Reducing Retailer Food Waste: A Revenue Management Approach*

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Abstract

Using time-stamped, granular purchase data from a major midwestern grocery chain, I demonstrate the viability of using intra-day price changes to reduce food waste and improve social welfare, particularly in conjunction with a food waste ban. I first use stylized models to demonstrate the circumstances in which revenue management (RM) is most beneficial to a profit maximizing monopolist, as well as the implications on total surplus, waste, and stockouts. I next examine cases when static pricing is socially inefficient, that is to say, when RM can be used to produce a pareto improvement (increasing firm profits while weakly increasing consumer surplus.) I find [results]. [Results] implies that is is necessary to empirically measure demand and uncertainty in order to assess equilibrium outcomes of RM. I estimate a model of consumer demand and document the necessary conditions for RM: demand uncertainty and substantial time-varying elasticity. Next, I construct the realistic RM model of the firm, including stockout and disposal costs, and using the data I simulate counterfactual welfare, inventory and waste levels, and stockout frequency. Under the profit maximizing policy, I find that welfare [results], that waste [results], decreasing [results]. Under the pareto improving policy, I find [result]. Finally, I examine the counterfactual welfare implications of a food waste ban, as has been implemented in Massaschusettes and California. I empirically assess the outcomes of RM under this policy, and as theory predicts, I find that the benefits of RM increase substantially during a ban due to the firm's decision to optimally reduce inventory levels.

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Cite Feng Luo and Zheng for inventory pricing joint decisions, matching uncertainty. etc importance of coordinating inventory and pricing decisions, realism, and profit potential.

need to lit review based on feng luo zheng

efficient value function iteration for BSLP policy?

Facts:

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(1) Grocery perishables markets are characterized by high (perceived) stockout costs, low disposal costs, and high margins items. As a result, the equilibrium amount of waste is very high in grocery stores. Some yields are as low as 50%.

(2) Legislatures have begun to propose and enact food waste bans in order reduce the amount of disposed food and its associated emissions. Retailers are obligated to contract either for donation or recycling services. While recycling/donation is more expensive, the emissions associated with food waste are also lower per pound.

(3) The bans have three effects in theory: (1) Disposal costs for firm are increased. (2) Inventories decrease so waste is lower. (3) The externality associated with waste is reduced.

(4) In light of the above facts in (3), we can expect that waste levels, and the total externality associated with waste, will reduce. However, there are several likely unintended consequences of a ban:

(a) Firm profits will decrease (policy-marker probaby aware of this, but how to optimally trade off?)(Prices rise? Output decreased? Stockouts increase?)

(b) Consumer surplus will fall, particularly through:

(c) Stockouts will become more frequent.

(5) Theory also predicts that RM is the precisely optimal tool for ofsetting the effects of the ban. Indeed I show that a social planner would institute a tax/ban on food waste with perishable pricing or something.

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Edit this part, look at simulations for the above to get at nuances Q:

(a) First, I document fact (1), that waste and margins are high. I also retrieve estimates of actual disposal costs and the social costs of waste.

(b) I then find estimates of how disposal costs and the social costs of waste change under a ban.

(c) I estimate consumer preferences, and given the firm production process, I estimate what would happen to profits, CS, and TS if a food waste ban were implemented in Wisconsin.

(d) Finally, I simulate a counterfactual RM pricing during a ban to show that the TS lost can be mitigated, while waste exteranlitiy is still reduced.

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(5) come up with intiution on how to break down TS and CS

(4) run all simulations to get intution and use

(4.3) program social planner and do (4) again, look at policy functions

(4) update code to include an arbitrary number of days w / replenishment

(4.5) retype abstract and send to JP with visualizations, show replenishment vs. not policy fxns etc.

(5) make code general to more than 2 weekdays, use interpolation for states and prices

(6)

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1 Introduction

■ In the last five years, the concept of "food waste" has garnered increased policy-maker and media attention, primarily due to the need for more sustainable economic practices. Firms have just begun experimenting with electronic price tags to manage yields, and governements have proposed and enacted legislation banning food waste altogether, some of which becomes active in 2017.

In this paper, I explore the consequences of a grocery retailer employing revenue management (RM). Furthermore, I examine both theoretically and empirically the prospect of using RM as a potential solution to food waste, in particular, one that serves as a complement to a food waste ban. I use stylized models to illustrate what might happen to quantities, prices, allocations, waste, consumer surplus, profits, and stockouts. The profitability of RM has been well studied in the operations and management science literature, but there has been limited research on outcomes economists and policymakers might care about, such as the allocation of perishable resources, effects on total welfare, and equilibrium waste. I also contribute to the industrial organization literature on price discrimination and pricing under uncertainty by developing several welfare results.

First, I examine the deterministic setting of a monopolist setting either a static or dynamic price for multiple independent temporally-distinct markets. I demonstrate that when capacities are very small, in the deterministic case, static pricing is socially optimal. I then illustrate the necessary (or sufficient) conditions for static pricing to be pareto inefficient, and show that when these hold, a monopolist can improve profits while keeping consumer surplus at least as high under RM.

I then turn to the second benefit of RM, pricing with uncertain demand. I develop a series of three stylized models. In each, I show the necessary conditions for RM to result in (a) a decline in optimal waste (b) an increase in total surplus, and (c) a pareto improvement. I first show that while in the deterministic, limited capacity case, static pricing is socially optimal, this is no longer true in the case of uncertain demand. I then [results].

The above results have the element in common that they depend on the shape of the various demand curves and the coefficient of variation in the uncertainty, which dictates new prices and outputs that must be tested empirically. I then turn to individual time-stamped purchase data from a major midwestern grocery company and esimate demand. I find evidence of substantial within-day and within-week temporal heterogeneity, indicating that within a day, firms are typically overpricing and sometimes under-pricing, absent menu costs. Using a realistic, dynamic firm pricing and inventory model that incorporates aspects of both heterogeneous consumers and demand uncertainty, I calculate the above outcome changes for the grocer if it were to price with RM. I find that [results].

Finally, I simulate how these outcomes change as a function of disposal costs, which in essence mimic a ban or a tax on food waste. There is an inherent conflict between the policy-makers' goal of food waste reduction and a social planners' goal of maximizing total surplus. I find that while bans reduce waste, it comes at the expense of total surplus [results]....When the firm engages in RM in a ban, this actually [results].

The implication of these results is that RM will be especially useful as the externality of organic waste becomes more socially-optimally priced. Secondly, I document substantial time-varying demand, some of which is within person, revealing a new aspect of demand for marketers to consider targeting. Furthermore, in line with the price discrimination literature in IO, the uncertainty results suggest that the welfare results of dynamic pricing are often ambiguous, and must be tested, ideally in the field.

This paper is divided into 6 sections. Section 1 reviews the related existing literature. Section 2 presents the models, both the stylized and complete firm models. Section 3 gives background, institutional details, and summarizes the data. Section 4 discusses demand estimation and the results of the simulations and counterfactuals. Section 5 concludes.

1.0.1 Related Literature

■ This paper focuses on revenue management, which is defined as, "a variable pricing strategy based on anticipating and influencing consumer behavior in order to maximize revenue or profits from a fixed, perishable resource (such as airline seats or hotel room reservations or advertising inventory)." (Netessine and Shumsky 2002) [14]. There are two primary benefits of conducting RM: (1) the adjustment of prices in response to statitstical fluctuations in demand and inventory levels and (2) third-degree price discrimination (particular when capacity is constrained). The operations research literature tends to focus primarily on solving the optimal policy function for revenue maximization under a variety of taxonomies[1] (e.g. finite horizon, no replenishment, multiple variants). Gallego and Van Ryzin (1994) [11] is the seminal paper that derives useful comparative statics, which provided indications of the most profitable conditions for RM over static pricing. The limitation of this literature is that it tends to focus on profitability as the primary outcome, rather than distribution, waste, or total welfare, which are of concern to most economists. One noteable exception is McAfee and Velde (2008) [12], which looks at the welfare implications of a monopolist practicing RM. However, their results depend upon the assumptions of constant elasticity of demand. Still, useful results apply from the RM literature, since profit improvement is a necessary condition for the firm to implement dynamic pricing. The model I discuss in section 3 is perhaps most similar to that of Bitran and Mondschein (1997) [2]. Notably, they allow demand to follow a nonhomogenous Poisson process where realized consumers have unit demand, which can be drawn from a general, nonstationary distribution. However, their model has only one season and does not allow replenishment of inventory, which is a critical feature of the retailer's problem. Additionally, they do not investigate the interaction of uncertainty and nonstationarity in demand. Since I answer an empirical question, I model the reality of nonstationary unit demand with substantial consumer heterogeneity.

This paper is also related to literature on welfare effects of third degree price discrimination with deterministic demand. Since one of the primary benefits of RM is the ability to price discriminate (in par-

[1] See Weatherford and Bodily (1992) [23], Bitran et al (2003) [1], and Talluri and Van Ryzin (2006) [21] for excellent extensive surveys and reviews.

ticular, when capacity is limited), examining the welfare results of this literature sheds insight on the effects dyamic pricing might have. Schmalensee (1981) [19] documents that in the capacity unconstrained, deterministic monopolist setting, price discrimination across multiple markets can only improve welfare if output increases enough to offset the inefficiency of using multiple prices, which depends on the curvature of the demand curves. Varian (1985) [22] offers bounds on welfare changes with imperfect price discrimination which are useful because they do not require firm profit maximization. Chiang and Spatt (1982) [4] derive more "ambiguity" results in the case of consumer heterogeneity and finite types: imperfect price discrimination by a monopolist can result in a pareto improvement over the single monopolist price. I am concerned with the welfare effects of implementing RM, and finding a pareto improving dynamic pricing policy is sufficient to show that static pricing was suboptimal. Chintagunta et al. (2003) [5] examine the welfare effects of imperfect price discrimination across multiple markets (zone-pricing vs store-level). They find that price discrimination (pricing at the store level) improves profit for the retailer, even when it is constrained to implement a pareto improving policy. These papers, however, ignore costly capacity and uncertainty, and some of their conclusions do not hold in these settings, as I show in the Section 3. Additionally, in the case of uncertainty, it will be important to account for the equilibrium amount of perished product, as the policies are primarily concerned with the externality of waste.

Finally, there is also a stream of literature in industrial organization that focuses on a monopolist pricing with uncertainty and costly capacity. Prescott (1975) [15], Dana (1999) [7], and Dana (2001) [8] explain the use of multiple prices when a firm faces costly capacity and price pre-comittment. While they use this to explain airline RM, that is only part of the story, since it omits the possibility of pricing for a subsequent period based off of realized, remaining inventory. Rather, this explains why inventory should optimally increase in price as it depletes. Closer to the RM problem is Meyer (1975) [13], which considers imperfect price discrimination with capacity constraints across multiple temporal markets, but with uncertainty. However, this still falls short of the RM situation, which provides the firm the option to change prices based off of realized demand (and thus remaining inventory) in early periods. On the empirical side, perhaps most similar to this paper is Williams (2013) [24], who constructs a model that precisely takes into account uncertainty, perishability, and price discrimination in the context of airline pricing.

2 Models

■ In this section, I first outline the welfare results of dynamic pricing that arise from third degree price discrimination. I then move on to discuss welfare, allocation, and waste changes that arise from using dynamic pricing to address uncertainty. I then attempt to combine them to illustrate the interactions between the two on the above outcomes. In each of these sections, I offer conditions for which the firm can implement a pareto improving policy (for reasons discussed in section 2).

Finally, I develop a model of the firm's pricing and inventory decisions that incorporates uncertainty, time-varying demand, stockout costs, and disposal costs. The final model will be solved numerically using dynamic programming methods rather, as the combination of these components renders it analytically intractible.

2.1 No Uncertainty, Limited Capacity

The operations research consensus is that the "first-order" effect of revenue management is allocating a scarce resource across heterogeneous demand curves (Talluri and Van Ryzin 2006) ([21].) In the imperfect price discrimination literature, we typically think of geographic or exogenously identifiable (student or senior discounts) markets, but in the case of perishable groceries and nonstrategic consumers, it makes sense to think of distinct temporal markets.[2]

To see this price discrimination effect, consider the monopolist solving the following deterministic allocation problem. The firm faces independent demands given by $Q_1(p)$ and $Q_2(p)$, which are continuously differentiable and strictly decreasing. Without loss of generality, assume $p_1^m > p_2^m$. Additionally, demand function is bounded above and below, and for high prices, demand tends to 0, $\inf_p Q_i(p) = 0$. The revenue functions are striclty concave, and the marginal revenue function is strictly decreasing. The inverse demand functions are $p_i(Q)$.

The firm has a maximum capacity of C units to sell. While of course in a repeated problem the monopolist would select $C = Q_1(p_1^m) + Q_2(p_2^m)$, this model serves to illustrate the effect of RM given an exogenous capacity outside of the firm's control. This will occur of course in reality as demand is uncertain, and sometimes remaining inventory is low or high at any given pricing decision. This model serves to demonstrate the effect of RM *distinct* from uncertainty however, which is why it is deterministic in this section. For example, if a firm is able to engage in dynamic pricing and it finds itself with very low inventory early in the sales cycle, then this RM effect will be meaningful. Furthermore, if a waste ban reduces optimal inventory levels, then it is possible it might be optimal to stockout more frequently.

The resource is perishable, and the firm must pay k to produce each unit. For simplicitly, let $k = 0$ in this setting. Let p_i is the price of the product in market i. Let $p_{i,max}$ = the price in market i that results in 0 demand, or the maximum of feasible prices.

The firm must set p_1 and p_2 to maximize total profit:

$$\Pi = p_1 Q_1(p_1) + p_2 Q_2(p_2)$$
$$s.t.\ Q_1(p_1) + Q_2(p_2) \leqslant C$$

[2] One can assume independent markets as long as prices do not change sufficiently so that they elicit a large strategic response. This reasoning holds for geographic markets as well.

