending on the previous period’s price ending. While the frequency of all price changes was not used in the estimations, the models produce frequencies comparable to but slightly less than the empirical data.²¹ More importantly, in the empirical data the frequency of price change is higher conditional on non-nine-ending prices than it is conditional on nine-ending prices. Such a pattern is qualitatively present in the model that allows a role for price points.

Section I also documented that the frequency with which post-sale prices differ from their pre-sale level varies with the pre-sale price ending. Such a pattern is generated endogenously by the model if one allows for a nine-ending price point effect. Taken together, these facts and the above results provide strong evidence that price points play an important role in the memory prices exhibit around sales.

²¹ The Dominick’s data contain sale-to-sale changes that were ruled out for the sake of tractability in the model in Section III; this explains most of the discrepancy between the models and the data.

V. Discussion

Developing models in which prices return to their pre-sale levels has proven challenging. In one approach, Kehoe and Midrigan (2015) present a model featuring multiple menu costs: a large menu cost for non-sale price changes, a smaller menu cost for price changes associated with the start of a sale, and a de facto zero menu cost to change from the sale price back to the regular price.²² Because of the latter zero menu cost, this framework generates many prices that return exactly to their pre-sale levels. However, it arguably departs from the notion of a menu cost as the literal cost of implementing a price change, because no changes in such a setting should be costless. Further, it is not clear a priori that the physical costs of implementing a price change associated with a sale are lower than those associated with making a non-sale price change, especially if the former involves special tags, signs, promotional materials, etc. For these reasons, this paper posits a single menu cost.

In a second approach, Eichenbaum et al. (2011) present a model in which a firm chooses a “price plan,” which consists of a set of two prices. Firms can change between prices in the plan costlessly, but altering the plan requires paying a fixed cost. Intuitively, limiting the number of prices in the plan to two—for instance, to one regular and one sale price—and requiring a cost to changing the plan prevents firms from making the types of small adjustments seen in Figure 4 that plague menu cost models around sales. However, it is less clear why a profit-maximizing firm would select a plan with only two prices; specifically, when facing drift in the price level, the firm would optimally wish to have a cluster of “regular” prices to choose from, along with at least one sale price. The nine-ending price point model in this paper can

²² Kehoe and Midrigan (2015) focus on “regular” and “temporary” price changes, where the latter include both sales and temporary price increases above the regular level. For comparison with this paper, I reframe the issue in terms of only sales.

explain why firms would endogenously choose to use relatively few prices.²³ In addition, the trivial size of the estimated menu costs is not too far from the assumption in Eichenbaum et al. (2011) of costless price changes within a plan.

Clearly, price changes per se are not costless. Levy et al. (1997) provide direct evidence from time-use studies on the costs of changing prices for supermarkets: cumulatively, they average more than \$100,000 per year per store, or about 0.70% of firm revenues. The results above suggest that the estimated nine-ending price point effect is roughly two orders of magnitude larger than the cost associated with a single price change. Another way to compare these estimates is to combine them with the actual Dominick's pricing data across stores, items, and time to form the ratio:

$$(9) \quad \frac{\sum_{s=\text{stores}} \sum_{i=\text{items}} \sum_{t=\text{time}} \hat{\kappa} [I(p_{s,i,t} \in \{\text{9-ending price points}\})]}{\sum_{s=\text{stores}} \sum_{i=\text{items}} \sum_{t=\text{time}} \hat{\Phi} [D_{s,i,t}]}, \quad D_{s,i,t} = \begin{cases} 1 & \text{if } p_{s,i,t} \neq p_{s,i,t-1} \\ 0 & \text{otherwise.} \end{cases}$$

In words, equation (9) computes the ratio of the benefits that Dominick's received from setting nine-ending prices to the costs incurred from paying the menu cost for every price change.

Based on the parameter estimates above, this ratio is 591.0. Assuming that Dominick's is similar to the supermarket chains in the study by Levy et al. (1997) and pays 0.70 percent of revenues in the form of menu costs on average each year, this ratio would imply that Dominick's received a benefit from setting nine-ending prices of 413.7% of revenues per year.

