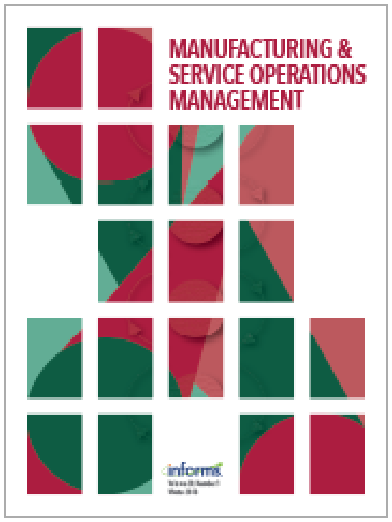

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Grocery Store Density and Food Waste

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Abstract. We study the impact of grocery-store density on the food waste generated at stores and by households. Food waste is a major contributor to carbon emissions (as big as road transport). Identifying and influencing market conditions that can decrease food waste is thus important to combat global warming. We build and calibrate a stylized two-echelon perishable-inventory model to capture grocery purchases and expiration at competing stores and households in a market. We examine how the equilibrium waste in this model changes with store density. An increase in store density *decreases consumer* waste due to improved access to groceries, whereas *increasing retail* waste due to decentralization of inventory increased variability propagation in the supply chain (cycle truncation) and diminished demand by customers. Higher density also induces more competition which further increases (decreases) waste when stores compete on prices (service levels). Overall, consumer waste reductions compete with store waste increases and the effects of increased competition. Our analysis shows that *higher density reduces food waste up to a threshold density; it leads to higher food waste beyond this threshold*. Put differently, in so far as food waste is concerned, there exists an optimal store density. Calibration using grocery industry, economic, and demographic data reveals that actual store density in most American cities is well below this threshold/optimal level, and modest increases in store density substantially reduce waste; for example, in Chicago, just 3–4 more stores (per 10 sq km) can lead to a 6%–9% waste reduction, and a 1%–4% decrease in grocery expenses. These results arise from the principal role of *consumer* waste, suggesting that activists and policy makers' focus on retail waste may be misguided. Store operators, urban planners, and decision makers should aim to increase store densities to make grocery shopping more affordable and sustainable.

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1. Introduction

More than one-third of all food produced is wasted. The carbon footprint of wasted food is comparable to that of *all* road transport and is just behind the *entire* footprint of the top-two emitting economies, the United States and China. In developed countries, more than two-thirds of food waste arises at the retail and consumption stages of the fresh grocery supply chain (Lipinski et al. 2013). Reducing food waste at these stages can play an important role in combating global warming.

This study identifies the impact of store density, or the number of grocery stores in a given market area, on the food waste generated in the market. Store density strongly influences households' shopping patterns, store size and scale, grocery prices, inventory decentralization, all phenomena known, from past academic work, to highly affect food waste (Gunders et al. 2012, Gustat et al. 2015, Ramkumar 2016, Jiao et al. 2016, Rabobank 2016). Although the relationship between store density and food waste has not been explored, past work has identified store density as a lever of interest to urban planners and grocery store operators and a lever that plays a key role in determining the travel-related emissions from grocery retail and consumption (Cachon 2014).

Overall, this suggests an important influence of and interest in the study of store density, yet the direction and extent of the impact of density on food waste is less clear. Casual arguments suggest store density influences market competition which could change the grocery store offer (prices, service), which, in turn, could influence waste (Gunders et al. 2012). On the other hand, store density also directly changes households' shopping patterns (Gustat et al. 2015), which should also affect households' waste. Further, store density, the resultant market competition, and households' behavior likely also influence retail inventory management and thus also store waste. This study builds and calibrates a stylized model of inventory management in stores and households, to characterize the relationship between store density and food waste, while incorporating the above-mentioned phenomena.

Specifically, we build a two-echelon perishable-inventory model with inventory-carrying stores and households. Fresh-grocery stores, differentiated by their location in the market, build inventories and set prices and/or service levels to compete for households. Households are also geographically distributed in the market. They choose among stores and decide how often and how many groceries to purchase, so as to minimize their grocery-acquisition costs and satisfy their random grocery needs. Stores' demand arises from the aggregation of households' purchase patterns and store choices. We identify equilibrium store inventory levels, prices/service levels offered, and households' inventory-replenishment policies. The expiring/unsold inventory at each tier represents the corresponding food waste. We then examine how this equilibrium food waste changes with store density.

We find that store density has competing effects on consumer and retail food waste: higher density leads to *lower consumer* food waste and *higher retail* waste. Households have to travel less to visit a store in denser markets, which incents more frequent trips to grocery stores and smaller basket sizes or households' inventory levels. Smaller inventory levels imply less food waste as it is less likely that the inventory will expire before it is consumed. Essentially, the improved access that households have to grocery stores leads to lower consumer food waste.

On the other hand, higher density leads to *higher retail* food waste. Higher density lowers the mean retail demand as customers are now closer to grocery stores, and, thus, they waste less (as discussed above), and, as result, they also need to buy less. At the same time, with higher density, inventories in the retail network are more decentralized: each store now serves a smaller portion of demand. This diminishes the benefits from pooling of demand and leads to more variable demand for stores. The cycle-truncation effect, an additional, novel effect, also increases variability.

The cycle-truncation effect posits that store demand that arises from aggregation of purchase patterns of households with smaller basket sizes is more irregular and thus more variable. It arises because product perishability truncates replenishment cycle lengths when households buy larger basket sizes. The cycle-truncation effect is akin to the bullwhip effect, in that it also concerns variability propagation in the supply chain, yet its origins (in perishability) and direction (decreasing upstream variability rather than increasing it) are different. Further, its extent depends on the basket size.