2.1.1 Profit Maximizer

Case 1: Large C: $Q_1(p_1^*)+Q_2(p_2^*) < C$**,** $Q_1(p_0^*)+Q_2(p_0^*) \leqslant C$**,** That is, capacity does not bind in the RM pricing policy. Then the welfare results of moving from static pricing to dynamic pricing (multiple prices) are well known from Schmalensee (1981) [19] and Varian (1985) [22]. It is necessary but not sufficient that total output increases for $\Delta W > 0$. It is sufficient for welfare to increase if $p_1(Q(p_1)-Q(p_0))+p_2(Q(p_2)-Q(p_0)) > 0$.

Whether total output expands depends on the curvature of the demand curves in the strong ($p_i^* \geqslant p_0^*$) and weak ($p_i^* \leqslant p_0^*$) markets, and thus ultimately an empirical question.

Case 2: Very Small C: $Q_1(p_1^*) + Q_2(p_2^*) = C$**,** $Q_1(p_0^*) + Q_2(p_0^*) = C$**,** If capacity is binding in both the static and dynamic pricing setting, then total welfare will decline, a result pointed out by Robinson (1933) [16]. If output cannot expand, but multiple prices are used to achieve the same output, then marginal valuations diverge across markets, which has a negative effect on social welfare due to allocative inefficiency (though profit will still weakly increase). That is, the "wrong" types are getting the scarce resource. Thus, RM is socially inefficient in the low-capacity deterministic setting.

Case 3: Intermediate C: $Q_1(p_1^*) + Q_2(p_2^*) = C$**,** $Q_1(p_0^*) + Q_2(p_0^*) < C$**,** That is, capacity does not bind if the firm uses one price, but when the firm is allowed to use two prices, output expands but *only* to the point at which maximum capacity is reached. The Varian bounds apply here, so as output expansion is sufficiently large and not too limited by capacity, welfare might increase [Would like to say something more specific here than just Varian results. I think probably some form of Schmalensee 1981 applies but perhaps the result is not very interesting.]

RM Profitability It is also important to answer the question of when RM is most profitable. For example, consider $f(C; Q_1, Q_2) = \Pi^{RM}/\Pi^{Static}$. Under what conditions is $\dfrac{\partial f}{\partial C}$ negative? Does that depend on Q_1 and Q_2 's shape? [Results]

RM and Consumer Surplus When the firm is profit maximizing and capacity is more or less binding, can we say anything about how much consumers are hurt by the firm's decision to engage in dynamic pricing? That is, let $g(C; Q_1, Q_2) = CS^{RM}/CS^{Static}$. Under what conditions is $\dfrac{\partial g}{\partial C}$ negative? and how does that depend on Q_1 and Q_2 's shape? [Results]

RM and Consumer Surplus Finally let $h(C; Q_1, Q_2) = W^{RM}/W^{Static}$. Under what conditions is $\dfrac{\partial h}{\partial C}$ positive? and how does that depend on Q_1 and Q_2 's shape? [Results]

2.1.2 Pareto Optimality

A firm might not want to be strictly short-term profit maximizing if it results in stealing consumer surplus. Consumer surplus can be thought of as a metric of consumer satisfaction and value, and omitted margins (e.g. competition) might mean the monopolist model over-estimates the true effect of RM on firm profits. If the firm can increase profits without stealing consumer surplus, then it is pareto improving, indicating that a single price across time is *pareto inefficient* and not socially optimal. Consider the cases of nonzero capacity (marginal, since no uncertainty) costs k.

That is, the firm can solve the following problem:

$$\Pi^{cs} = (p_1 - k)\, Q_1(p_1) + (p_2 - k)\, Q_2(p_2)$$
$$Q_1(p_1) + Q_2(p_2) \leqslant C$$
$$\sum_{i=1}^{2} \left(\int_{p^i}^{p*} [Q_i(s_i)]\, ds_i \right) \geqslant 0$$

Where $p*$ is the solution to the above statically priced profit-maxizing problem. The firm, rather than employ monopoly prices, will shade its prices in each market to conserve consumer surplus but still increase profits. It will do so in such a way that the firm will efficiently trade off welfare against profit. Consider the lagrangian:

$$\mathcal{L} = (p_1 - k)\, Q_1(p_1) + (p_2 - k)\, Q_2(p_2) + \lambda(C - Q_1(p_1) - Q_2(p_2)) + \mu \left(\sum_{i=1}^{2} \left(\int_{p^i}^{p*} [Q_i(s_i)]\, ds_i \right) \right)$$
$$= Q_i(p_i) + (p_i - k)\, Q_i'(p_i) - \lambda Q_i'(p_i) - \mu(Q_i(p_i))$$

Resulting in the optimal price

$$\frac{k + \lambda}{(1 + (1 - \mu)\frac{1}{\epsilon_i})} = p_i^{*cs}$$

The standard monopoly price is $p^m = k\frac{1}{(1 + \frac{1}{\epsilon})}$.

Here, the monopolist prices higher when capacity is binding, and lower due the CS constraint binds (if $0 < \mu \leqslant 1$ (proof?) Find relation between λ, μ). The surplus constrained monoplist will set prices so that

$$
\begin{aligned}
p_1 + (1-\mu)\frac{Q_1(p_1)}{Q_1'(p_1)} &= p_2 + (1-\mu)\frac{Q_2(p_2)}{Q_2'(p_2)} \\
(p_1 - p_2) &= (1-\mu)\left[\frac{Q_1'(p_1)Q_2(p_2) - Q_2'(p_2)Q_1(p_1)}{Q_2'(p_2)Q_1'(p_1)}\right] \\
(p_1 - p_2) &= (1-\mu)\left[\epsilon_2 p_2 - \epsilon_1 p_1\right] \\
p_1(1+\epsilon_1 - \mu\epsilon_1) &= p_2(1+\epsilon_2 - \epsilon_2\mu) \\
\frac{p_1}{p_2} &= \frac{(1+\epsilon_2-\epsilon_2\mu)}{(1+\epsilon_1-\epsilon_1\mu)}
\end{aligned}
$$

When capacity is binding, $\mu = 1$. [Prove...]

Since $\Delta CS \geqslant 0$, we are guaranteed a pareto improvement if the monopolist would choose to use multiple prices rather than one price. In this case, it is sufficient to identify the conditions for which $p_1^{*cs} \neq p_2^{*cs}$. The monopolist can always create a pareto improvment using multiple prices as long as capacity is not binding and $\epsilon_1 \neq \epsilon_2$. Thus, in the case of identical marginal cost, deterministic, time-varying demand with capacity constraints, a pareto improving policy always exists when capacity is slack, and the above outlines how the constrained monopolist achieves it.

2.2 Uncertain Demand, Limited Capacity, Perishability

In reality, however, demand is stochastic. As such, it is important to see to what extent the above results still hold when demand is uncertain. First, I review the case of stochastic, stationary demand with exogenous capacity (and initial inventory here) C, for the same reason as in the previous section. Talluri and Van Ryzin (2006) [21] set up this problem fairly generally and derive useful results and intuition. I borrow their notation to review their results here, and extend them to welfare implication and waste implications. I then extend the model to optimize over initial inventory, and compare the static and dynamic pricing policies. I consider welfare maximizing prices and the sufficient conditions for the existence of a pareto improving policy.

2.2.1 Exogenous Inventory, Uncertainty, Stationary Demand:

Profit Maximizer without disposal costs Assume one shopper per period arrives, and that her demand is given by $d(p,t) = (1 - F_t(p))$, where $F_t(p)$ is the probability that her reservation price is less than p. For now, assume time-invariant demand: $F_t(p) = F(p)\forall t$. Suppose the firm is making discrete pricing decisions until period T, after which all inventory perishes. Let x be remaining inventory to sell, The Bellman equation is thus

$$
\begin{aligned}
V_t(x) &= \max_{d \geqslant 0} \left[d\left(p(d) + V_{t+1}(x-1)\right) + (1-d)V_{t+1}(x) \right] \\
&= \max_{d \geqslant 0} \left[r(d) - d\left(V_{t+1}(x) - V_{t+1}(x-1)\right) + V_{t+1}(x) \right]
\end{aligned}
$$

With boundary conditions

$$
\begin{aligned}
V_t(0) &= 0 \forall t \\
V_{T+1}(x) &= 0 \forall x
\end{aligned}
$$

Then first order condition with some regularity conditions gives:

$$
\frac{\partial r(d)}{\partial d} = V_{t+1}(x) - V_{t+1}(x-1)
$$

which says that the marginal revenue equals the marginal opportunity cost of capacity, so that the firm trades off the decision to sell one unit now with the option value of keeping that unit to sell next period. Talluri and Van Ryzin (2006) [21] prove that the marginal opportunity cost of capacity is decreasing in t and x. Suppose marginal revenue curve is strictly decreasing. Then:

1. $p*(t, x)$ falls over time for a given level of inventory.
2. $p*(t, x)$ rises as inventory depletes for a given time.

The intuition is as follows: (1) If a firm has more inventory to clear for a given time period, it will have a lower price because it has less of a chance to sell it all before it perishes. (2) If a firm has more time to sell a given amount of inventory before it perishes, it is optimal to price higher because the probability of the inventory going unsold decreases the longer time left, and as a result, the firm can use price more aggressively in hopes that they collect more sales with high WTP consumers.

The above assumed, however, that the marginal revenue curve is static over time. Suppose now that $r(d, t)$ changes over t. The gains to dynamic pricing can increase if the chage in the marginal revenue curve compound with the effects of uncertinaty. For example, that $\frac{\partial^2 r(d,t)}{\partial d \partial t} < 0$, the in the deterministic setting, price will fall over time, and in the stochastic setting these effects compound. Alternatively, these effects could offset if marginal revenue were increasing over time, thus rendering static pricing close to optimal.

[Comparative statics: Show show $\Pi^{RM}/\Pi^{static}, CS^{RM}/CS^{static}, TS^{RM}/TS^{static}$ change as a function of C, indicating the general effects of a food waste ban.]

When calculating total welfare with a model of uncertainty, consumer heterogeneity, and finite capacity, it is necessary to to assume a form of rationing. The two standard models of rationing are parallel rationing (allocated in order of highest willingness-to-pay) and proportional rationing (conditional on reservationg price $> p$, consumers are equally likely to receive the unit.) In the context of a grocery store practicing RM, I argue that proportional rationing clearly makes sense.

Welfare Maximizer without disposal costs or stockout costs Switch to latent utility framework to consider consumer surplus. Consumer has logit demand, then

$$\begin{aligned} CS(p) &= \frac{\mathbb{E}\left[\max\left\{\epsilon_0, \mu - \alpha p + \epsilon_1\right\}\right]}{\alpha} \\ &= \frac{1}{\alpha}\log\left(\exp\left(\mu - \alpha p\right) + 1\right) \end{aligned}$$

$$\begin{aligned} W_t(x) &= \max_{d \geqslant 0}\left[d\left(p(d) + W_{t+1}(x-1)\right) + (1-d)W_{t+1}(x) + \frac{1}{\alpha}\log\left(\exp\left(\mu - \alpha p\right) + 1\right)\right] \\ &= \max_{d \geqslant 0}\left[r(d) - d\left(W_{t+1}(x) - W_{t+1}(x-1)\right) + W_{t+1}(x) + \frac{1}{\alpha}\log\left(\exp\left(\mu - \alpha p(d)\right) + 1\right)\right] \\ \frac{\partial r}{\partial d} &= \left(W_{t+1}(x) - W_{t+1}(x-1)\right) - d \cdot p'(d) \\ p(d) &= \left(W_{t+1}(x) - W_{t+1}(x-1)\right) \end{aligned}$$

The last second term on the left-hand side of the third line is the amount of consumer surplus gained that is gained by increasing quantity sold (by lowering price) an infinitesimal amount, which is thus positive. As such, the social planner would want to set price equal to the marginal opportunity cost of capacity. This intuitively makes sense, and is a form of marginal cost pricing. The value function contains the surplus created from transacting, and it declines over time since there is less likely a given amount of inventory will be sold (particularly to a high reservation type person). Thus, marginal cost is essentially from the perishability, and this is the socially optimal way to price waste.

Profit Maximizer with disposal costs In this section I show how the profit maximizer would price, given an increase in disposal costs. I show that as disposal costs increase, optimal prices for a given t, x are fall. This is of course because the firm seeks to end up with less inventory at the end.

$$
\begin{aligned}
V_t(x) &= \max_{d\geqslant 0}\left[d\left(p(d)+V_{t+1}(x-1)\right)+(1-d)V_{t+1}(x)\right] \\
&= \max_{d\geqslant 0}\left[r(d)-d\left(V_{t+1}(x)-V_{t+1}(x-1)\right)+V_{t+1}(x)\right]
\end{aligned}
$$

With Boundary conditions now

$$
\begin{aligned}
V_t(0) &= 0\forall t \\
V_{T+1}(x) &= \gamma_D x \ \forall x
\end{aligned}
$$

Where $\gamma_D < 0$ would be a "disposal cost", and $\gamma_D > 0$ would be a "salvage" or "scrap value."

Welfare Maximizer without disposal costs The firm could certainly improve social welfare at the expense of its own profit, as shown in the welfare maximizing section. However, under what conditions can the firm improve

$$
\begin{aligned}
CS(p) &= \frac{\mathbb{E}\left[\max\left\{\epsilon_0, \mu-\alpha p+\epsilon_1\right\}\right]}{\alpha} \\
&= \frac{1}{\alpha}\log\left(\exp\left(\mu-\alpha p\right)+1\right)
\end{aligned}
$$

$$
\begin{aligned}
W_T(x) = &\max_{d\geqslant 0}\left[d\left(p(d)-\gamma_D(x-1)\right)-(1-d)\gamma_D x+E[CS]\right] \\
&r(d)+d\gamma_D-\gamma_D x+E[CS] \\
&=\max_{d\geqslant 0}\left[r(d)+d\gamma_D+\frac{1}{\alpha}\log\left(\exp\left(\mu-\alpha p(d)\right)+1\right)\right] \\
&p=\gamma_D \\
W_{T-1}(x) = &\max_{d\geqslant 0}\left(r(d)+d\left(W_T(x-1)-W(x)\right)\right)+W_T(x)+E[CS]\Big]
\end{aligned}
$$

Normally at the last period you would drop price to 0 to sell to the last guy, here you would drop price below 0 to get rid of it. The marginal cost of selling is negative, because it *avoids* a cost from not selling.