²³ Limiting the set of prices to those between \$0.50 and \$3.00 may increase the estimated importance of nine-ending prices if these are used to a greater extent for lower prices, or if they are a bigger factor in effecting price rigidity at lower levels simply because—in percentage terms—the distance between consecutive nine-ending prices is a decreasing function of the price level itself. However, price changes tend to be large in percentage terms (greater than 15% across all price changes), so above \$0.69 the distance between any two consecutive nine-ending prices is smaller than the average price change, suggesting this is not likely a binding constraint. In addition, firms may actually be more apt to focus on nine-ending prices at higher price levels, especially if they are used to simplify firms' pricing decisions; e.g., they limit the realm of possible prices to one-tenth of the feasible pricing set. This latter point appears to be more likely: between \$0.50 and \$3.00, 62.2% of prices end in the digit nine, whereas 63.6% of all prices use this digit, signifying that they are more heavily used outside of the range of prices that are the focus of this study. Knotek (2011) finds that the probability of a product's price being at a price point rises with the level of the price.

This number is implausibly large. An alternative interpretation of the evidence is that Dominick's views menu costs differently from the standard menu cost set-up outlined above. Two previously modeled possibilities include economies of scale in changing prices (Midrigan 2011) and time variation in menu costs (Dotsey et al. 1999). But Dominick's may also simply view menu costs as a fixed cost of doing business rather than an impediment to price changes, as they are modeled in state-dependent pricing frameworks.

This paper's finding that menu costs are largely irrelevant as a source of price rigidity *per se* is in keeping with several recent lines of research that have looked to other explanations for sticky prices. In a case study of a large industrial manufacturer, Zbaracki et al. (2004) document that physical menu costs associated with changing prices were an order of magnitude smaller than the costs associated with collecting information and negotiating with customers. Blinder et al. (1998, p. 179) document that 15 of the 17 retailers in their survey identified price points as a significant source of price rigidity; by contrast, menu costs were cited by a below-average proportion of these same firms (p. 233). Overall in the Blinder et al. (1998) survey, the fear of antagonizing customers ranked very high as a primary reason behind firms' desires to keep their prices unchanged. Anderson and Simester (2010) and Rotemberg (2005, 2011) consider customer antagonization, anger, and perceptions of fairness over firms' prices as mechanisms that can generate price rigidity, even in the absence of menu costs. Related to antagonization, Knotek (2008, 2011) shows that under certain circumstances firms may choose to set convenient prices, which simplify and expedite transactions and result in price rigidity in a manner similar to price points.

VI. Aggregate Implications

Deriving a structural explanation for price points and embedding this within a general equilibrium framework to generate macroeconomic dynamics is beyond the scope of this paper. As an approximation to the aggregate implications arising from the model with price points and menu costs, I consider the following exercise.

I assume the quantity equation with unit velocity holds, $M_t = P_t \times Y_t$. Money follows the dynamics previously assumed for the “price” component of nominal marginal cost, equation (5),

$$(10) \quad \ln M_t = \bar{\pi} + \ln M_{t-1} + \zeta_t, \quad \zeta_t \sim \text{i.i.d. } N(0, \sigma_\zeta^2),$$

with $\bar{\pi}$ and σ_ζ as in Section III. Individual prices aggregate to the price index P_t via

$$(11) \quad \ln P_t = \frac{1}{N} \sum_{i=1}^N \ln p_{it}.$$

The model in Section III assumed nominal marginal cost for a good was $mc_t = P_t \times c_t$, where P_t was the “price” component and c_t was the “real” component of marginal cost. If monetary shocks are neutral, then $Y_t = \bar{Y}$ and recasting nominal marginal cost as $mc_t = M_t \times c_t$ differs from its earlier incarnation by a constant factor, which I omit to focus on dynamics. If monetary shocks are not neutral, however, then a price setter would more accurately need to take aggregate dynamics into account when making decisions; i.e., movements in output would enter marginal cost. In keeping with the partial equilibrium nature of the model above, I assume no strategic complementarity (or real rigidity) among price setters and that individual price setters’ problems are not affected by the decisions of other price setters.