Customers in denser markets are closer to the store thus their basket-sizes are smaller which leads to more variable demand due to the cycle-truncation effect. Overall, higher density leads to lower and more variable retail demand (due to inventory decentralization and cycle truncation), both of which increase store waste. Essentially, the smaller scale of the stores, and more irregular orders by households lead to higher retail waste.

In addition, there are *strategic effects.* Higher density implies stores are closer and more spatially substitutable which intensifies the competition in the market. This changes the equilibrium price/service level, which, in turn, changes both households' and store inventory management decisions and the waste arising from them. Our analysis shows that the food waste impact of the strategic effects is higher on households' waste than on retail waste when stores compete on price; this is reversed when stores compete on service levels. Essentially, every unit change in households' waste on account of a price change is accompanied by an opposite but smaller change on retail waste. Overall, strategic effects contribute to waste increases with higher density in the price setting, while contributing to waste decreases in the service setting.

In sum, an increase in density directly decreases consumer waste due to improved *access* to groceries, while increasing retail waste due to decentralization of inventory, diminished cycle truncation, and demand by customers. Higher density also induces more competition which further increases (decreases) waste when stores compete on prices (service levels). The overall effect is determined by the combination of consumer waste reductions, store waste increases, and the strategic effects.

Our analysis reveals that in markets with low density, the consumer waste reductions are higher than the retail waste increases; this result reverses at higher densities. This leads to our key finding: *higher density reduces food waste up to a threshold density, and it leads to higher food waste beyond this threshold*. Put differently, in so far as food waste is concerned, there exists an optimal store density. Our numerical calibration shows that the optimal value lies in a practically relevant range.

We calibrate our model using grocery industry, economic, and demographic data for a number of representative urban areas: ultradense areas like Manhattan, densely populated cities like Chicago and Los Angeles, more spread-out cities like Denver and, suburban college towns like Ithaca. We find that for all urban areas studied, the actual store density is *well below the threshold density*. As such, for all areas *higher* *store density reduces food waste*. Having said that, the effects are less pronounced for areas like Manhattan, which have both high store and population density; the actual density is nearest to the optimal in this case. On the other hand, for more typical cities like Chicago, our results show that even modest increases in store density can lead to substantial decreases in food waste. For example, just three to four more stores (per 10 sq km) would lead to a 6%–9% reduction in food waste. Recall that the carbon footprint of food waste is comparable to that of *all* road transportation; thus, these gains are very substantial. Finally, we also find that these carbon footprint reductions are accompanied by 1%–4% decrease in grocery expenses for households (on account of lower waste, travel, and prices). Thus, density increases combat emissions, while also making groceries more affordable, achieving two goals that are often considered competing.

Our findings arise from the fact that at current density levels, the level of, and the reductions in, consumer waste, dominate the same for retail waste. This highlights that a singular focus on retail waste, as is often the case for interventions proposed by activists and in the popular press, might be misplaced and even misleading in some cases (the effects of density on retail waste are opposite to the overall effects).

Our study provides the first analysis of the impact of store density on food waste and shows that even small increases in store density can lead to substantial reductions in greenhouse gas emissions while making groceries more affordable.

2. Related Literature

Our paper contributes to the literature on food supply chains and the literature on the environmental impact of grocery retail. Methodologically, we employ models from perishable and competitive inventory management.

2.1. Food-Supply Chains and Food Waste

Recent research on food-supply chains (e.g., Dawande et al. 2013, Boyabatli and Wee 2016, Hu et al. 2016) has explored crop-planting decisions, farm-yield management, and water distribution between farms, among other issues. Within this research stream a small but growing body of work on food waste has emerged. Akkas et al. (2014), using large-scale data, identify the drivers of *in-store* product expiration. Akkas and Honhon (2018) study product display and discount pricing for perishable products. In addition to the store waste that these studies consider, we include households' waste, which plays a key role in our context.

2.2. Environmental Impact of Grocery Retail

Cachon (2014) compares the environmental impact of store density in the *offline* retail of *nonperishable* products, focusing primarily on *travel* emissions. Belavina et al. (2017, 2018) study delivery pricing for *online* retail of perishable and nonperishable products and consider travel and food-waste emissions. They find that perishables are the primary driver of emissions and that food-waste emissions far dominate travel emissions. Our study is set in the context of *offline* retail (like Cachon 2014) but focuses on the primary driver identified in Belavina et al. (2017, 2018): food-waste emissions from perishables. Overall, we are the first to study the impact of store density on food waste.

2.3. Inventory Models with Perishable-Inventory, Endogenous Demand, or Competition

Our inventory management model adapts the analysis from the perishable inventory management literature (see Nahmias 2011 for an extensive review); our model includes two-echelons and multiple heterogenous competing players at each tier, features rarely considered in past work (Ketzenberg and Ferguson 2008). Past inventory models with endogenous demand (e.g., Dana and Petruzzi 2001) employ generic demand functions to capture the dependence of *mean* demand on price. In our model, store demand arises from the explicit aggregation of households' ordering decisions, which allows us to capture two additional phenomena: the effect of service levels on store demand and the effects of service/price on demand *variability*, both of which are crucial to accurately considering food waste. Finally, most inventory competition models (e.g., Dana and Petruzzi 2001) do not consider spatial competition, a key aspect in grocery retailing, whereas the previous work on spatial competition (see Balachander and Farquhar 1994 and references therein) does not consider demand variability, which our model does.