2.2.2 Endogenous Inventory, Uncertainty, Stationary Demand:

When the firm is able to adjust prices, this also changes the initial inventory decision. Given the option to change prices, it can be shown that optimal initial inventory will increase. It is not obvious, however, whether optimal expected waste will increase (either by magnitude or by proportion).

Profit Maximizer without disposal costs [Again Comparative statics]

Profit Maximizer with disposal costs [Again Comparative statics]

CS Constrained Profit Maximizer without disposal costs [Again Comparative statics]

CS Constrained Profit Maximizer with disposal costs [Again Comparative statics]

2.2.3 Simulation: Interaction of Time-Varying WTP and Uncertainty

In this section I simulate optimal waste, CS, TS, and profits while performing comparative statics of capacity, extent of nonstationarity in demand (and shape), and amount of uncertainty. I show [results].

2.3 Final Firm Model

The firm's model incorporates the realistic elements faced by the actual grocery chain. Consider a monopolist selling a single[3] product over T periods (dayparts*days), with the option of replenishment every $K + 1$ periods. The problem is to find a policy function that consists of an optimal reorder quanity and price, conditional on current states of inventory vector $\boldsymbol{I}$, weekday w, and daypart d_k. Consumers arrive according to a nonhomogenous Poisson process and have unit demand with a stochastic reservation price so that their probability of purchase is $1 - F_t(p; \Theta)$, as in Bitran and Mondschein (1997) [2], where Θ is the household's preferences. Since products have shelf-lives longer than 1 day, the firm will have multiple vintages in the inventory, so I must allow assume a drawdown method. Depending on the category, inventory is either drawn-down either FIFO (first-in-first-out) or LIFO (last-in-first-out). Bread, which is behind the counter, could be drawn down FIFO if the firm prefers, while fresh cut pineapple is out on display for consumers to pick whichever vintage they prefer. Additionally, as mentioned, the rationing method is *proportional*, so that if a stockout occurs, the consumers who are simulated to purchase are equally likely to obtain the product.

The three potential price paths I will consider are static pricing, monotonically declining, and unconstrained. I consider monotonically declining price path because past literature (Bitran and Mondschein (1997) [2]) has shown that imposing monotonicity often very closely approximates the flexible path, and it also is realistic to assume the firm would mark down inventory, rather than ever mark it back up due to depletion. I can compare outcomes of such a constraint ex post in the estimation section. Additionally, the

[3] Whether or not I consider multiple products depends upon the substitutability of products and the computational feasibility. The model below can be extended to matrix notation for the case of multiple products.

firm may change price up to K times per day (resulting in $K+1$ periods per day). Let d_k be the kth part of the day at which a firm makes a decision. The maximum amount of inventory the firm may have at a given time is N.

Below I outline the sequence of events:

1. If $d = 1$, new inventory can be produced according to the firm's choice, else go to 2.
   (a) Capacity costs c is paid for the additional units ordered.
2. Firm picks a price for the daypart.
3. The set of potential buyers arrives.
4. These buyers make a discrete choice (buy among the products, or pick the outside option), with a firm capacity constraint.
5. Inventory is drawn down over vintages (FIFO or LIFO) within a product, and stockouts are rationed.
   (a) If stockout occurs, firm pays stockout cost γ_S.
6. If $d = K + 1$, see below, else go to 6.
   (a) Remaining inventory decays.
   (b) w (the day, which is important for measuring demand intensity (and potentially Θ_t)) changes over.
   (c) If there is any waste (inventory that now has reached T_p days since production), then this waste is disposed of at cost γ_D per unit.
7. The day-part moves to next day part.
   (a) Unless it is the end of finite horizon and we are at T, in which case all inventory is discarded (at cost γ_D per unit) and the process terminates.

Having established the order of events, I now define additional terms and setup the Bellman equation. For the static and down-price constrained paths, let the statespace be given by $\mathcal{X} \equiv \{\mathcal{I}, d, w, \mathcal{P}\}$ (Since the unrestricted price path has no constraints on price, I do not need to keep track of it in the state space, so $\mathcal{X} \equiv \{\mathcal{I}, d, w\}$). Let $\mathcal{I}$ be the set of feasible inventory matrices:

$$\boldsymbol{I}_{1\times T_h} = \begin{pmatrix} I_1 & I_2 & \dots & I_{T_p} \end{pmatrix} \in \{\boldsymbol{I} : \sum_{\tau=1}^{T_p} I_\tau \leqslant N\}$$

where inventories decay to the left (so $I_{j,1}$ is set to become waste at the end of the day), $d \in \{d_1, ..., d_K\}$ be the current day-part, $w \in \{1, 2, ..W\}$ be the current weekday, and for static price $p \in \{p : \in [p_l, p_u], \ p_{d+1} = p_d \ \ \forall d\}$ and for down-price: $p \in \{p : \ p \in [p_l, p_u], \ p_{w,d+1} \leqslant p_{w,d} \ \ \forall w\}$ be the set of feasible prices last period.

Let $\lambda_{t,w}$ denote customers' arrival rate for the nonhomogenous-Poisson process at time t on day w, which will be estimated using maximum likelihood (see esimation section.) The arrival intensity is a continuous function, so we must get the mean arrival intensity $\lambda_{d,w}$ by letting $\lambda_{d,w} = \int_{d,w} \lambda_t dt$. Also, call $I_{tot} \equiv \sum_\tau I_\tau$

The Bellman equation for the profit-maximizing monopolist The firm chooses a new inventory $\boldsymbol{I}'$ from it's feasible set (which is the singleton $\boldsymbol{I}$ if $d_k \neq 1$) and prices $\boldsymbol{p}$ each decision period:

$$\begin{aligned} V_t\left(\boldsymbol{I}, d, w, p_{last}\right) = \max_{\boldsymbol{I}' \in \mathcal{Q},\, p \in \mathcal{P}} \mathbb{E}_q \Bigg[& p \cdot \min\left\{I_{tot}, q\right\} - \left[\mathbb{I}_{\{d=d_1\}} c \cdot I_{T_p}\right] \\ & + \left[\gamma_S \cdot \max\left\{q - I_{tot}, 0\right\}\right] + \left[\gamma_D \cdot \mathbb{I}_{\{d=d_K\}} I_1\right] \\ & + V_{t+1}\left(g\left(\boldsymbol{I}', \min\left\{I_{tot}, q\right\}\right), d+1, w', p\right) \Bigg] \end{aligned} \tag{1}$$

With the boundary condition:

$$V_{T+1}\left(\boldsymbol{I}, d, w, p\right) = 0 \ \forall \mathcal{X}$$

Where $q = q\left(p, n, \Theta\right)$, and n is the number of customer arrivals, Θ is the preference draw, and q is the sum of individual multinomial draws of the n consumers, as discussed in the consumer model below. Note also that the action space on $\boldsymbol{I}'$ is not only constrained by the maximum capacity, but also by whether or not it is the replenishment period, and only the vintage with T_p days left until expiration may be restocked.

The first term of the Bellman equation represents revenue from sales that period. The second term is production costs, paid only when inventory can be produced. The third term is stockout costs, and the fourth term is disposal costs, to be paid only on the final period of the day and if there is perished inventory. Finally, the last term is the continuation value, where $g(\cdot, \cdot)$ is the FIFO or LIFO decay function that takes in the current inventory-vintage vector and the total demand.

The state space transitions as follows:

Day part changes:

$$\begin{aligned} d_i &= d_{i+1}, \quad \forall i < K \\ d_i &= d_1 \text{ if } i = K \end{aligned}$$

Inventory decays:

$$I_\tau = \begin{cases} I_{\tau+1} & \forall \tau < T_p \text{ if } d = d_K \\ 0 & \tau = T_p, \text{if } d = d_K \\ I_\tau & \forall \tau \text{ if } d \neq d_K \end{cases}$$

Day of the week changes:

$$\begin{aligned} w_i &= w_{i+1}, \;\; d = d_K \\ w_i &= w_i \quad , \quad \text{else} \end{aligned}$$

Price of last period, if price constraint is static: $p' = p$, and if the constraint is monotonic decline:

$$\begin{aligned} p' &= p \text{ if } d \neq 1 \\ p' &= p_{MAX} \text{ if } d = 1 \end{aligned}$$

I discuss how I operationalize the estimation procedure in section 4, including how I take expection over arrivals, preferences, and purchase decisions.

Caveats The above model has endogenous inventory for a given exogenous capacity. While it is true that current shelf space costs are sunk, there is still an opportunity cost of capacity. Consequently, to capture the true profit and welfare effects, it might make more sense to consider a model for which the firm initially optimizes over capacity $C^* \leqslant C$, and any unused capacity $C - C^*$ earns its opportunity cost. For now, I omit this until further discussion. Ultimately, it should not be too difficult to perform the outer optimization, but measuring the opportunity cost of capacity for the firm and consumers might prove trickier. Furthermore, if one is willing to take the stance that the firm is producting the optimal static price inventory, then absent a ban, the optimal initial inventory should increase under RM, since price can be used to manage demand perturbations. (Proven in RM paper?)

The Pareto Improving Policy The pareto improving policy will be found by taking into account that expected consumer surplus must be at least as high as in the static setting. To operationalize this, I fist calculate expected consumer surplus under the optimal static pricing plan[4]:

$$CS^{\text{static}} = \mathbb{E}_{n,\Theta,H,I}\left[\sum_{w=1}^{W}\sum_{d_k=1}^{K}\sum_{h=1}^{H}\left(\mathbb{I}_{\{\sum_\tau I_\tau > 0\}}\right)\frac{\left[\ln\left(\exp(\beta_h + p_t\alpha_h + x_t'\gamma_h)\right) + 1\right]}{-\alpha_{h,t}} + \gamma + \mu\right] \tag{2}$$

[4]This assumes that $\epsilon_{j,h,t} \sim$ (GEV) Type 1 distribution with location parameter $\mu = 0$ and scale parameter $\beta = 1$.

where γ is the Euler-Mascheroni constant, μ is the location parameter of the disturbance term, $\mathbb{I}_{\{\sum_\tau I_\tau > 0\}}$ is an indicator for whether there is any inventory left, $\alpha_{h,t} = \alpha_h$ + all time-varying characteristics interacted with price at time t (see below section for the modeling of preferences), and d_k and w are sufficient for the information contained in preferences in t. This shows that consumer surplus is the sum of the expected surplus from the arriving consumers over each daypart and weekday.

To implement the constrained optimization problem, the firm solves the constrained problem:

$$\begin{aligned} V_t\left(\boldsymbol{I}, d, w, p_{last}\right) = \max_{\boldsymbol{I}' \in \mathcal{Q},\ p \in \mathcal{P}} \mathbb{E}_q \Big[& p \cdot \min\left\{I_{tot}, q\right\} - \left[\mathbb{I}_{\{d=d_1\}} c \cdot I_{T_p}\right] \\ & + \left[\gamma_S \cdot \max\left\{q - I_{tot}, 0\right\}\right] + \left[\gamma_D \cdot \mathbb{I}_{\{d=d_K\}} I_1\right] \\ & + V_{t+1}\left(g\left(\boldsymbol{I}', \min\left\{I_{tot}, q\right\}\right), d+1, w', p\right) \Big] \end{aligned} \tag{3}$$

$$\begin{aligned} \text{s.t.} \quad & V_{T+1}\left(\boldsymbol{I}, d, w, p\right) = 0 \ \forall \mathcal{X} \\ & CS^{\text{dynamic}} - CS^{\text{static}} \geqslant 0 \end{aligned}$$

Caveats I cannot use regular dynamic programming to solve this.

Possibilities:

1. Consider a state variable tracking cumulative $S_t = \sum_{i=1}^{t} CS_i$, and impose the end constraint as a terminal condition. This is a lower bound on profitability/pareto improvement (not a global search over policies).

$$\begin{aligned} V_t\left(\boldsymbol{I}, d, w, S, p_{last}\right) = \max_{\boldsymbol{I}' \in \mathcal{Q},\ p \in \mathcal{P}} \mathbb{E}_q \Big[& p \cdot \min\left\{I_{tot}, q\right\} - \left[\mathbb{I}_{\{d=d_1\}} c \cdot I_{T_p}\right] \\ & + \left[\gamma_S \cdot \max\left\{q - I_{tot}, 0\right\}\right] + \left[\gamma_D \cdot \mathbb{I}_{\{d=d_K\}} I_1\right] \\ & + V_{t+1}\left(g\left(\boldsymbol{I}', \min\left\{I_{tot}, q\right\}\right), d+1, w', S', p\right) \Big] \end{aligned} \tag{4}$$

$$\text{s.t.}\quad V_{T+1}\left(\boldsymbol{I}, d, w, S, p\right) = 0 \;\forall \mathcal{X}$$
$$S_{T+1} \geqslant CS^{static}$$

(a) With the extra transition: $S' = S + \sum_{h=1}^{H}\left(\mathbb{I}_{\{\sum_{\tau} I_{\tau} > 0\}}\right) \dfrac{\left[\ln\left(\exp(\beta_h + p_t\alpha_h + x_t'\gamma_h)\right) + 1\right]}{-\alpha_{h,t}} + \gamma + \mu$

(b) Solve this with backward programming, now we have a continuous variable S, use linear interpolation or splines.

2. Can try to use stochastic maximum principle, DP conditions are sufficient conditions, they are necessary, but it doesnt always give you sufficient conditions for a maximum. must optimize over an entire policy, need to look at optimality conditions on the entire policy, that also satisfy that constraint.

3. Relax constraint and solve relaxation of this problem

I compare the firm's dynamic pricing and inventory policies to the optimal static pricing and inventory policy, rather than the currently employed policy. Since the goal of the paper is primarily about revenue management and using prices to allocate the perishable item, it is of less interest to consider the benefits from reoptimizing their current static price and production decisions.