To compare and contrast the behavior of the typical menu cost model with the model with price points and menu costs, I simulate and aggregate a very large (1 million) panel of price

setters. Both models use the parameter estimates from Section IV and are simulated under the conjecture that monetary shocks are neutral, in keeping with the partial equilibrium model above. In line with strategic neutrality among price setters, I initially assume that firms are uniformly distributed on the interior of the interval from \$0.50 to \$3.00 at time 0 and then simulate the model economies for 250 weeks, discarding the first 50 weeks to reduce dependence on initial conditions. Figure 5 illustrates the simulated path of output deviations from trend over 200 weeks, using the same money process across models.^{24,25}

The figure shows that output in the model with price points and menu costs is very nearly equal to its trend value throughout the simulation: the largest absolute deviation is 0.008 percent. That is, the model ex post largely confirms the ex ante conjecture that money is neutral. This result echoes Caplin and Spulber (1987), wherein price rigidity at the individual level is washed away in the aggregate. By contrast, the typical menu cost model produces considerable movements in output related to changes in money: the largest absolute deviation is 0.684 percent.²⁶

This result has two implications. First and foremost, the aggregate dynamics of the price point model appear to be quite distinct from those of the menu cost model. As such, the choice of a mechanism for generating price rigidity matters. However, the second point is that assuming ex ante monetary neutrality is more problematic in the menu cost case, since price

²⁴ Because of the different parameter estimates for the arrival rate and size of idiosyncratic real marginal cost shocks, and the frequency and size of sales shocks, the same cannot be said for all the shocks hitting individual price setters.

²⁵ While imposing the same money process across the two models is necessary for comparing aggregate responses, it generates one difference from the estimations in Section IV. The estimations constrain all movements and actions to the grid of relevant discretized state variables— p/mc in 0.1 percent intervals in the standard menu cost model, and p and mc in one cent increments in the price point model. To allow for comparisons with the exact same money process between both models in this exercise, I simulate equation (10) directly and store M for both models; then simulate c directly for each price setter via equation (5) and the estimated values of λ and θ for each model separately; then use these simulated values for nominal marginal cost mc to find the nearest relevant discretized state variable, which is used in the price setter's decision problem.

²⁶ The standard deviation of output deviations from trend is 0.002 percent in the price point model and 0.208 percent in the typical menu cost model.

setters would need to incorporate movements in Y_t into marginal cost in their price-setting problem. Furthermore, the simulation makes strong assumptions regarding a lack of strategic behavior among price setters which could affect the results. Thus, a more detailed comparison of these two competing models requires a complete general equilibrium framework.

VII. Conclusion

This paper considers the extent to which menu costs—interpreted literally as the physical costs of changing a price—provide a structural explanation for price rigidity. Using scanner data from Dominick’s Finer Foods, I show that in a simple menu cost model one would estimate a statistically and economically significant menu cost based on moments commonly used in the sticky price literature. By expanding the model to allow a role for price points, using additional empirical data in the estimation, and jointly estimating the frictions coming from both menu costs and price points, the results change dramatically. In this case, the price point model can match the additional empirical facts, but menu costs are now effectively irrelevant as a source of price rigidity. These results suggest that treating menu costs as a structural explanation for sticky prices may be spurious.

This paper has made a number of simplifying assumptions for the sake of estimation feasibility. Most notably, in this paper prices that end in the digit nine raise the level of profits, while all other prices do not have any special effects. This tractable approach only adds one additional parameter to the estimation, but the exact manner in which price points enter the firm’s problem is a subject of contention. While the marketing and retailing literatures have suggested many alternative theories to explain the prevalence of price points, further work is

necessary to justify a structural interpretation of how they affect firms' decision-making and therefore produce price rigidity. Embedding this structural framework into a fully dynamic, stochastic general equilibrium model is left for future research.

VIII. Appendix: The Sales Filter

For the sake of compatibility and comparability between the Dominick's data, the IRI data, and the simulated price data, I construct a sales filter that is applied to all datasets. In any given period, the filter determines whether a price observation is a sale or not by comparing the current price with an inferred "regular" price for the item. In short, if the price today has fallen below the "regular" price and increases within the next F periods, then it is a sale price; otherwise, it is not a sale price. The window size, F , is set to four weeks in this paper; moments computed using a window size of three or five weeks are similar.

Formally, the following steps were used for a given item i .