3. Model Setup

3.1. Fresh-Grocery Supply Chain

Consider a grocery market of area A. Households are distributed uniformly in the market area with density ρ. This market is served by N uniformly distributed *fresh*-grocery stores; higher N implies higher store density in the market. Grocery stores buy fresh groceries and build *store inventories* to meet demand from individual households. In turn, households buy fresh groceries from grocery stores and build *households' inventories* to satisfy their continuing and uncertain grocery consumption needs. Expiring store and households' inventories lead to food waste.

3.2. Grocery Stores

Store $n \in \{1, 2, \ldots, N\}$ procures a quantity S_n of fresh groceries every τ periods at a unit price ζ and retails them at a price p_n and with a service level β_n. Groceries unsold after τ periods are beyond their sell-by date and are discarded (store food waste). Stores compete for households by setting prices and/or service levels. In the price-setting case, stores decide on the price p_n (service level is exogenous). In the service-setting case, price level is exogenous, and stores decide on the desired service level (fill rate) β_n, or, equivalently, they choose the quantity S_n to be procured. The market's demographics, income levels, customer expectations, etc., determine the retailer's focus on price or service.

3.3. Households

Households have random consumption needs for groceries, owing to changes in dining plans (e.g., eating outside food due to work, leisure), randomness in the number of the household members eating at home, falling short of plans/aspirations for cooking, and so on (WRAP 2007, Glanz 2008). Each household's grocery consumption is generated according to a Poisson process whereby instances of consumption occur at a rate μ. Households satisfy these needs by purchasing fresh groceries from stores, which expire T days after purchase (our results apply equally if T is random).

Each trip to the grocery store incurs a fixed cost Γ and a cost c per unit of distance traveled. These costs subsume the customer inconvenience, transportation expenses, and the opportunity cost of time. The idiosyncratic location of a household θ influences its distance to store n, denoted as d_n^θ. To account for the urban environment, we use "Manhattan" distances (ℓ_1 norm). Our results are unchanged if we use "as-the-crow-flies" (Euclidean) distances.

Upon visiting store n, the household purchases a quantity Q_n of groceries, or it encounters a stockout, w.p. $\bar{\beta}_n = 1 - \beta_n$. Upon stockout, the "immediate" or very short-term demand is met by a "reactive" or instant outside option, for example, by having food delivered, ordering takeout, or eating at a restaurant. Mathematically, on observing a stockout, the household consumes a small quantity q via an outside option to tide over the stockout, paying a unit price p_o. Groceries that expire before consumption represent households' waste.

Together, the households' and store inventory management form a two-echelon perishable-products supply chain with *multiple*, *spatially differentiated* firms at the upstream tier that *compete* for inventory holding, *spatially heterogenous* households at the downstream tier.

4. Households' Inventory Management and Store Choice

We start by understanding a household's optimal store choice, replenishment timing, and basket size as a response to given store prices and service levels.

4.1. Households' Inventory Management

A household continuously reviews its inventory level and replenishes groceries when it runs out (through consumption or expiration of groceries—whichever happens earlier). At each household replenishment, we assume that the households' ex-ante odds of finding groceries at the store are the same. While, in general, this probability could vary with time due to replenishments by other households and the stores, but with a large number of households and high service levels this dependence is insignificant. Thus, at each replenishment point, the household's inventory system returns to the same state and, as a result, the household chooses the *same* store and the *same* basket size, those that minimize its *expected long-run cost rate*. From standard renewal-theory arguments, this rate is equal to the average cost per replenishment cycle divided by the expected cycle length.

In particular, consider a household at a distance d_n^θ from store n that charges prices p_n and offers service level β_n. For any basket size Q, the *expected long-run cost rate* of this household is

$$\mathbb{C}(d_n^\theta, p_n, \beta_n, Q) = \left(\Gamma + 2cd_n^\theta + \beta_n p_n Q + \bar{\beta}_n p_o q\right) \cdot E[T(Q)]^{-1}.$$

The average cost per trip (replenishment cycle) is $\Gamma + 2cd_n^\theta + \beta_n p_n Q + \bar{\beta}_n p_o q$; the first two terms capture the fixed and distance costs of a store visit, and the last two terms capture the grocery purchase costs, incorporating the possibility of finding groceries in stock and the possibility of stockout (in which case, the reactive outside option is used).

The expected cycle length $E[T(Q)] = \bar{\beta}_n q \mu^{-1} + \beta_n E \cdot [CT(Q)]$, with $E[CT(Q)] = \mu^{-1}(Q - \omega(Q))$ see Lemma 5 in the online appendix. The first component of the expected length covers the case of the stockout: q units sourced from the outside option are consumed in time $q\mu^{-1}$. The second component captures the case in which groceries were found in stock: Q units purchased are consumed in time $E[CT(Q)]$. In particular, out of Q units purchased, in expectation only $Q - \omega(Q)$ will be consumed, as $\omega(Q)$ units will expire before consumption. Specifically, the number of units expiring is

$$\omega(Q) \equiv \sum_{k=0}^{Q} (Q - k)\psi_k(\mu T). \tag{1}$$

Here, $\psi_k(\mu T) = \frac{(\mu T)^k}{k!} e^{-\mu T}$ is the probability that consumption during shelf-life T equals k, and the associated CDF is $P(Q, \mu T) \equiv \sum_{j=0}^{Q} \psi_j(\mu T)$. If consumption during the shelf life T was k, $k \in [0, Q]$, then $Q - k$ units would expire and be wasted. For $k > Q$, no food waste is generated. Equation (1) takes the expectation over these outcomes. These $\omega(Q)$ units constitute the expected food waste generated by a household in a replenishment cycle; the long-run equilibrium rate of this waste generation is the key metric in subsequent analysis.