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2.4 Consumer Model of Demand

Consumers are assumed to be myopic and nonstrategic in response to dynamic pricing. This is a reasonable assumption in the situations relevant to this paper. First, it is costly for consumers to shop, and that this cost is large enough for most individuals such that it is not feasible to plan trips around expectations of dynamic prices on a few categories. That is, trip time is exogenous to price faced by a consumer. I futher justify this by limiting the state space of prices so as to not evoke outrage over "fairness", which in turn makes stategic planning even less worthwhile. Specifically, the simulations limit prices to fluctuate between sales of 30% and markups of 30%. On a $3 product, the price space is only [2.10, 3.9]. If the categories considered were a larger portion of the household budget, then it might be necessary to model consumer strategic response. Nevertheless, with the categories I use, it is likely not a problematic assumption.

2.4.1 Random Coefficients

The consumer h maximizes her utility at time t by choosing the product j such that $j = \arg\max_j(u_{h,j,t})$, where:

$$
\begin{aligned}
u_{h,j,t} &= \beta_{h,j} + p_{h,j,t}\alpha_h + x_t'\gamma_h + \varepsilon_{h,j,t} \qquad (5)\\
&\equiv V_{h,j,t} + \epsilon_{h,j,t} \ \forall j \\
u_{h,0,t} &= \varepsilon_{h,0,t}
\end{aligned}
$$

Where x_t' are various time characteristics (such as time trends interacted with price, taste) to be determined via model selection. Let $\beta_h = \begin{pmatrix}\beta_{h,1} & \ldots & \beta_{h,J-1} & \beta_h^{price} & \ldots & \gamma_{t_1}\ldots\end{pmatrix}'$ be the vector of household specific taste coefficients.

To obtain these household level parameters, I follow a bayesian estimation approach with the hierarchical model.

$$
\begin{aligned}
\mathcal{L}\left(\boldsymbol{y}|\boldsymbol{x}, \beta_1, \ldots\beta_H\right) &\propto \prod_{h=1}^{H}\prod_{t=1}^{T_h}\prod_{j\in J_t}\left(\frac{\exp\left(x_{jt}'\beta^h\right)}{1+\sum_{k=1}^{J_t}\exp\left(x_{kt}'\beta^h\right)}\right)^{y_{j,t}^h} \qquad (6)\\
\beta_1, \ldots\beta_H|\mu, \Sigma &\sim^{iid} \mathcal{N}_d\left(\mu, \Sigma\right)
\end{aligned}
$$

With the priors:

$$
\begin{aligned}
\mu|\Sigma &\sim \mathcal{N}\left(\mu_0, a^{-1}\Sigma\right)\\
\Sigma &\sim \mathcal{IW}\left(v_0, V_0^{-1}\right)
\end{aligned}
$$

Implying the graph:

$$
\begin{tikzcd}
(v_0, V_0) \arrow[r, dashed] & \Sigma \arrow[dr] \arrow[dd] & & \\
& & \beta^h \arrow[r] & \boldsymbol{y}_i \\
\left(\mu_0, a^{-1}\Sigma\right) \arrow[r, dashed] & \mu \arrow[ur] & &
\end{tikzcd}
$$

The estimation of this model proceeds as follows with MH within Gibbs MCMC See Rossi et al 2005 [17] for more details.

2.4.2 Consumer Welfare (for J products)

To measure consumer welfare, I use the concept of compensating variation (CV) with the results of Small and Rosen (1981)[20]. That is, the aggregate CV is the sum of individual CV's and if (1) the marginal utility of income is approximately independent of the prices, and (2) income effects are negligable, then

$$\Delta CS = \mathbb{E}_{n,H,\Theta^h}\left[\sum_{w=1}^{W}\sum_{d=1}^{K+1}\sum_{h=1}^{H} -\frac{\left[\ln\left(\sum \exp(V_{h,j,t}(p_t^{\text{dynamic}},\Theta^h))\right)\right]^{\text{New}} - \left[\ln\left(\sum_j \exp(V_{h,j,t}(p_t^{\text{static}},\Theta^h))\right)\right]^{\text{Old}}}{\alpha_{h,t}}\right] \tag{7}$$

This equation says that for each daypart for a given set of households, we calculate total expected consumer surplus across households under the dynamic price and subtract the total expected CS across HH's under the static price. We keep track of inventory and add surplus across all dayparts and the week. Then, we take expectation over the number of customers, the preferences of those customers, and the econometric uncertainty about their preferences Θ^h

Note that welfare can change due to (1) stockouts or (2) price changes, both of which might change after the firm reoptimizes due to (1) employing RM or (2) a food waste ban or (3) both. Additionally, both $V_{h,j,t}$ and $\alpha_{h,t}$ might be time varying parameters, which means RM might impact consumers differently depending on when they are in the store.

3 Background

■ As discussed, in the last five years, the concept of "food waste" has garnered increased policy-maker and media attention, primarily due to the need for more sustainable economic practices. The primary contributors to the increased concern have been climate change and food insecurity. In particular, the tremendous use of resources involved in the production of the world's food supply has contributed greatly to climate change through the emission of greenhouse gases (GHGs). The United Nation's Food and Agriculture Organization has determined that foodloss accounts for 3.3 gigatonnes of GHGs. To add some context, that would be more than one-third of all global emissions in 2014, and if food waste were a country, it would be the third largest emitter, after China and the United States ([10].) Furthermore, in 2015, 42.2 million Americans lived in food insecure households ([6]).

Consequently, there has been a resurgence in efforts to address the problem, most of which involve improving supply chain efficiency and collecting better data. With respect to grocery retailers[5] specifically, governments have begun to call for bans on food waste.

Food Waste Bans In typical food waste bans, firms are forced to contract recycling or donation services rather than use disposal, or face large penalties such a jailtime or hefty fines. France nearly passed such a ban, while California[6] has already begun implementing one, which enters full force in January 2017. Massachusetts was the first state to enact such a ban, beginning in 2014. The bans have the important consequences of

[5]Grocery strore food waste accounts for 10% of all food waste, totaling 13 billion pounds per year, or $10-15 billion excluding the GHG externality.

[6]AB-1826 Solid waste: organic waste.

potentially reducing grocery store inventory levels, which the USDA argues are suboptimally high due to firms not internalizing the externality of waste. Firms over produce from a social perspective because they compete not only on prices, but also product availability, however, this “high inventory” equilibrium is something policy-makers seek to change. (*cite report mentioning*) However, there is an potential conflict between the policy-makers’ goal of food waste reduction and a social planners’ goal of maximizing total surplus. An individual consumer prefers to have fully-stocked inventory, and in the event of stockouts faces a reduction in expected utility (and potentially further an unmodeled search cost). If a food waste ban causes firms to reduces inventories, stockouts might occur more frequently. Furthermore, in the presence of a ban, firm profits and consumer surplus might decrease more than the corresponding gain to society from lower waste levels.

Revenue Management There has been little effort directed toward helping retailers use prices to better manage their perishable inventories. Yet revenue management has a long, successful history of helping firms manage perishable assets in the presence of uncertain and time-varying demand, beginning with airlines in 1981, and moving to hotels and fashion retailers in 1990s. As demand data and technology for the implementation of RM improves, we have seen it applied in more settings and thus more relevant.[7] With bayesian demand estimation techniques and granular purchase data, I show that there is indeed an opportunity where there was not before. Indeed, there are already a few instances of firms in Europe experimenting with electronic price tags (which would facilitate RM), but these policies are still in the trial stages and not widely practiced. The viability of a variable pricing strategy increases as optimal inventories are lower, which would indicate such a practice would be a complement to a food waste ban.

Under certain circumstances, it might be particularly desirable for a retailer to adopt RM. Just as airlines are able to both manage capacity and segment business and leisure consumers, retailers may be able to simultaneously segment price-sensitive and price-insensitive consumers and reduce waste. If heterogeneous customers sort temporally, dynamic pricing can facilitate both third-degree price discrimination. Additionally, demand volatility, cost of stockouts, shelf-life of the product, and the replenishment process all affect the profitability and outcomes of dynamic pricing.

3.1 Data

The data originate from a partnership with Roundy’s, the parent company of several midwestern supermarket chains. I use data from both “Mariano’s” and “Pick ’N Save” chains. The database comprises four sources: (1) transaction-level data collected through shoppers’ loyalty cards, (2) SKU-level data tracking daily price by store, (3) shelf-life data for the perishable products, and (4) production process information (replenishment frequencies). These data are part of a series of projects resulting from a partnership between University of

[7]There were 3.6 times as many papers containing the term "dynamic pricing" in 2010-2013 as in 2000-2003 (Source: Google Scholar)

Chicago and Roundy's, including Bronnenberg et al [9] and Sanders [18]. (*NOTE*: remove these from JMP if unavailable by then..)

3.1.1 Loyalty Card Data

I have individual transaction-level data for across 12 categories. The data span from July 2010 to March 2015. Mariano's consists of 70,635,896 transactions time-stamped by day, hour, and minute, with 1,329,900 unique customers I.D.'s across 29 stores. Pick 'N Save, the larger of the two chains, consists of 102,388,139 transactions with 4,574,551 unique customers across 116 stores. Of the 12 categories, 9 are perishable and 3 are shelf stable: bakery bread, bakery cookies, bakery desserts, donuts, bakery brownies, bakery coffee cake, fresh berries, fresh cut pineapple, greek yogurt, and shelf stable cookies, ice cream (pint) and ice cream (48oz). The purchase data contains a household loyalty card number, the quantity of each product purchased, the net (of discounts) price paid, the trip date and time (to the minute), the unique store number, and product per-unit cost.

3.1.2 Store-Level Data

I also obtained a store-level database tracking prices for each of the UPCs, with the exception of fresh berries. However, fresh berries are sold nearly every day, so for this category I recover prices from the loyalty card data set. The data at the location-product-date level are from 150 stores, 10,477 UPCs, between January 2007 through and April 2015.

3.1.3 Shelf-Life Data

These data are at the SKU level. Each department has its own policy of shelf life, and the firm commits to discard any inventory before noticeable degradation occurs. The bakery provided an exhaustive list of shelf-lives, and the rest of the category shelf life was collected via personal correspondence with the firm, including talking with category managers. The shelf lives range from 1 to 7 days for products in these categories.

3.1.4 Production Process

These data were provided by category managers. Categories have the option replenish only once a day in the morning and then inventory is drawn down throughout the day. I am not sure about berries or greek yogurt, for which delivery orders might come in 1-3 times per week, rather than daily.

3.1.5 Capacity Data

Currently, I do not have this data, which means that I must calibrate it from the data. However, I hope to retrieve it from the firm.

3.1.6 Demand Estimation Samples

For my analysis, I focus on the population of shoppers purchases within each category at least once. I also limit category analysis to exclude periods of major product entry or exit. Additionally, I prune the data so each category has between 1 and 3 years of purchase data. This limits concern that preferences are not stable over longer periods. In total, these categories comprise $29.1 million in revenue (7.5% of all parent company revenue in 2014) and $14.7 million in profits (14.5%). Table 1 breaks down each of the above figures by category, including the remaining number of customers and transactions per category.

3.1.7 Estimation Sample for Structural Analysis

For the final demand analysis, I construct household choice panels that control for prices and promotions[8]. In this process, I define the 12 markets so that the included items capture no less than 65% of market share of their sub-category (e.g. BAKERY - Bread, YOGURT - Greek Yogurt, FRUIT - Fresh Cut Fruit, FRUIT - Berries). The outside goods are defined to be any other purchase in the broader category (e.g. the words in capitals above), so long as purchase incidence is at least 10%. Most categories seem to satisfy the "discrete choice" assumption. Trips that failed to violate discrete choice were dropped, which for most categories was <10%, but higher for others (berries were the highest at 25%.)

For categories without too many flavor variants (< ~10), I did not combine UPCS, since consumers might not find different flavors to be near perfect substitutes, in which case inventories must be considered separately. UPCs were combined for greek yogurt, shelf stable cookies, and the ice cream categories. The data appendix discusses the criteria used to combine UPCS into items.

Table 2 shows the final category descriptive statistics, including unique customers, transactions, and median trip length. Figures 1, 2, and 3, plot market shares of items over time on the left side, and prices over time on the right. The full set of figures is available in the data appendix.

For the bayesian structural analysis, I focus my analysis to several stores per category, since pricing would be done at the store level.

3.1.8 Costs

Median costs were pulled from the transaction-level data set. Table 3 shows costs, markups, margins, and the implied monopolist elasticity (for single good) for four categories: fresh cut pineapple, fresh baked bread, berries, and shelf stable cookies. The full set is available in the data appendix.

[8] In the current analysis, this variable is not used, since it seems to indicate promotions for some categories, but not others. The firm would not elaborate on the meaning. As a robustness check, I may add this to the categories for which this variable seems to indicate promotions.

4 Estimation and Results

■ In this section, I use the data to obtain empirical estimates of both demand and firm side parameters. I then carry out the firm's optimization and simulate results.

On the demand side, I document the existence of substantial within-day and within-week time-varying demand. Further, I show that there is substantial across-store heterogeneity in these estimates, indicating that RM may be more suited to some locations than others. I then turn to a linear probability model with the household panel level data to assess the nature of time-varying demand, and document that for most categories it seems to be driven by within-household changes in preferences, but for a few, a systematic time-sorting of customer types. I conclude the demand section by estimating a hierarhical logit model on a subset of stores (those ideal for RM and those that are less promising). I use model selection to test whether the time-varying price sensitivity is driven by within-person taste variation or within-person price sensitivity variation. The improvement from adding time-covariates in the bayes factors is almost as large as the improvement of adding random coefficients over a homogenous logit, indicating substantial fit improvement by accounting for within-day variation.

On the firm side, I calibrate estimates of capacity using two different methods. To estimate stockout and disposal costs, I also take two approaches described below. As a robustness check, I assess the final results' sensitivity to these different parameter estimates. I then optimize the firm's dynamic pricing and inventory policy, given current disposal costs. Finally, I simulate the results of counterfactual ban on food waste via increased disposal costs. I find [key findings].

4.1 Demand Estimation

I first explore time-varying demand through weekly-aggregate store-level data. Prices are aggregated to the weekly level by a quantity-sold-weighted average. I subset the purchase data from 7AM - 8PM because hours outside of this range see minimal store traffic

4.1.1 Reduced Form Demand Models and Estimates

The first specification examines if there is time-varying price sensitivity either (1) across hours of the day or (2) across days of the week, with the assumption of log-linear functional form. The second specification is a linear probabilty model to test whether time-varying price sensitivity is driven by within-household variation or between-household variation. In the aggregate weekly data section, let h = hour, l = location. I cluster the below regressions conservatively at the store-level.