1. Initially set "regular" prices $\{r_t\}$ to their observed values $\{p_t\}$ for all t .
2. Compare the current price with the previous period's regular price: if $p_t \geq r_{t-1}$, the observation is not a sale, move to the next period; if $p_t < r_{t-1}$, then continue to step 3.
3. Over the next F periods, does the price increase? If so, then time t was part of a sale and the previous "regular" price needs to be carried forward to this period ($r_t = r_{t-1}$); if not, there was not a sale at time t .
4. Move to the next period ($t = t + 1$) and return to step 2.

Note that the "regular" prices are only used in the sales filter; none of the moments presented in the paper rely on these "regular" prices per se.

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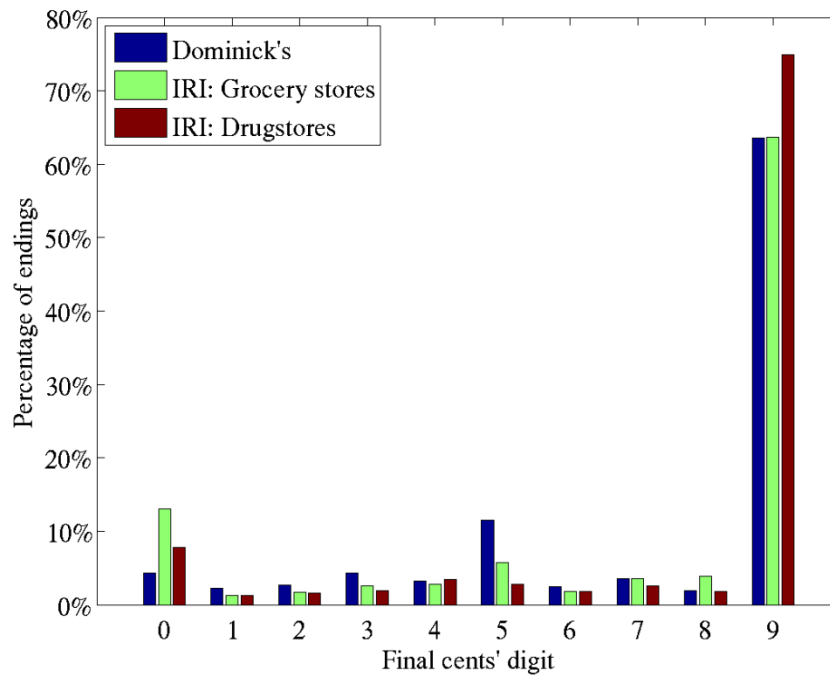
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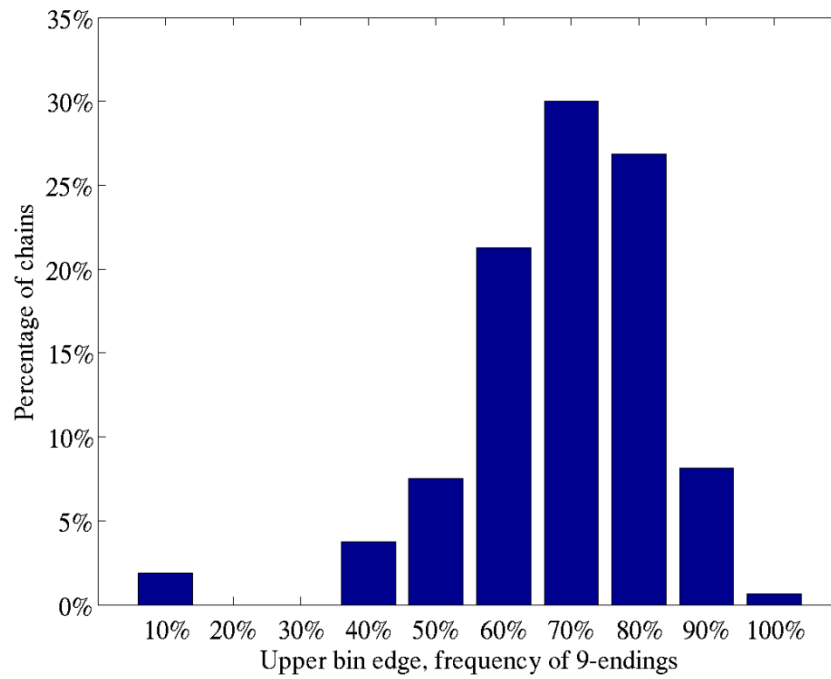
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Figure 1. The Distribution of Price Endings