The optimal basket size $Q_n \equiv Q^*(d_n^\theta, p_n, \beta_n)$ minimizes grocery-acquisition cost, that is $Q^*(d_n^\theta, p_n, \beta_n) = \arg\min_Q \mathbb{C}(d_n^\theta, p_n, \beta_n, Q)$. It is characterized in the proof of the Lemma 1 along with the corresponding optimal waste $\omega_n = \omega(Q_n)$, optimal cost $\mathbb{C}_n \equiv \mathbb{C}(d_n^\theta, p_n, \beta_n, Q_n)$ and the optimal grocery-acquisition rate $R_n \equiv R(d_n^\theta, p_n, \beta_n) \equiv Q_n E[T(Q_n)]^{-1}$.

Lemma 1. *Unilateral increase in price p_n, service level β_n of store n, or lower distance to the store d_n^θ leads to a smaller basket size, lower waste, and a lower grocery-acquisition rate for households shopping at store n, that is, $\frac{d}{dv}Q_n$, $\frac{d}{dv}\omega_n$, $\frac{d}{dv}R_n < 0$, where $v \in \{p_n, \beta_n, -d_n^\theta\}$.*

Proofs for all results are given in the online appendix. The optimal basket size trades off the risk of buying too many groceries against the risk of buying too few. Buying more groceries per trip increases the chances of food being wasted. Buying fewer groceries, on the other hand, leads to higher odds of running out of groceries, which triggers additional store visits and the potential of having to resort to the (expensive) outside option.

A higher grocery price increases the consequences of buying too many groceries, resulting in a smaller basket size. Higher service reduces the chances of having to use the outside option, whereas a shorter distance d_n^θ reduces the cost of additional store visits. Both reduce the consequences of buying too few groceries and lead to smaller basket sizes. Smaller basket sizes lead to lower food waste—note from Equation (1), smaller Q means a lower limit of the summation and a lower summand. Intuitively, if a household buys fewer groceries, it is less likely that some will expire before they are consumed. Finally, a household that wastes less will also buy less groceries in aggregate, and thus have a lower grocery acquisition rate. Overall, *smaller basket sizes lead to lower food waste and lower grocery acquisition rates* (a fact we will use later). Combining this with the previous observation that higher price or service or lower distance induce smaller basket sizes and leads to the statement of the lemma.

4.2. Households' Store Choice and Resultant Store Catchment Area

We assume that the market area is of regular shape, that stores are located according to a uniform lattice, and that each store is at the center of a square with area AN^{-1}; that is, we use the square-tiling approximation for the market area (Cachon 2014); other tiling structures would yield the same insights. We orient the axes along the diagonals of the square containing the store as this is known to minimize the average Manhattan or l_1-norm distances between customers and stores.

In our store choice calculation, we ignore edge effects; that is, we assume the same competitive environment for the few stores at the edge of the area as those in the center of the area. This overestimates the competitive interactions for these few stores. However, subsequent analysis will show that even these overestimated competitive interactions are overshadowed by other effects; thus, this approximation does not drive any of our findings.

The household's optimal store choice is simply the store with the lowest expected long-run average cost, $n^* = \arg\min_n\{\mathbb{C}_n\}_{n\in\{0,1,\ldots,N\}}$; $\mathbb{C}_0 \equiv p_o\mu$ captures the possibility of always using the outside option. That is household chooses to shop at store n if the cost of shopping at this store is lower than that at all other stores (denoted as $-n$), and the outside option. Such households lie in a contiguous area, the "catchment area" of the store, which depends on the store n's own price and service (p_n, β_n) and those at all other stores, denoted by the vectors $\boldsymbol{p}_{-n}$ and $\boldsymbol{\beta}_{-n}$.

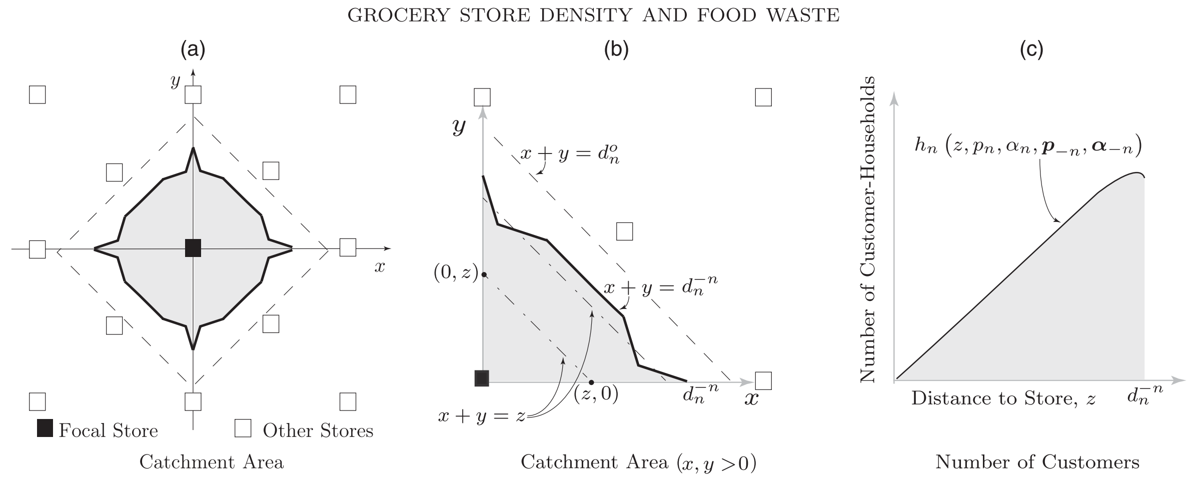
The shaded area in Figure 1(a) shows the catchment area of store n when $p_n < p_{-n}$ or $\beta_n > \beta_{-n}$, and all elements of $\boldsymbol{p}_{-n}$ $(\boldsymbol{\beta}_{-n})$ are set to the same value p_{-n} (β_{-n}), the case most useful for considering deviations from a symmetric equilibrium. Other cases are provided in Figure C.1 of the online appendix. Panel (b) focuses on the first quadrangle of the coordinate space.