Pooled:

4.1.2 Specification 1: Hour of the Day Heterogeneity

$$\log\left(1 + Q_{j,t,l}\right) = \theta_{hour,l} + \theta_{month,l,year} + \sum_{h=9}^{21} \alpha^{h} \log\left(p_{j,t,l}\right) \mathbb{I}_{\{hour=h\}} + \sum_{h=9}^{21} \sum_{i \neq j} \beta_i^{h} \log\left(p_{i,t,l}\right) \mathbb{I}_{\{hour=h\}} + \epsilon_{j,t,l} \tag{8}$$

$$H_0 : \alpha_{hour} = \alpha_{hour+1} = ... \ \forall hour \in \{h_{min}, .., h_{max}\}$$

$$H_a : \text{at least one } \alpha_{hour} \neq \alpha_{hour+1} \neq .... \ \forall hour \in \{h_{min}, .., h_{max}\}$$

Testing this specification reveals substantial within-day heterogeneity across several categories, but not for all. Tables 4 and 5 display two products' regression results, fresh cut pineapple and greek yogurt. Figures 5 and 4 plot the price elasticity by hour of the day next to cumulative category traffic. This shows that a meaningful portion of traffic occurs during each part of the elasticity curve. These categories have similar traffic patterns but display reverse time-variation in elasticity: greek yogurt is most elastic in the morning and evening, and less elastic in the middle of the day, whereas pineapple is least elastic in the morning and evening, most elastic in the middle of the day.

4.1.3 Specification 2: Day of the Week Heterogeneity

$$\log\left(1 + Q_{j,t,l}\right) = \theta_{day,l} + \theta_{month,l,year} + \sum_{d=0}^{6} \alpha^{d} \log\left(p_{j,t,l}\right) \mathbb{I}_{\{day=d\}} + \sum_{d=0}^{6} \sum_{i \neq j} \beta_i^{d} \log\left(p_{i,t,l}\right) \mathbb{I}_{\{day=d\}} + \epsilon_{j,t,l} \tag{9}$$

$$H_0 : \alpha^{d} = \alpha^{d+1} = ... \ \forall day \in \{\text{Mon,Tues...,Sun}\}$$

$$H_a : \text{at least one } \alpha^{d} \neq \alpha^{d+1} \neq .... \ \forall hour \in \{h_{min}, .., h_{max}\}$$

There also appears to be substantial between-day heterogeneity across several categories. For example, tables 6 and 7 display two products' regression results, one from donuts and one from baked bread. Figure 6 and 7 plot the price elasticity by day of the week. (There is meaningful category traffic every day of the week, so I do not display the distribution of traffic by weekday.)

Note that there is meaningful variation across days, and this is not only limited to a "weekday/weekend" effect. For donuts, the chain tends to experience less elastic demand on Mondays, Saturdays, and Sundays, and more elastic demand in the middle of the week. For bread, demand tends to be less elastic Monday - Thursday, and more elastic Friday - Sunday, with Sunday being sharply less so than Saturday, however.

4.1.4 Specification 3: Weekday-Weekend / Hour of the day Heterogeneity

While weekday-weekend is not always the appropriate divide, in this section I examine that functional form to limit the number of parameters and simplify the analysis. Furthermore, this tests indirectly the hypothesis that customers' work schedules dictate their price sensitivity (via changes in current opportunity cost of time.) For example, the before work / after work crowd might have different willingness-to-pay, but that effect is lost on the weekend. Let $K = \{\text{weekday, weekend}\}$.

$$\begin{aligned}\log(1+Q_{j,t,l}) = \theta_{hour,l} + \theta_{day,l} + \theta_{month,l,year} + \sum_{k\in K}\sum_{d=0}^{6} \alpha^{h,k} \log(p_{j,t,l})\,\mathbb{I}_{\{day=k,hour=h\}} \\ + \sum_{k\in K}\sum_{d=0}^{6}\sum_{i\neq j} \beta_i^{h,k} \log(p_{i,t,l})\,\mathbb{I}_{\{day=k,hour=h\}} + \epsilon_{j,t,l} \qquad (10)\end{aligned}$$

Where $Q_{j,t,l}$ is the quantity of product j sold at time t at store l. Let $\theta_{(.)}$ represent fixed effects. Leading to the joint test of whether adding weekday vs weekend to hourly coefficients helps.

$$H_0: \alpha_{hour,k} = \alpha_{hour,k+1} \text{ and } \alpha_{hour+1,k} = ... \; \forall hour \in \{h_{min}, .., h_{max}\}, k \in \{0,1\}$$
$$H_a: \text{at least one } \alpha_{hour,k} \neq \alpha_{hour,k+1} \text{ or } \alpha_{hour+1,k} \neq .... \; \forall hour \in \{h_{min}, .., h_{max}\},, k \in \{0,1\}$$

Here I observe four main different results, depending on the category: (1) Elasticity on Weekday vs. Weekend: Level Shift (2) Weekday vs. Weekend, Work vs. No work Effect, (3) No Difference between Weekday and not, but substantial within-day variation, (4) Weekend vs. Weekday trend different direction, (5) No time-varying markets.

For effect (1), consider coffee cake in figure 8. The blue line represents hourly elasticity on the weekday, and the red on weekends. We see that demand is less elastic on the weekends. The hourly price schedule (by hour, weekday vs. weekend) of a price discrminating monopolist (with certainty) is plotted on the right of the elasticity shcedules. This effect seemed to be the most prevalent across the categories.

For effect (2), for some products there was a clear pattern of "lunch" (~12:00 PM) and "after work" (~ 5:30 PM) increase in price sensitivity on the weekdays but not on the weekends. This most likely is the "work" effect, as people respond to sales when they go to the grocery store to pick up their lunch or dinner. Figure 9 shows this the most clearly with garlic bread, and for a price discriminating monopolist, prices should drop during lunch and dinner on weekdays.

For effect (3), I find a few categories/products with this pattern. Figure 10 documents the 48oz ice cream category such an example.

For effect (4), this was a lesson common finding, but present nonetheless, indicating the importance of empirically estimating hourly demand curves. Figure 11 illustrates one such example in the greek yogurt category.

Finally, a few products did not exhibit much meaningful price variation at all. Figure 12 plots one such example, cookies.

Store Hierarchical Linear Model: The next regression allows for heterogeneity in the price coefficients across stores. Different stores face different market segments, and its likely that some stores will have more across day heterogeneity than others. The specifications are the same as in the above section, but with the hierarchical sampling model:

$$\log\left(1+Q_{j,t,l}\right) = \theta_{h,l} + \theta_{month,l,year} + \sum_{h=9}^{21} \alpha_l^h \log\left(p_{j,t,l}\right) \mathbb{I}_{\{hour=h\}} + \sum_{h=9}^{21} \sum_{i \neq j} \beta_{i,l}^h \log\left(p_{i,t,l}\right) \mathbb{I}_{\{hour=h\}} + \epsilon_{j,t,l}$$

$$\begin{aligned} \{\epsilon_{j,t,l}\} &\sim \mathcal{N}\left(0, \sigma_l^2\right) \\ \alpha_{1,\ldots,L} &\sim \mathcal{N}_p\left(\bar{\alpha}, V_\alpha\right) \end{aligned}$$

With the priors:

$$\begin{aligned} V_\theta &\sim IW(\nu_0, V_0) \\ \bar{\theta}|V_\theta &\sim \mathcal{N}\left(\theta_0, V_\theta \otimes A^{-1}\right) \\ \sigma_l^2 &\sim \frac{\nu_l s_{0,l}^2}{\chi_{\nu_l}^2} \end{aligned}$$

The Directional Acyclical Graph is:

$$\begin{tikzcd}
(\nu_0, V_0) \arrow[r, dashed] & V_\theta \arrow[d] \arrow[dr] & & \\
(\theta_0, A) \arrow[r, dashed] & \bar{\theta} \arrow[r] & \theta_l \arrow[r] & \boldsymbol{y}_l \\
(\nu_l, s_{0,l}^2) \arrow[rr, dashed] & & \sigma_l^2 \arrow[ur] &
\end{tikzcd}$$

Specification 1: Coefficients split by hour.

Specification 2: Coefficients split by weekday-weekend and hour.

To avoid estimating a very large number of fixed effects, I demean the hour-location and month-location-year effects.

The results reveal substantial between store heterogeneity, indicating that RM will be more suited to some stores in the chain than others. Figure 13 plots the price elasticity of catgeory coffee cake over time, across stores. Notice that some stores exhibit substantial variation across the day, while others exhibit very little. Figure 14 plots a similar plot for fresh cut pineapple, and divides by weekday vs. weekend.

Linear Probability Model: To inform a sensible structural model, it is useful to know whether the time-variation in demand is driven primarily by systematically different customers shopping at different times, or whether households exhibit different demand depending on when they shop. In this section, I test a between-household specification and a within-household specification.

Between:

$$y_{t,h,l} = \theta_{month,year} + \theta_{l,hour} + \sum_{hour=9}^{21} \alpha_{hour} p_{t,l} \mathbb{I}_{\{\text{hour at } t\}} + \sum_{hour=9}^{21} \sum_{i \neq j} \beta_i^{hour} p_{i,t,l} \mathbb{I}_{\{\text{hour at } t\}} + \epsilon_{t,h,l} \tag{11}$$

Within:

$$y_{t,h,l} = \theta_h + \theta_{month,year,l} + \theta_{l,hour} + \sum_{hour=9}^{22} \alpha_{hour} \left(p_{t,l}\right) \mathbb{I}_{\{\text{hour at } t\}} + \sum_{hour=9}^{22} \sum_{i \neq j} \beta_i^{hour} p_{i,t,l} \mathbb{I}_{\{\text{hour at } t\}} + \epsilon_{t,h,l} \tag{12}$$

Results: The within-variation specification's elasticity curve looks similar to the between specification's, indicating that the model of household time-specific heterogeneity in preferences is appropriate. [Insert results, show curves are robust, suggesting the demand model.]

4.1.5 Structural Demand Model and Estimates:

Given the results of the above, I confirm that the individual-level parameter random coefficients model is sensible.

Random Coefficients: I begin by running a homogenous logit model on each category, followed by a static random coefficients (RC) model (no time-covariates), and finally RC on a variety of flexible, time-varying preference specifications.

Since the micro reason for the above documented time-varying heterogeneity is not known *a priori*, I employ a variety of specifications and use bayes factors [9] to select the final model. First, I test parametric specifications through trends, from linear up to quartic in either (1) taste intercepts, (2) price sensitivity α, or (3) both. I also employ a semi-parametric specification where I divide the day into Pre-10am, 10am - 2pm, 2pm - 5pm, 5pm - 8pm and interact these time-dummies with either (1), (2), or (3). Ideally, I would

[9] As approximated by trimmed log-marginal densities, see Rossi et al. 2005 [17].

employ a regularized technique, such as LASSO, and include all interactions with each day of the week. Sanders 2017 [18] does this analysis when rigorously estimating the returns to time-based targeting.

Results: Table [results] shows the results of the homogeneous logit by category, the static RC model, and the chosen time-varying specification for each category. Notice that the fit improvement from homogeneous to RC is substantial, as is the improvement from static RC to time varying RC for most categories. Finally, I plot the aggregate elasticity curve over time for several categories in figure [results].

Most of the categories did indeed seem to prefer specifications that favor time-varying marginal utility of income, rather than time varying taste coefficients. The exceptions to this were [results]. This has two implications: the within-person heterogeneity implies that the expected welfare of the same choice set viewed at different times will have different welfare changes, not only due to the difference in indirect utilty but also due to α. Secondly, this suggests the theory that there is within-person heterogeneity in the opportunity cost of time, which manifests through search costs, and is perhaps driven by dynamic value of time.

4.2 Revenue Management Model of Dynamic Pricing:

Having established time-varying demand, we now turn to the firm's problem. For estimates of T_h replenishment frquency, see table 8 for shelf-life data and production process by category.

4.2.1 Capacity and Waste Estimation

Most grocery stores, including this one, practice a policy of high-waste, high availability for perishable inventory. As a result, stockouts are currently very rare. To identify capacity, I take two approaches: First, I examine histograms of sales by category for several stores, in hope that I observe bunching at a maximum bin. I observe this for a few categories, but most rarely stock out so the histograms are smooth. The second approach I take is to assume that a profit-maximizing monopolist would have long run capacity at mean demand plus some uncertainty buffer, directly proportional to the variance of demand. I operationalize this by assuming capacity equals mean demand plus k-standard deviations. I estimate sensitivity of results to k.

Table 9 displays the median (across stores) maxium units sold by category. This was obtained by examining the histogram of category level sales for 15 stores for each category. Notes are included, particularly, when the cutoff seemed somewhat sharp or consistent across stores (no fat tail). Figure 15 displays coffee cake sales data from two stores where minor bunching occurs, suggesting perhaps a stockout at demand beyond this (capacities identified as 20 and 25.)

Waste To obtain an estimate of current waste and the externality associated with it, I turn to a recent report by the California EPA[3] and the FAO [10]. The report estimates that between [] and [] metric tons of CO_2 equivalent are emitted per metric ton of organic food waste.

Table [] plots the distribution of current waste as a function of inventory for each category. [Need to map the externality to pounds, estimate the externality of waste in pounds]. In total, [] units are wasted per year. Mapping each category to roughly its weight, this amounts to [] pounds per year. Some organizations have attempted to quantify the cost of emissions in order to implement economic policies (cap-and-trade) and exise taxes on pollution. This organization suggests \$/metric ton of CO_2 equivalent. The cost to society of the externality is [] per year. (cite.)

4.2.2 Stockout and Disposal Cost Estimation

To estimate stockout costs to consumers, I assume simply that the consumer's cost is the expected utility reduction by the restriction of her choice set.