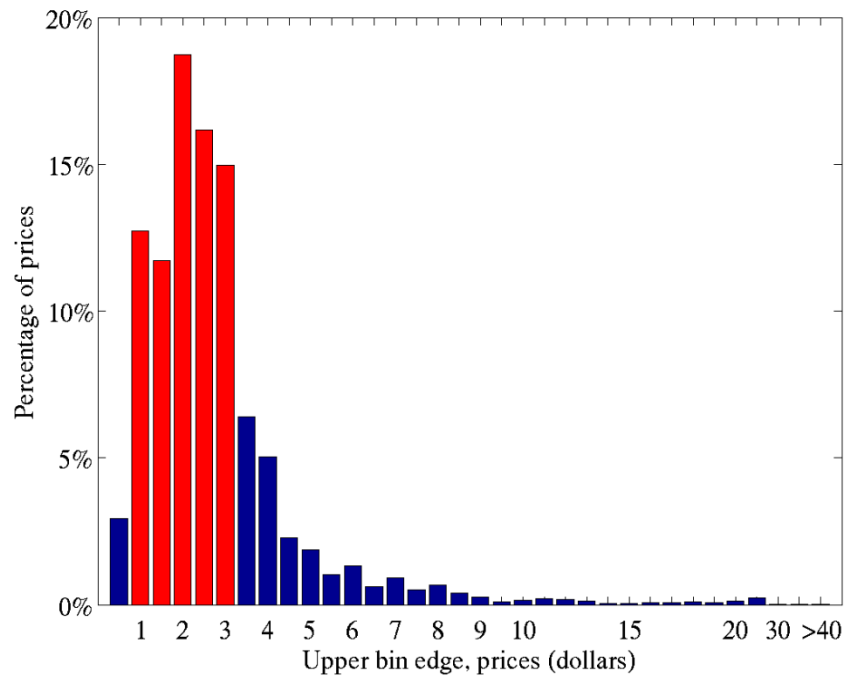
Notes: Observations: 98.9 million for Dominick's, 2.3 billion for IRI: Grocery stores, and 163.7 million for IRI: drugstores. Author's calculations based on scanner data from Dominick's Finer Foods and IRI.

Figure 2. The Distribution of the Frequency of 9-ending Prices across Chains



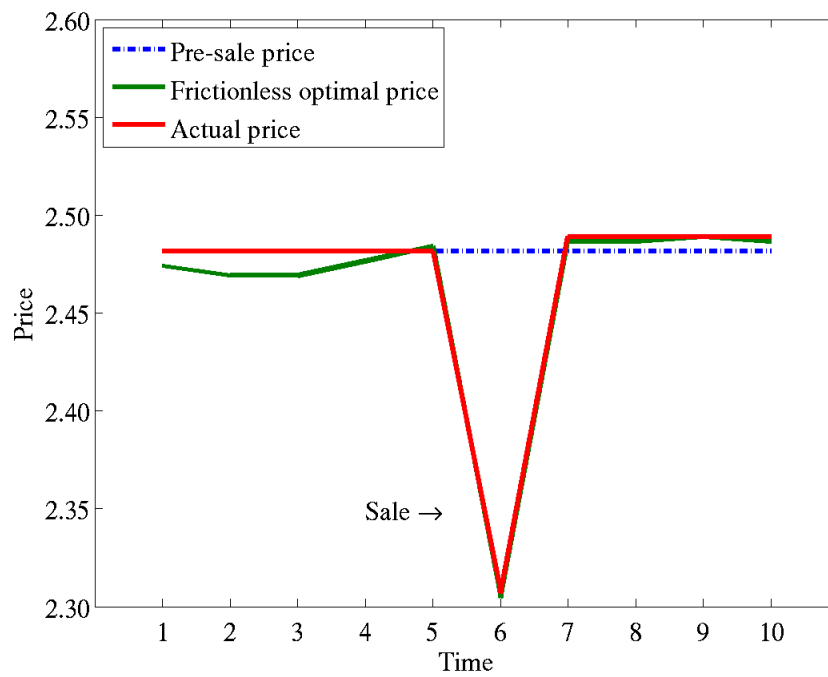
Notes: There are a total of 160 chains in the scanner datasets. Each chain receives equal weight. Author's calculations based on scanner data from Dominick's Finer Foods and IRI.