The catchment area arises out of the *intersection* of two areas: a superellipse-like area that captures the effect of competition with neighboring stores, and a rhomboid area that arises from the outside option (the solid line and the dashed line respectively in Panels (a) and (b)). Because the grocery-acquisition cost is increasing in distance (see proof of Lemma 1), the boundary of the first area is defined by locations at which the costs of shopping from the two neighboring stores become equivalent.

Specifically, mindful of the fact that we use Manhattan distances, the boundary is defined by $\mathbb{C}(|x+y|, p_n, \beta_n) = \mathbb{C}(\chi_n(x,y), p_{-n}, \beta_{-n})$, where x and y are the coordinates for the boundary-households and $\chi_n(x,y)$ is the distance to the nearest competing store, $\chi_n = 2\bar{d} - (y-x)$ for $(x,y) \in \mathcal{A}_2$, $\chi_n = y - x$ for $(x,y) \in \mathcal{A}_3$ and $\chi_n = 2\bar{d} - (x+y)$ for $(x,y) \in \mathcal{A}_{31}$, the areas $\mathcal{A}_2$, $\mathcal{A}_3$ and $\mathcal{A}_{31}$ are defined in the proof of Lemma 6, and $\bar{d} \equiv \sqrt{A/(4N)}$. The distance covered by the farthest-away customer that chooses store n over other stores is denoted by d_n^{-n}. When $p_n = p_{-n}$, or $\beta_n = \beta_{-n}$, the superellipse degenerates into a rhomboid, defined as $|x+y| = \bar{d}$.

Finally, a household buys from store n only if the cost is lower than the outside option, $\mathbb{C}_n \le p_o\mu$, which can be rewritten as $|x+y| \le d_n^o$ (rhombus area in (a) and dashed line in (b)), where d_n^o is a solution to

Figure 1. Catchment Area and Customer-Household Density



$P(Q^*(d_n^o, p_n, \beta_n), \mu T) = 1 - p_n p_o^{-1}$. Together, the farthest distance any customer travels to shop at store n is $\bar{d}_n \equiv \min\{d_n^{-n}, d_n^o\}$.

The number of households that choose store n *and are located at a distance* z is obtained by considering the "l_1-norm-length" of the iso-(l_1)-distance line that lie within the catchment area (the part of the dash-dot line, $x + y = z$, in Figure 1(b) that lies in the shaded area). The resultant number of customer-households at a given distance z is $\mathbb{I}\{z \le \bar{d}_n\} h_n(z, p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n})$, see Lemma 6 for the formal expressions; the function h_n is depicted in Figure 1(c).

5. Equilibrium Choices in the Grocery Retail Network

We start our analysis by providing a sketch of the drivers of store demand. We compute a store's mean demand and its variance, given prices and service levels at all stores, and how the mean and variance of this demand change with the deviations in the focal store's price/service. We then use these observations to understand the equilibrium.

5.1. Store Demand

Stores get replenished every τ periods. The demand of interest is then the demand at store n between two replenishments as a function of the prices and service levels. This demand is obtained by identifying the households that choose to visit this store (as described in Section 4) and superposing the demand patterns of these *customer*-households between the store replenishments.

Combining Lemma 6, which provides the number of customer-households at a distance z, with the analysis of Section 4, which provides the grocery-acquisition rate $R(z, p_n, \beta_n)$ and ordering pattern of a household at a given distance, allows us to obtain the random demand at store n between two replenishments, $D_n(p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n})$. The mean and variance of this demand are as follows (see the online appendix Lemma 7 for more details):

$$m_n \equiv E[D_n] \approx \tau \int_0^{\bar{d}_n} R(z, p_n, \beta_n) h_n(z, p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n}) dz;$$

$$\sigma_n^2 \equiv \mathrm{var}[D_n] \approx \tau \int_0^{\bar{d}_n} R^2(z, p_n, \beta_n) \frac{\mathrm{var}[T(Q^*(z, p_n, \beta_n))]}{E[T(Q^*(z, p_n, \beta_n))]} \cdot h_n(z, p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n}) dz. \quad (2)$$

Lemma 2. *Unilateral increase in price of store n leads to lower mean demand for the store* ($\frac{dm_n}{dp_n} < 0$), *while unilateral decrease in service may increase or decrease mean demand.*

An increase in price (decrease in service) by store n leads to a smaller catchment area because some households formerly in the catchment area would now prefer to travel a longer distance to access other stores or would use the outside option rather than pay the higher prices (experience lower service) at this store. This implies that the store serves fewer customers, and these customers are located closer to the store. Recall, closer customers buy and waste less (Lemma 1). Further, higher prices also lead each customer to buy less (Lemma 1). Overall, higher prices lead to fewer, closer customers each of which buys less (on account of being closer and due to higher prices), lowering mean demand. Lower service also leads to fewer, closer customers, however each of them buys less on account of being closer, but *more* due to lower service (Lemma 1), which leads to competing forces.