For firms, I estimate stockout costs in two distinct ways. First, the firm's expected stockout cost loss is the alteration in expected margin (without this reduction)[10], plus a small probability p that the consumer switches chains forever and the NPV associated with such a switch[11]. The second approach I take is to assume that given a static pricing policy, the firm is producing the profit maximizing level of inventory given some disposal and stockout cost. (what is identified here? ratio? difference?) [Need to explain more on how I will do this.]

4.2.3 Estimation of $\lambda_{t,w}$

To estimate the arrival intensity by time in the nonhomogenous-Poisson arrival process, I use a model with flexible semi-parametric functional form. I use a logarithm link, to ensure positive λ, so that $\log\left(\lambda\left(t;\beta\right)\right) = \exp\left(\boldsymbol{x}'\left(t\right)\beta\right)$, where $\boldsymbol{x}(t)$ is a vector of flexible time covariates[12]. For each store included in the analysis, I estimate $\lambda_{t,location,w}$ using maximum likelihood. Given a dataset of n arrivals by hour-minute for the store history, the likelihood function is:

$$L\left(\beta;\left(t_i\right)_{i=1}^{n}\right) = \exp\left[-\int_A \lambda\left(t;\beta\right)dt\right]\prod_{i=1}^{n}\lambda\left(t_i;\beta\right)$$

where A is the space where the point process is defined (all hour-minutes). The results show that weekend arrival intensity tends to be greater. Figure 16 plots one category example, baked cookies, divided by Monday vs. Saturday. It also reveals that on weekdays, the largest mass of customers tends to appear after work, whereas on weekends it is in the morning. This is of course a critical difference when considering continuation value of pricing perishable assets.

[10]Note that in the multi-product case, some stockouts might be profitable if consumers are willing to switch to higher margin items.

[11]Since data containing the entire basket was pulled for the Pick 'N Save, I observe the distribution of yearly profits contributed to the firm by a statistical consumer.

[12]τ = hour-minute, $\boldsymbol{x} = \left[1\ \cos\left(2\pi\frac{\tau}{24}\right)\ \sin\left(2\pi\frac{\tau}{24}\right)\ \frac{\tau}{10}\ \left(\frac{\tau}{10}\right)^2\ \left(\frac{\tau}{10}\right)^3\ \left(\frac{\tau}{10}\right)^4\right]$

4.2.4 Estimation of RM Under Current Legislation

To solve for the policy function, I use value-function interation. To calculate the expectation, I simulate preference draws, arrivals, and finally multinomial draws. [Results].

4.2.5 Estimation of RM Under Food Waste Ban

[Results]

5 Conclusion.

■ I show that RM can be useful in mitigating food waste, increasing firm profits, and improving customer welfare, provided grocery stores are willing to engage in sophisticated micro-marketing. In particular, I show that stores with relatively lower capacity, high uncertainty, and strong time-varying demand stand to gain the most from RM. The benefits of RM are amplified in the presence of a food waste ban, in which firms optimally reduce initial inventories to lower disposal costs. [More results]

[Broader implications]

In a world of increasing weather volatility and rising sea levels, it is essential society and policy-makers engage in efforts to curb harmful emissions. If firms and policy-makers can find solutions that do so yet also increase social surplus, they are more likely to disseminate quickly and continue their impact. As the technology improves, analytics becomes more sophisticated, and consumers begin to understand the consequences of waste, this appears to be one promising potential solution.

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Table 1: Descriptive Statistics of Estimation Sample

All Stores (In millions)	Customers	Transactions	Avg Yr. Revenue	Avg Yr. Profit
Bakery:				
Fresh baked bread	482,675	5,248,277	1.80	0.93
Fresh baked cookies	1,040,124	14,027,179	3.65	2.08
Brownies	317,536	2,441,794	0.40	0.19
Coffee Cakes and Crumb Cakes	257,133	5,537,107	0.65	0.32
Doughnuts and Danish	1,399,737	16,686,084	5.61	5.09
Desserts and Pastries	503,715	6,283,737	1.44	0.91
Fresh Fruit:				
Fresh cut pineapple	1,150,275	6,077,412	2.10	1.25
Fresh berries	1,187,354	6,165,822	8.51	3.09
Fresh Dairy:				
Greek Yogurt	633279	6011243	2.48	0.8
Frozen and Shelf Stable:				
Shelf Stable Cookies	288,855	1,034,863	0.40	0.01
16oz Ice Cream Pint	427,528	2,012,331	0.84	0.14
48oz Ice Cream Tub	427,528	2,012,331	1.19	-0.07
Total:	-	-	29.1	14.7

Table 2: Descriptive Statistics of Individual Panels

	Customers	Transactions	Median Panel Length
Bakery:			
Fresh baked bread	380,190	4,600,242	6
Fresh baked cookies	698,840	10,765,138	8
Brownies	132,444	1,040,765	4
Coffee Cakes and Crumb Cakes	147,604	3,330,308	14
Doughnuts and Danish	1,020,179	13,207,623	6
Desserts and Pastries	315,606	4,046,948	7
Fresh Fruit:			
Fresh cut pineapple	540,252	3,630,204	3
Fresh berries	1,003,448	4,659,689	2
Fresh Dairy:			
Greek Yogurt	369,931	4,821,691	5
Frozen and Shelf Stable:			
Shelf Stable Cookies	100,843	564,347	3
16oz Ice Cream Pint	158,053	1,011,399	3
48oz Ice Cream Tub	239,628	1,416,116	3

Table 3: Costs, Margins, Markups, Implied E †

Item_Desc	cost	price	margin	markup (%)	Implied E
Gold Pineapple	1.8	3.79	0.53	110.56	-1.9

Item_Desc	cost	price	margin	markup (%)	Implied E
Artisan Roasted Garlic Loaf	1.70	3.79	0.55	122.94	-1.81
Artisan Asiago Cheese Bread	2.24	4.49	0.50	100.45	-2.00
Artisan French Baguette	0.99	2.29	0.57	131.31	-1.76
Artisan Pane Di Altumura	1.90	3.99	0.52	110.00	-1.91
Artisan Pugliese Rosemary	2.06	3.99	0.48	93.69	-2.07
Artisan Sourdough Loaf	1.38	2.99	0.54	116.67	-1.86
Artisan Whole Grain Bread	2.05	3.99	0.49	94.63	-2.06
French Demi Baguette	0.45	0.99	0.55	120.00	-1.83

Item_Desc	cost	price	margin	markup (%)	Implied E
Blueberries	2.04	2.88	0.29	41.18	-3.43
Red Raspberries	1.48	3.49	0.58	135.81	-1.74
Strawberryagg	1.50	2.50	0.40	66.67	-2.50

Item_Desc	cost	price	margin	markup (%)	Implied E
Chipsahoy	2.81	2.69	-0.04	-4.27	22.42
Fignewton	3.33	3.99	0.17	19.82	-6.05
Matts	2.63	3.54	0.26	34.60	-3.89
Oreodouble	3.33	2.99	-0.11	-10.21	8.79
Roundysos	1.45	2.49	0.42	71.72	-2.39
Roundyssandwich	1.52	2.59	0.41	70.39	-2.42

† For loss leaders, implied E is not defined.

Table 4: Hourly Log-Linear Regression: Fresh Cut Pineapple

	Dependent variable:	
	Log(Q)	Log(Q), Control
	(1)	(2)
Price * Hour 7	−0.89*** (0.06)	−0.89*** (0.06)
Price * Hour 8	−1.60*** (0.07)	−1.60*** (0.07)
Price * Hour 9	−2.07*** (0.08)	−2.07*** (0.08)
Price * Hour 10	−2.31*** (0.08)	−2.31*** (0.08)
Price * Hour 11	−2.35*** (0.08)	−2.35*** (0.08)
Price * Hour 12	−2.40*** (0.08)	−2.40*** (0.08)
Price * Hour 13	−2.30*** (0.07)	−2.30*** (0.07)
Price * Hour 14	−2.27*** (0.07)	−2.27*** (0.07)
Price * Hour 15	−2.28*** (0.08)	−2.28*** (0.08)
Price * Hour 16	−2.16*** (0.07)	−2.16*** (0.07)
Price * Hour 17	−1.93*** (0.07)	−1.93*** (0.07)
Price * Hour 18	−1.69*** (0.06)	−1.69*** (0.06)
Price * Hour 19	−1.47*** (0.06)	−1.47*** (0.06)
Price * Hour 20	−1.19*** (0.06)	−1.19*** (0.06)
Price * Hour 21	−0.86*** (0.06)	−0.86*** (0.06)
Hour-Location FE	Yes	Yes
Month-Year-Location FE	Yes	Yes
Control for Other Prices	No	Yes
F-test against static model	0	0
Observations	244,140	244,140
R^2	0.79	0.79
Adjusted R^2	0.78	0.78
Residual Std. Error (df = 238886)	0.47	0.47
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 5: Hourly Log-Linear Regression: Greek Yogurt

	Dependent variable:	
	Log(Q)	Log(Q), Control
	(1)	(2)
Price * Hour 7	−2.18*** (0.53)	−2.43*** (0.50)
Price * Hour 8	−2.30*** (0.35)	−2.29*** (0.38)
Price * Hour 9	−2.46*** (0.30)	−2.06*** (0.31)
Price * Hour 10	−1.95*** (0.30)	−1.65*** (0.34)
Price * Hour 11	−1.93*** (0.31)	−1.45*** (0.37)
Price * Hour 12	−1.93*** (0.31)	−1.27*** (0.38)
Price * Hour 13	−2.12*** (0.32)	−1.47*** (0.37)
Price * Hour 14	−1.92*** (0.28)	−1.32*** (0.34)
Price * Hour 15	−2.08*** (0.30)	−1.54*** (0.36)
Price * Hour 16	−2.05*** (0.29)	−1.51*** (0.35)
Price * Hour 17	−2.13*** (0.28)	−1.59*** (0.34)
Price * Hour 18	−2.26*** (0.29)	−1.91*** (0.38)
Price * Hour 19	−2.35*** (0.28)	−2.09*** (0.37)
Price * Hour 20	−2.28*** (0.32)	−2.14*** (0.38)
Price * Hour 21	−2.46*** (0.27)	−2.59*** (0.34)
Hour-Location FE	Yes	Yes
Month-Year-Location FE	Yes	Yes
Control for Other Prices	No	Yes
F-test against static model	0.00146223301539106	0
Observations	37,575	37,575
R^2	0.72	0.73
Adjusted R^2	0.71	0.72
Residual Std. Error	0.97 (df = 36540)	0.97 (df = 36465)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 6: Hourly Log-Linear Regression: Donuts

	Dependent variable:	
	Log(Q)	Log(Q), Control
	(1)	(2)
Price * Weekday 0	−0.68*** (0.04)	−0.69*** (0.04)
Price * Weekday 1	−0.76*** (0.05)	−0.78*** (0.04)
Price * Weekday 2	−0.94*** (0.04)	−0.95*** (0.04)
Price * Weekday 3	−0.85*** (0.04)	−0.85*** (0.04)
Price * Weekday 4	−0.94*** (0.04)	−0.91*** (0.04)
Price * Weekday 5	−0.68*** (0.03)	−0.68*** (0.03)
Price * Weekday 6	−0.54*** (0.03)	−0.57*** (0.03)
Weekday-Location FE	Yes	Yes
Month-Year-Location FE	Yes	Yes
Control for Other Prices	No	Yes
F-test against static model	0	0
Observations	101,500	97,815
R^2	0.74	0.74
Adjusted R^2	0.73	0.72
Residual Std. Error	0.52 (df = 97511)	0.52 (df = 93917)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 7: Hourly Log-Linear Regression: Baked Bread

	Dependent variable:	
	Log(Q)	Log(Q), Control
	(1)	(2)
Price * Weekday 0	−1.54*** (0.11)	−1.70*** (0.12)
Price * Weekday 1	−1.49*** (0.11)	−1.48*** (0.11)
Price * Weekday 2	−1.52*** (0.11)	−1.62*** (0.12)
Price * Weekday 3	−1.73*** (0.11)	−1.79*** (0.12)
Price * Weekday 4	−2.29*** (0.12)	−2.39*** (0.13)
Price * Weekday 5	−2.66*** (0.13)	−2.69*** (0.13)
Price * Weekday 6	−2.01*** (0.11)	−1.98*** (0.11)
Weekday-Location FE	Yes	Yes
Month-Year-Location FE	Yes	Yes
Control for Other Prices	No	Yes
F-test against static model	0	0
Observations	101,500	101,500
R^2	0.51	0.52
Adjusted R^2	0.49	0.50
Residual Std. Error	0.45 (df = 97511)	0.45 (df = 97462)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 8: Shelf Lives and Production Process

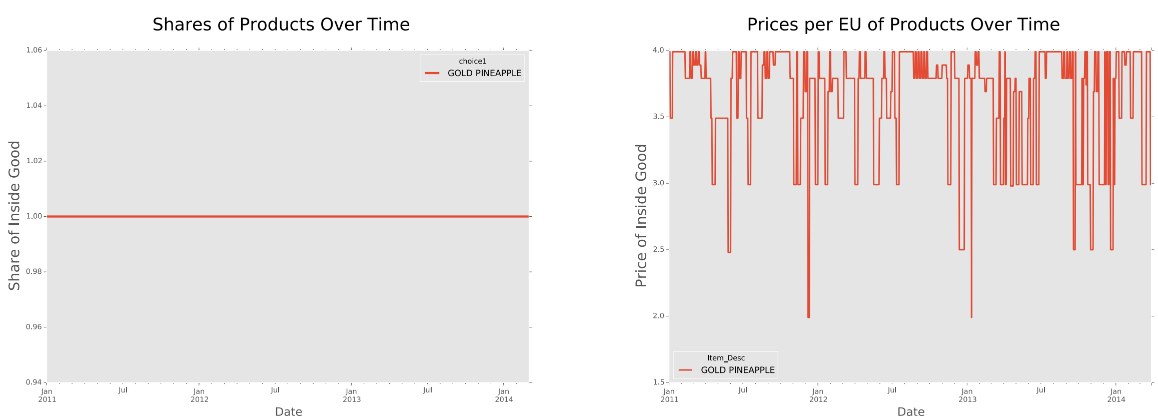
All Stores	Shelf Life (Days)	Replenishment Freq. (Days)
Bakery:		
Fresh baked bread	2	1
Fresh baked cookies	5	1
Brownies	5	[missing]
Coffee Cakes and Crumb Cakes	5	[missing]
Doughnuts and Danish	1	1
Desserts and Pastries	3	[missing]
Fresh Fruit:		
Fresh cut pineapple	3	1
Fresh berries	3	[missing]
Fresh Dairy:		
Greek Yogurt	7	[missing]
Frozen and Shelf Stable:		
Shelf Stable Cookies	-	-
16oz Ice Cream Pint	-	-
48oz Ice Cream Tub	-	-

Table 9: Estimated Capacities

All Stores	Approximate Capacity	Notes:
Bakery:		
Fresh baked bread	15 - 60, increments of 15	Fairly sharp
Fresh baked cookies	80, 160	
Brownies	10-20	A few sharp
Coffee Cakes and Crumb Cakes	20-25	Fairly sharp
Doughnuts and Danish	*	*
Desserts and Pastries	20 - 160	Not sharp
Fresh Fruit:		
Fresh cut pineapple	30, 60, 120	
Fresh berries	250, 500, 1000	
Fresh Dairy:		
Greek Yogurt	1000 - 2000	Not Sharp
Frozen and Shelf Stable:		
Shelf Stable Cookies	-	-
16oz Ice Cream Pint	-	-
48oz Ice Cream Tub	-	-

*Distribution has very fat tail.