Figure 3. The Distribution of Prices in the Dominick's Dataset



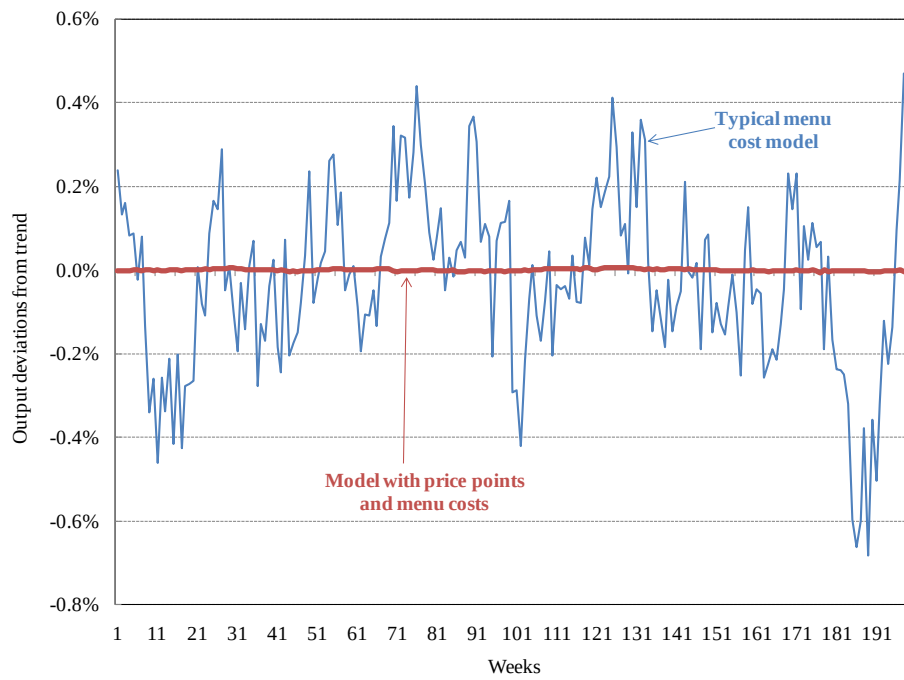
Notes: The red bars denote observations between \$0.50 and \$3.00. Observations: 98.9 million. Author's calculations based on scanner data from Dominick's Finer Foods.

Figure 4: Sales and the Problem with Menu Cost Models



Notes: The frictionless optimal price in each period is given by nominal marginal costs mc times the desired markup μ .

Figure 5: Simulated Output Deviations from Trend in Two Models



Notes: The thin blue line shows output deviations from trend for the typical menu cost model. The thick red line shows output deviations from trend for the model with price points and menu costs. Both models were simulated using the parameter estimates from Section IV. Both models assume ex ante that monetary shocks are neutral.

Table 1. Frequency of Adjustment, Sales Behavior, and Price Endings

	Dominick's	IRI: Grocery stores	IRI: Drugstores
Frequency of all price changes	25.2	31.9	36.2
Frequency $p(i,t-1)$ ended in 9	22.1	20.0	25.8
Frequency $p(i,t-1)$ did not end in 9	30.2	51.2	63.2
Frequency of change no sale at $t-1$ or t	5.7	8.0	7.4
Frequency $p(i,t-1)$ ended in 9, no sale at $t-1$ or t	4.3	5.3	4.9
Frequency $p(i,t-1)$ did not end in 9, no sale at $t-1$ or t	8.3	15.2	19.7
Frequency, post-sale price differs from pre-sale level	10.8	28.2	21.0
Frequency last non-sale price ended in 9	6.2	15.9	10.6
Frequency last non-sale price did not end in 9	21.2	47.7	65.8

Notes: All numbers are expressed as percentages. Author's calculations based on scanner data from Dominick's Finer Foods and IRI.