Note that although losing customers to other stores/outside option is typical of all demand systems, the change in the grocery-acquisition-rate effect (due to a change in waste) is unique to our context and arises from the fact that the households themselves hold and manage inventory. This effect also drives the distinction between the effects of price and service deviations.

Lemma 3. (i) *Unilateral increase in price at store n leads to more variable cycle times for households shopping at the store* ($\frac{d}{dp_n}\frac{\mathrm{var}[CT(Q_n)]}{E[CT(Q_n)]} > 0$), *whereas unilateral decrease in service leads to less variable cycle times* ($-\frac{d}{d\beta_n}\frac{\mathrm{var}[CT(Q_n)]}{E[CT(Q_n)]} < 0$) *(cycle-truncation effect).* (ii) *Unilateral increase in price/decrease in service lead to less statistical economies of scale (pooling) due to fewer households in the store's catchment area. Overall,* (iii) *higher price leads to lower standard deviation of store demand, but higher coefficient of variation* ($\frac{d\sigma_n}{dp_n} < 0, \frac{dc_{vn}}{dp_n} > 0$), *whereas lower service can incr. or decrease the two.*

Change in variability occurs for two reasons, both of which have to do with how household-demand patterns aggregate to lead to store demand: the first in time (cycle-truncation effect) and the second in space/market area (statistical economies of scale).

To understand the first, we need to understand the relationship between the variability of household cycle times and the basket size. Consider two extreme cases. The first is when the household buys the smallest elemental quantity of groceries every trip, say, $Q = 1$. In this case, the household essentially has no inventory and must replenish every time consumption occurs—the replenishment process and consequent store demand from this household will look exactly like the underlying consumption process. That is, the interreplenishment times will have the same variability as the interconsumption times. The second case is when the household orders a very large basket size, such that the possibility of using up all groceries within their lifetime T is exceedingly small. Now, the time between successive replenishments is always going to be T, because the household will visit the store only when existing groceries expire. Importantly, it will have no variability.

Our formal analysis shows this effect goes beyond the two extreme cases—smaller basket sizes lead to more variability in the time between the two successive replenishments ($\partial_Q \frac{\mathrm{var}[CT(Q)]}{E[CT(Q)]} < 0$), or more irregular replenishments. More variability in cycle times translates into higher variability in the number of visits by the household to the store within the store's replenishment period and consequently higher variability in the demand at the store within the replenishment period. Thus, *smaller basket sizes lead to more variable demand*, because of what we call the "*cycle-truncation effect*." In effect, the basket size controls the extent of variability propagation in the supply chain. Like the bullwhip effect, the cycle-truncation effect also concerns variability propagation in the supply chain.

However, as a result of cycle truncation, variability of household replenishment times and, thus, variability of the store demand (variability of demand of the upstream tier) is lower (not higher) than variability of the household's consumption (variability of demand of the downstream tier). Further, the key driver in our context is the perishability of inventory, which to the best of our knowledge is a new driver of variability propagation in supply chains.[1]

Price/service deviations affect the variability of store demand via the cycle-truncation effect. Higher prices imply smaller basket sizes ($\partial_{p_n} Q_n < 0$, Lemma 1), smaller basket sizes imply more irregular orders (cycle-truncation, $\frac{d}{dp_n}\frac{\mathrm{var}[CT(Q_n)]}{E[CT(Q_n)]} > 0$), leading to higher demand variability with price (via its impact on the second part of the integrand in Equation (2)). On the contrary, lower service leads to bigger basket sizes, thus, less variable cycle times ($-\frac{d}{d\beta_n}\frac{\mathrm{var}[CT(Q_n)]}{E[CT(Q_n)]} < 0$) and lower demand variability. Part (i) of the Lemma now follows.

In addition to cycle truncation are the effects of traditional demand pooling. Higher price/lower service implies a smaller catchment area (as described in the explanation of Lemma 2). The smaller catchment area implies the demand at the store is a result of aggregating fewer households. Thus, the statistical economies are smaller (less demand pooling occurs) and demand has higher variability. This effect is exacerbated by the fact that these fewer customers also buy smaller basket sizes because they are closer, which implies fewer smaller orders are pooled at the store to generate its demand. The limit and the first part of the integrand in Equation (2) capture this. Part (ii) of the lemma now follows.

The cycle-truncation and pooling effects reinforce each other in the case of price deviations, but compete for service deviations; this leads to part (iii) of the lemma.

Note that all existing models in the literature that consider spatial competition (e.g., Balachander and Farquhar 1994), do not consider variability in consumption and its propagation within the supply chain. At the same time, competitive-inventory models (e.g., Dana and Petruzzi 2001, Netessine and Rudi 2003), although adept at capturing variability, do not have the effects of location and distances. As such, the effects in Lemma 3 have never been identified in this or other contexts. Not surprisingly, these effects on demand variability will influence store-waste comparisons directly and households' waste comparisons via how they change the equilibrium outcomes, which we describe next.