Figure 1: Market Shares and Prices of Fresh Cut Pineapple†



† There was only one item in this category.

Figure 2: Market Shares and Prices of Fresh Baked Bread

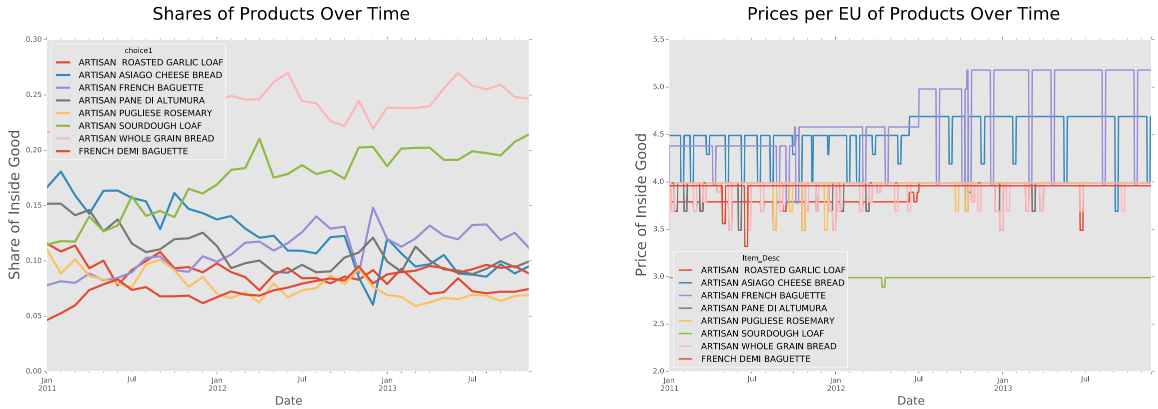


Figure 3: Market Shares and Prices of Greek Yogurt

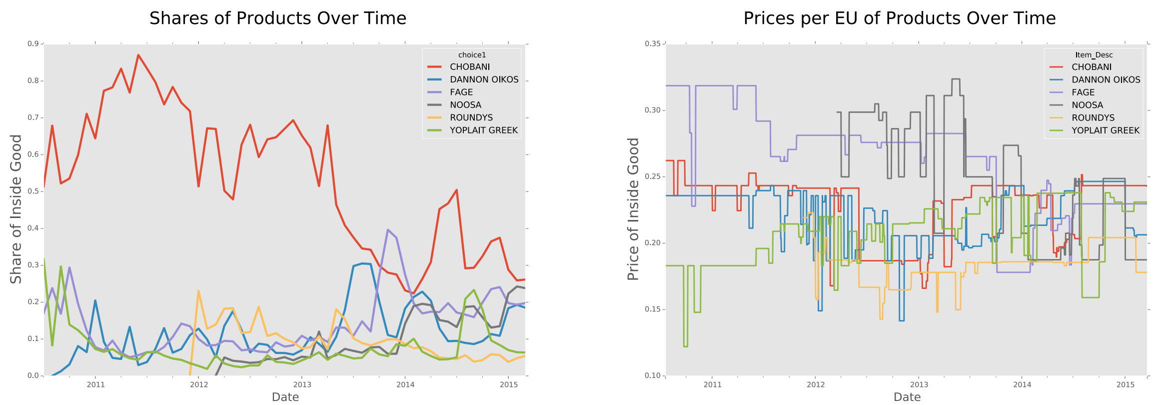
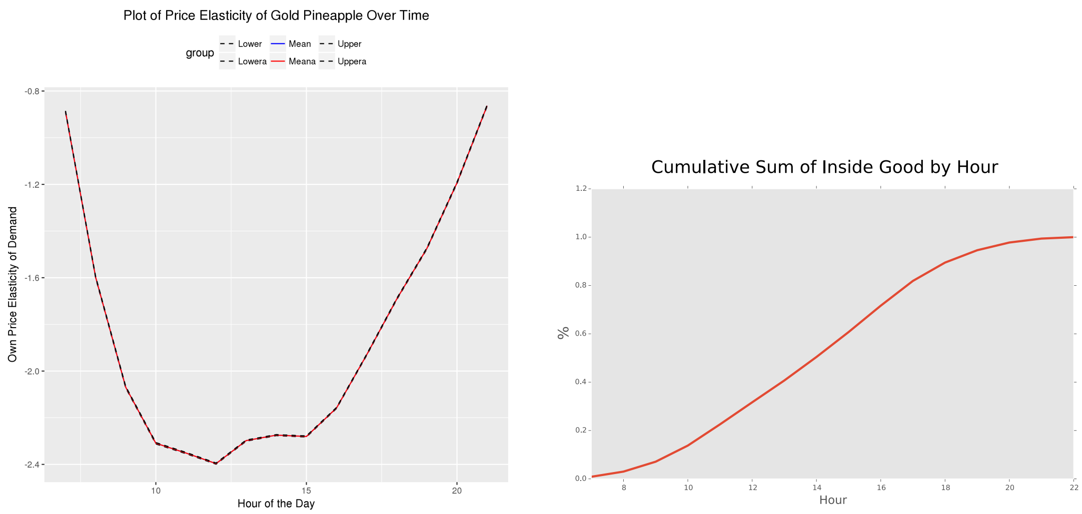
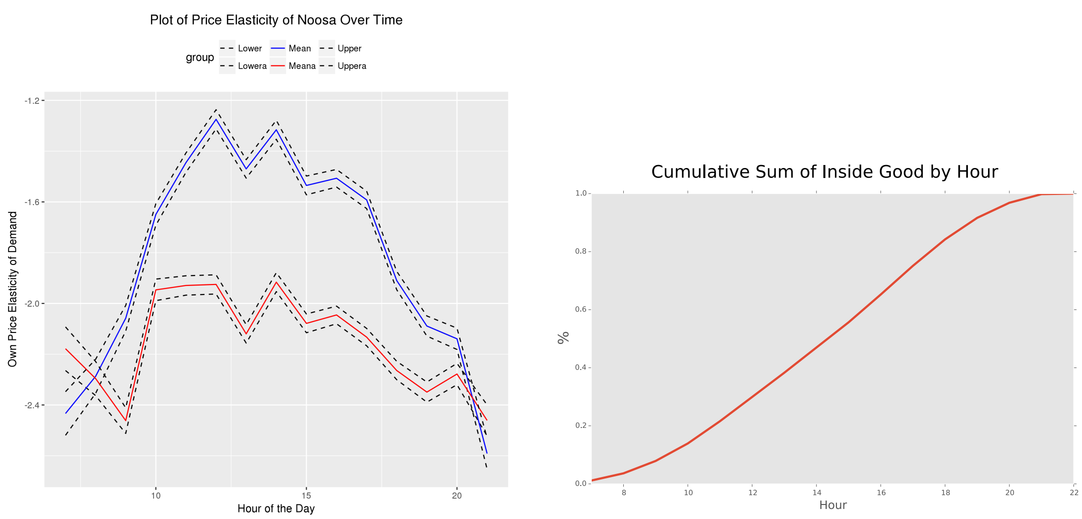


Figure 4: Fresh Cut Pineapple Elasticity* Over Time, with 95% CI, Traffic Over Time



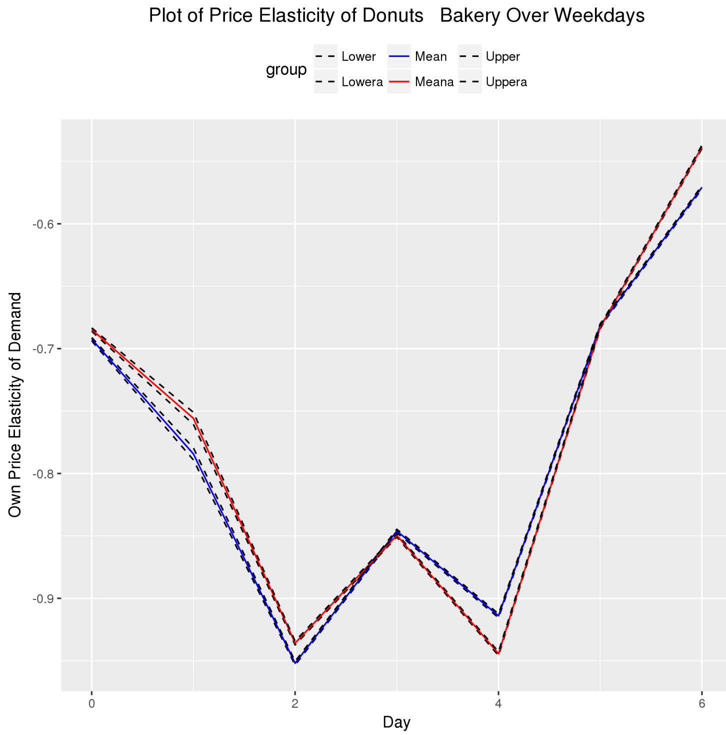
* The blue line refers to the price elasticity after controlling for other products' prices.

Figure 5: Noosa Greek Yogurt Elasticity* Over Time, with 95% CI, Traffic Over Time



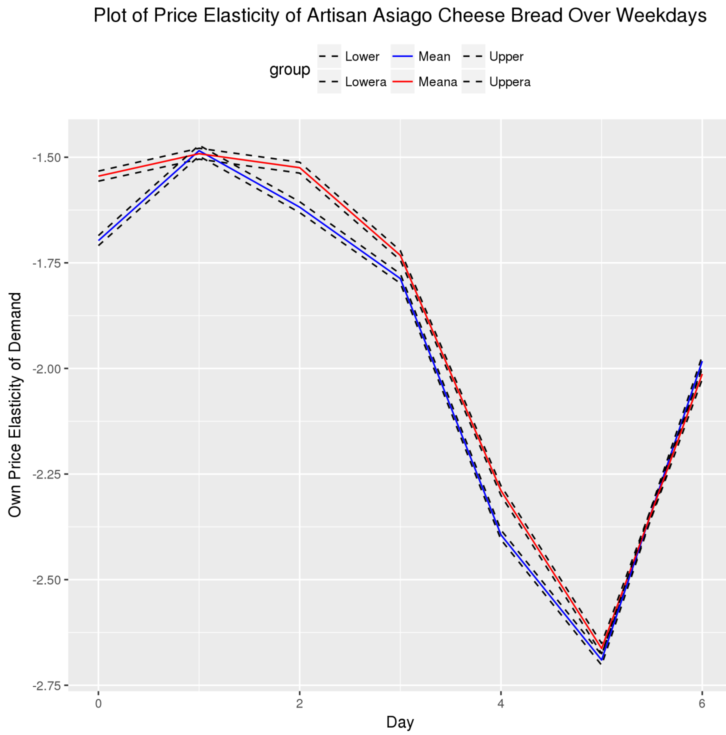
* The blue line refers to the price elasticity after controlling for other products' prices.

Figure 6: Donuts Elasticity* Over Weekday, with 95% CI



* The blue line refers to the price elasticity after controlling for other products' prices.

Figure 7: Baked Bread Elasticity* Over Time, with 95% CI, Traffic Over Time



* The blue line refers to the price elasticity after controlling for other products' prices.