Table 2. Empirical Moments of Interest across Scanner Datasets

	Dominick's: \$0.50-\$3.00	Dominick's (all prices)	IRI: Grocery stores	IRI: Drugstores
1. Frequency of non-sale price changes	5.6	5.7	8.0	7.4
2. Avg. absolute size of non-sale price changes	7.7	7.8	11.3	14.4
3. St. dev. of absolute size of non-sale price changes	9.0	9.8	13.5	18.1
4. Frequency of beginning a sale	10.0	10.0	11.1	14.0
5. Frequency of ending a sale	50.5	51.1	44.2	56.0
6. Avg. size of price changes at start of sales	-22.0	-22.5	-24.5	-27.7
7. St. dev. of size of price changes at start of sales	18.7	19.1	20.8	30.5
8. Percentage of all prices that end in 9	62.2	63.6	63.7	75.0
9. Frequency, post-sale price differs from pre-sale level	11.0	10.8	28.2	21.0

Notes: All numbers are expressed as percentages. The IRI columns use all prices. Author's calculations based on scanner data from Dominick's Finer Foods and IRI.

Table 3. Parameter Estimates and Simulated Moments

	Dominick's data	Menu cost model	Price point and menu cost model
<u>Estimates</u>			
Nine-ending price point effect: κ		--	6.80×10^{-4} [6.49,6.87] $\times 10^{-4}$
Menu cost: Φ		3.99×10^{-3} [2.88,4.21] $\times 10^{-3}$	3.29×10^{-6} [0.65,19.8] $\times 10^{-6}$
Arrival probability of cost shocks: λ		0.067 [0.063,0.070]	0.028 [0.027,0.030]
Absolute bound on cost shocks: θ		0.091 [0.089,0.095]	0.070 [0.068,0.081]
No sale to no sale transition probability: δ_0		0.895 [0.894,0.896]	0.877 [0.874,0.881]
Small sale to no sale transition probability: δ_s		0.330 [0.327,0.339]	0.398 [0.394,0.412]
Size of big sale: ζ_b		0.519 [0.518,0.522]	0.499 [0.491,0.518]
Size of small sale: ζ_s		0.100 [0.099,0.103]	0.099 [0.098,0.107]
<u>Moments</u>			
1. Frequency of non-sale price changes	5.6	5.6	5.7
2. Avg. absolute size of non-sale price changes	7.7	7.7	9.0
3. St. dev. of absolute size of non-sale price changes	9.0	9.0	11.8
4. Frequency of beginning a sale	10.0	10.0	10.3
5. Frequency of ending a sale	50.5	50.5	54.3
6. Avg. size of price changes at start of sales	-22.0	-22.0	-22.2
7. St. dev. of size of price changes at start of sales	18.7	18.6	17.9
8. Percentage of all prices that end in 9	62.2	9.5*	63.2
9. Frequency, post-sale price differs from pre-sale level	11.0	93.5*	9.8

Notes: Moments computed from the Dominick's data were for prices between \$0.50 and \$3.00 inclusive. All moments are expressed as percentages. The models were estimated using simulated method of moments. For the parameter estimates, 90% confidence intervals are reported in square brackets [-], as detailed in the text. * denotes that the simulated moment was not used to estimate the model parameters. Author's calculations based on scanner data from Dominick's Finer Foods and model simulations.

Table 4. Additional Moments of Interest

	Dominick's data	Menu cost model	Price point and menu cost model
<u>Small Price Changes</u>			
Percentage of non-sale changes < 5%	52.3	38.9	41.6
Percentage of non-sale changes < 2.5%	26.1	16.9	26.0
Percentage of non-sale changes < 1%	6.7	0.2	5.6
<u>Frequency Measures</u>			
Frequency of all price changes	25.0	22.8	23.2
Frequency last price ended in 9	21.5	–	22.1
Frequency last price did not end in 9	30.5	–	25.4
<u>Prices around Sales</u>			
Frequency of post-sale prices differing from pre-sale levels	11.0	93.2	9.7
Frequency last non-sale price ended in 9	6.1	–	8.1
Frequency last non-sale price did not end in 9	22.4	–	12.7

Notes: All numbers are expressed as percentages. Moments computed from the Dominick's data were for prices between \$0.50 and \$3.00 inclusive. Author's calculations based on scanner data from Dominick's Finer Foods and model simulations.