5.2. Profits and Equilibrium Definition

Profits. When store n orders S_n units, charges price p_n, and sees resultant demand $D_n(p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n})$, its expected profit in each replenishment period is $p_n E[\min\{S_n, D_n\}] - \zeta S_n$. Rewriting S_n in terms of the standardized stocking level s_n ($S_n = m_n + s_n\sigma_n$), and using the definition of β_n (recall we use type 2 service level or fill rate (Wikipedia 2018) $\beta_n = m_n^{-1}E\cdot[\min\{S_n, D_n\}]$), we obtain

$$\pi_n(p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n}) = p_n\beta_n m_n - \zeta(m_n + s_n\sigma_n).$$

The price p_n is collected only on a fraction β_n of the expected demand (as per the service level provided), whereas the procurement cost ζ is incurred on each unit purchased. The firm purchases the mean demand, plus a safety stock ($s_n\sigma_n$) to meet the desired service level.

Equilibrium. The relevant endogenous variable (price/service) is captured by $v_n \in \{p_n, \beta_n\}$, whereas the exogenous variable $\{p_n, \beta_n\}\backslash v_n$ is set to a given level (p or β) for all stores.

Each store chooses its price/service so that it constitutes a Nash equilibrium. Given the symmetric nature of stores and households in our model, we look for symmetric equilibrium. Specifically, the equilibrium prices/service levels $\boldsymbol{v}$ at the stores are given by the following system:

$$v_n(\boldsymbol{v}_{-n}) = \underset{v_n}{\operatorname{argmax}}\ \pi_n(p_n, \beta_n, \boldsymbol{p}_{-n}, \boldsymbol{\beta}_{-n}),$$
$$\forall n \in \{1, 2, \ldots, N\}; \quad v_1 = v_2 = \ldots = v_N.$$

The first expression captures the best response of each store to the strategy employed by all other stores, the last equation arises from the symmetry of the equilibrium.

Lemma 4. *The equilibrium price p^* is the solution to $\mathbb{P}(p_n) = 0$,*

$$\mathbb{P}(p_n) \equiv \beta_n m_n + (\beta_n p_n - \zeta)\frac{dm_n}{dp_n} + \zeta\xi_m^{ss}\frac{dm_n}{dp_n} - \zeta\xi_\sigma^{ss}\frac{d\sigma_n}{dp_n}. \tag{3}$$

The equilibrium service β^* is the solution to $\mathbb{A}(\beta_n) = 0$,

$$\mathbb{A}(\beta_n) \equiv p_n m_n - \zeta\xi_\beta^{ss} m_n + (\beta_n p_n - \zeta)\frac{dm_n}{d\beta_n} + \zeta\xi_m^{ss}\frac{dm_n}{d\beta_n} - \zeta\xi_\sigma^{ss}\frac{d\sigma_n}{d\beta_n}. \tag{4}$$

Here, $\xi_m^{ss} \equiv \bar{\beta}_n\bar{\Phi}(s_n)^{-1} > 0$, $\xi_\sigma^{ss} \equiv \bar{\Phi}(s_n)^{-1}(-\int_{-\infty}^{s_n} z\phi(z)dz) > 0$, $\xi_\beta^{ss} \equiv \bar{\Phi}(s_n)^{-1}$. Intuitively, ξ_x^y, captures the effect of a unit change in a variable x, on the variable y; ss denotes safety stock.

Equation (3) captures the trade-off in setting equilibrium prices. A unit increase in price leads to $1 \cdot \beta_n m_n$ more revenues from the higher prices charged to all customers (first term). It also lowers the mean demand (Lemma 2). A unit reduction in mean demand reduces profits by $\beta_n p_n - \zeta$ (second term). It also increases costs by $\zeta\xi_m^{ss}$ (third term), as safety stock the firm must maintain increases by ξ_m^{ss} (lower mean keeping standard deviation the same leads to more variable demand and, thus, higher safety stock). Finally, an increase in price also lowers the standard deviation of demand (Lemma 3). A unit decrease in the standard deviation of demand, lowers safety stock by ξ_σ^{ss}; the associated cost reduction is the last term of Equation (3).

Traditional price competition models include the first two effects/terms of price increase—higher revenues and lower sales—but exclude the operational effects. In particular, our model additionally includes the changes in the safety stock that must be carried due to lower and more variable demand with higher price, the last two terms. Incorporating the changes in safety stock is particularly important for the study of food waste, as it is the equilibrium safety stock that contributes to leftover inventory or waste. The positive coefficients ξ_m^{ss} and ξ_σ^{ss} that denote the change in safety stocks on a unit change in mean/standard deviation thus will be critical in our subsequent analysis of waste.

Equation (4) captures the trade-off in setting the equilibrium service level. An increase in service has direct and indirect effects. The first two terms capture the direct effects: a unit increase in service level increases revenues by $p_n m_n$ due to additional demand captured (fewer lost sales), but it requires the firm to carry additional safety stock of $\xi_\beta^{ss} m_n$ units, $\xi_\beta^{ss} \equiv \bar{\Phi}(s_n)^{-1}$. The remaining terms capture the indirect effects of service that arise via changes in mean and standard deviation of demand (Lemmas 2 and 3). These are just as in the price-setting case.