Figure 8: Coffee and Crumb Cake: Weekday v. Weekend Over Hour

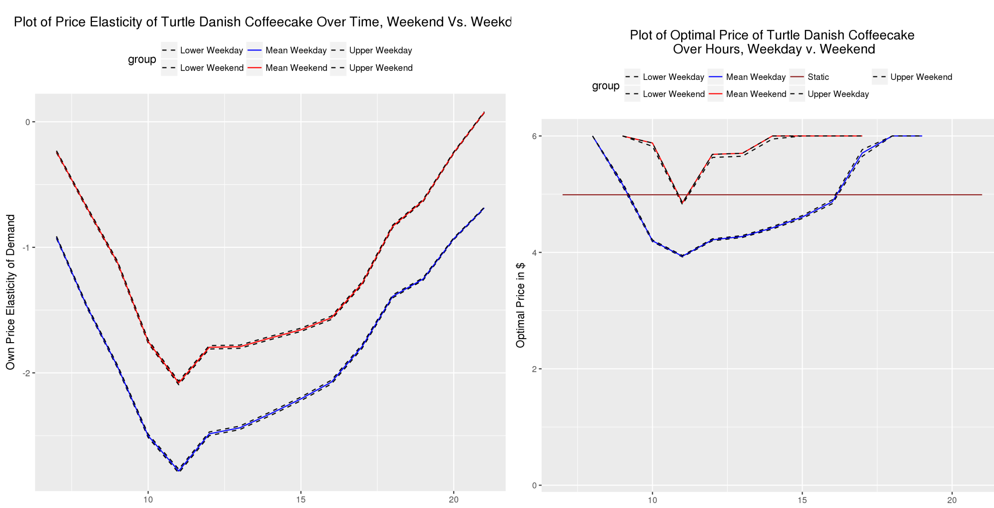


Figure 9: Garlic Roast Bread: : Weekday v. Weekend Over Hour

Figure 10: Icecream Full: : Weekday v. Weekend Over Hour

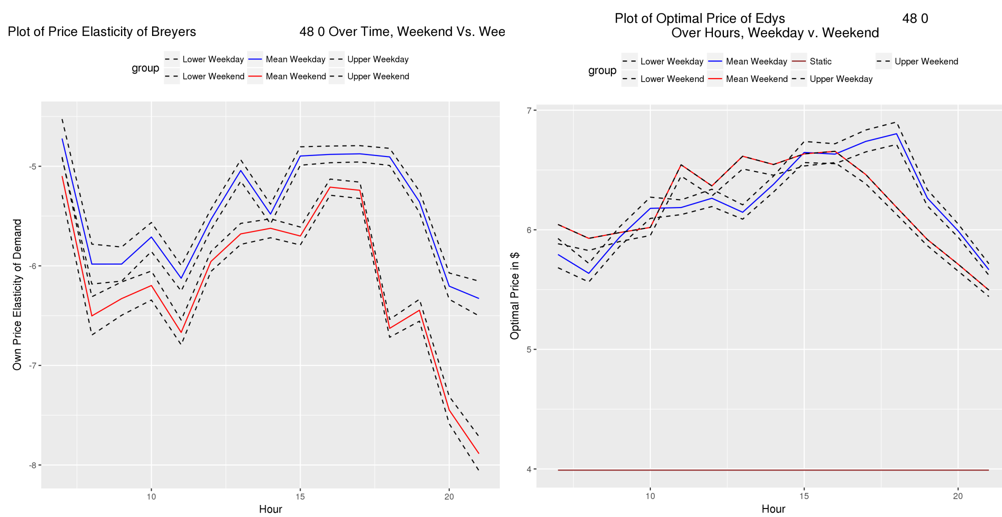


Figure 11: Greek Yogurt: Weekday v. Weekend Over Hour

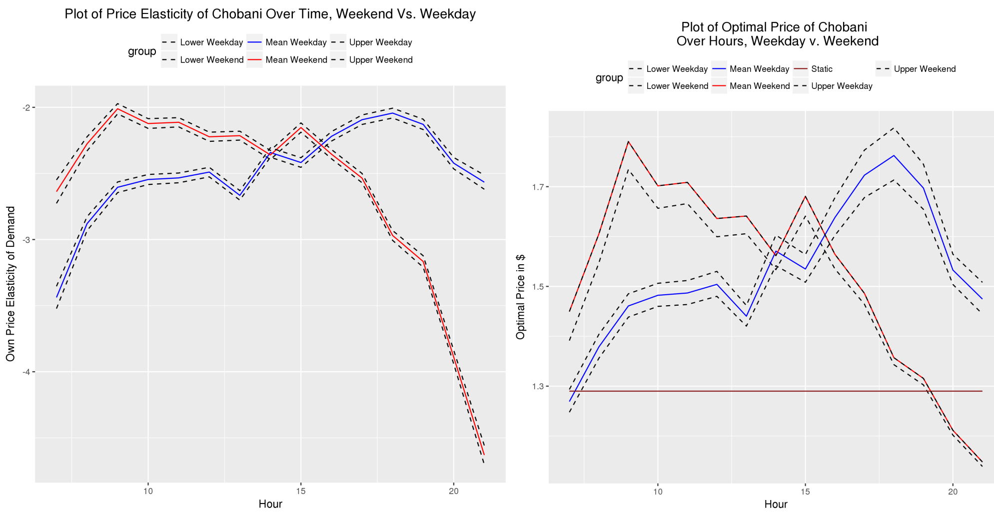


Figure 12: Shelf Stable Cookies: Weekday v. Weekend Over Hour

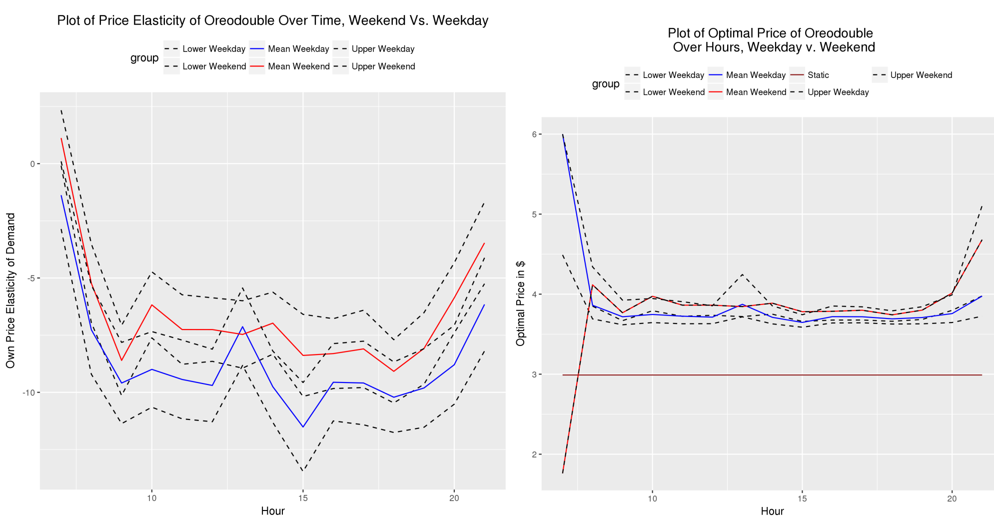
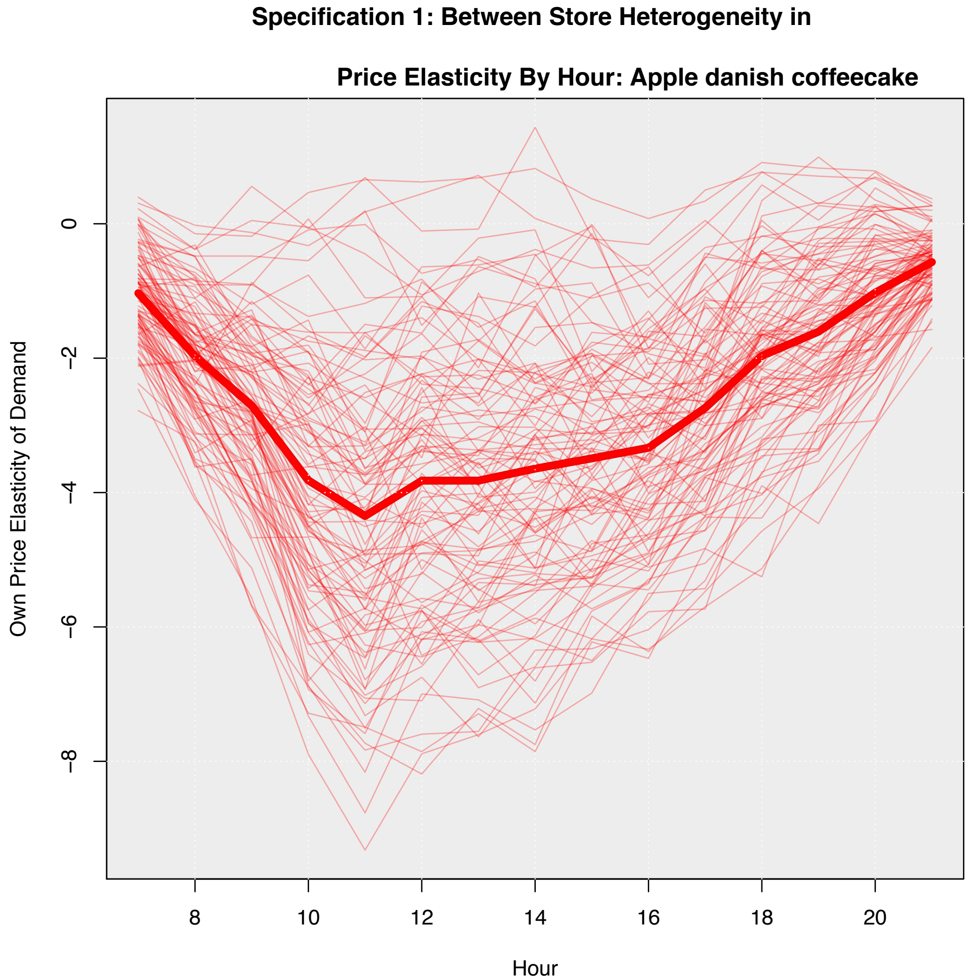
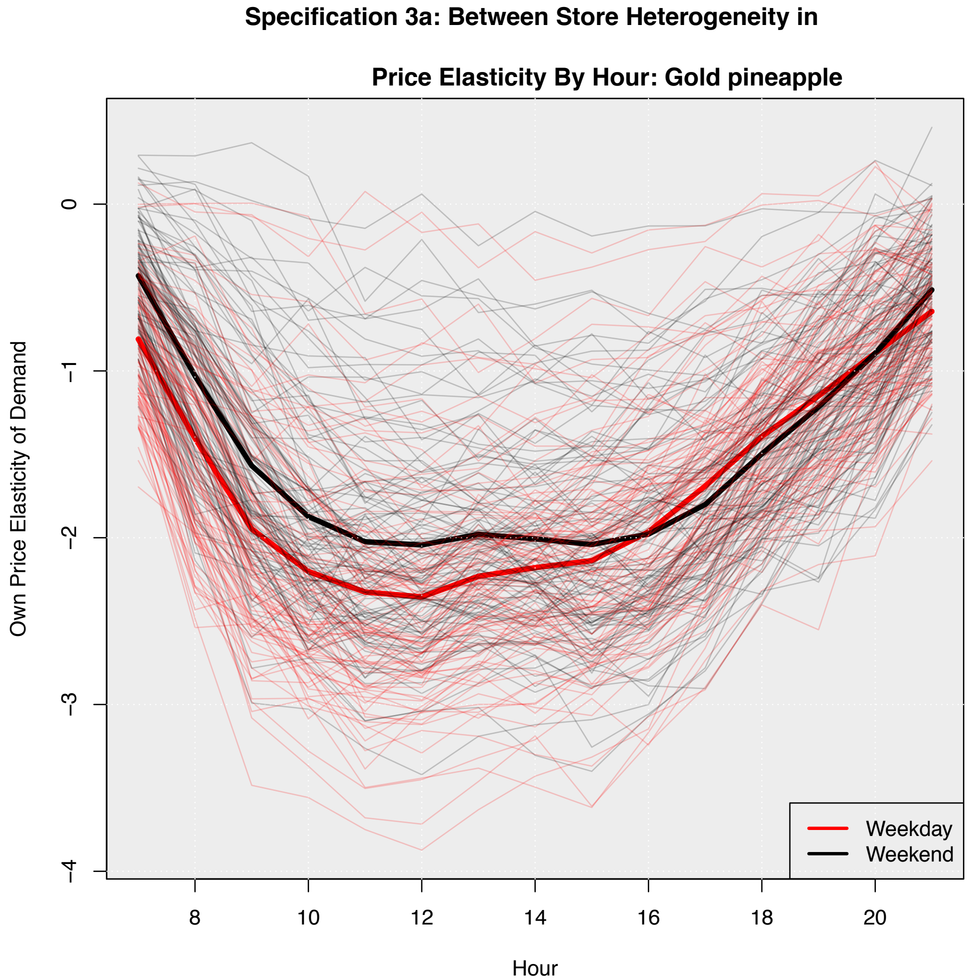


Figure 13: Coffee Cake Between Store Heterogeneity: Hierarchical Linear Model*



∗ Each curve represents the elasticity curve throughout the day of a particular store. The thick curve is the population average.

Figure 14: Fresh Cut Pineapple Between Store Heterogeneity: Hierarchical Linear Model*



∗ Each curve represents the elasticity curve throughout the day of a particular store. The thick curve is the population average.

Figure 15: Histogram of Units Sold, Coffee Cake, Examples of Identifying Stockouts, Two Stores (6308 and 6366 Pick 'N Save)

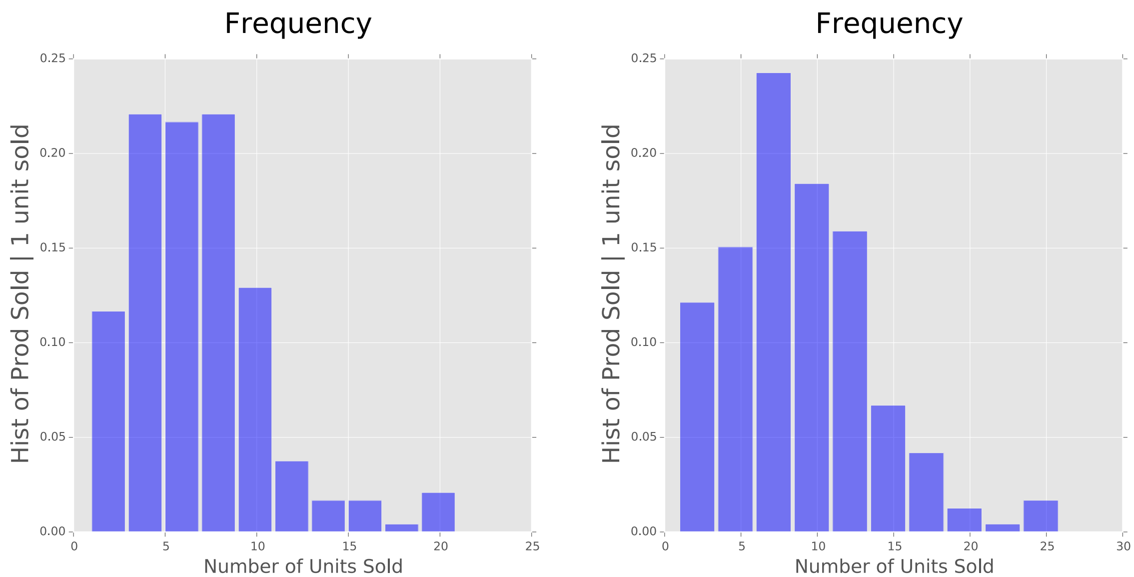


Figure 16: Nonhomogenous Poisson Process, Monday and Saturday