It is instructive to convert the optimality Condition 4 to a form more familiar in the traditional noncompetitive nonspatial inventory literature:

$$\bar{\Phi}(s_n) = \frac{\zeta}{p_n + \frac{1}{m_n}\left[\left(\beta_n p_n - \zeta + \zeta\xi_m^{ss}\right)\frac{dm_n}{d\beta_n} - \zeta\xi_\sigma^{ss}\frac{d\sigma_n}{d\beta_n}\right]}. \tag{5}$$

Note, if demand was exogenous, as in traditional inventory management, $\frac{dm_n}{d\beta_n} = \frac{d\sigma_n}{d\beta_n} = 0$, the optimality condition would reduce to the familiar newsvendor critical fractile $\bar{\Phi}(s_n) = \frac{\zeta}{p_n}$. In our case, store demand endogenously arises from the downstream tier's inventory management and store choice, bringing about the additional effects. If higher service increases the mean demand $\frac{dm_n}{d\beta_n} > 0$, the firm has incentives to shift the stocking quantity (and thus service level) higher than in the traditional newsvendor setup. Similarly, if standard deviation increases $\frac{d\sigma_n}{d\beta_n} > 0$, the firm will choose a lower than traditional stocking quantity, because higher variability in demand increases the costs of servicing the demand with a given service level. Note that including this endogenous store demand is critical to studying the impact of households' decisions on store operations and, consequently, on store waste.

6. Store Density and Food Waste: Price Setting

We discuss the impact of density on food waste in the price-setting case in this section; the service setting case is in Section 7. First, we rule out a trivial case in which store density is so low that some customers are too far from all grocery stores and always prefer using the outside option. That is, we assume that $N > \underline{N}$; $\underline{N}$ is the smallest N such that $\bar{d}_n = d_n^{-n}$. Practically, all urban areas that we are aware of have store densities high enough to meet this condition.

Expiring inventories at households and stores lead to waste. We first examine households, then stores, and finally the two combined, that is, the waste in the market.

6.1. Consumer Food Waste

A household shopping at store n located at distance z from it generates waste at a rate $w(z, p_n, \beta_n) \equiv \omega(Q^*(z, p_n, \beta_n))E[T(Q^*(z, p_n, \beta_n))]^{-1}$; where $\omega(Q) \equiv \sum_{k=0}^{Q}(Q-k)\cdot \psi_k(\mu T)$ is the expected waste per cycle, and $E[T(Q)]$ is the expected duration of the cycle (from Section 4). Note that, households' waste does not depend on the price or service levels of other stores conditional on selecting a given store. Accounting for the households' store choices (households at a distance $\bar{d}_n$ or less choose store n and the resultant number of customer-households at distance z is $h_n(z)$), we obtain the *equilibrium* total waste of all households in the market, or the *consumer waste*:

$$W_c(N, p^*(N)) \equiv N\int_0^{\bar{d}_n} w(z, p^*, \beta)h_n(z)dz.$$

The consumer waste W_c is a function of the density N, the equilibrium price $p^*(N)$ which itself is a function of the density. Thus, we examine the effects of density on consumer waste by decomposing the effects into two components:

$$\frac{dW_c(N, p^*(N))}{dN} = \frac{\partial W_c}{\partial N} + \frac{dW_c}{dp^*}\frac{dp^*}{dN}. \tag{6}$$

The first term in Equation (6) captures a direct effect: how an increase in density directly affects the waste generated. The second term captures a *strategic effect*: the impact of density on waste on account of changes in equilibrium prices.

Theorem 1. *An increase in store density leads to* (i) *a decrease in consumer waste due to improved store access for households (direct effect,* $\frac{\partial W_c}{\partial N} < 0$*), and* (ii) *an increase in consumer waste on account of lower equilibrium prices, iff* $\mathcal{P}(p^*) > 0$ *(strategic effect,* $\frac{dW_c}{dp^*}\frac{dp^*}{dN} > 0$*). Overall, consumer waste is lower (direct-access effect dominates the strategic effect) iff*

$$N^{-1}(w(\bar{d}) - w(\underline{d}))A\rho > \wp\mathcal{P}(p^*)\xi_{p^*}^{wc}; \tag{7}$$

$$\mathcal{P}(p^*) \equiv -\beta_n\partial_N m_n + \zeta\xi_{c_v}^{ss}\partial_N c_{vn}\frac{dc_{vn}}{dp_n} - [\beta_n p_n - \zeta + \zeta\xi_m^{ss}]\cdot\frac{\partial}{\partial N}\frac{dm_n}{dp_n} + \zeta\xi_\sigma^{ss}\frac{\partial}{\partial N}\frac{d\sigma_n}{dp_n}. \tag{8}$$

Here, positive terms $\underline{d}$ *and* $\wp$ *are formally defined in Section D.5 in the online appendix;* $\xi_{p^*}^{wc} > 0$ *captures the effect of equilibrium price on consumer waste;* $\xi_{c_v}^{ss} \equiv m_n\phi(s_n)\bar{\beta}_n^2 \times (\bar{\Phi}(s_n)c_{v_n})^{-3} > 0$ *and* $c_{vn} \equiv \sigma_n m_n^{-1}$.

Direct-Access Effect. Higher density implies that stores on average are closer to the customers. This leads to lower store-visit costs due to shorter travel distances. The lower store-visit costs imply more frequent trips with smaller basket sizes on each trip, which leads to lower waste for each household (Lemma 1). Lower waste at each household implies a decrease in the overall customer-tier waste. This decrease originates from the increased *access* that households have to stores. Thus, we call the direct effect on the consumer waste the *access effect*. The LHS of Equation (7) quantifies the waste reduction due to this effect. These gains are primarily proportional to N^{-1}; that is, they are highest at low density levels and diminish as density increases.

Strategic Effect. Higher density intensifies the competition between stores as it makes stores more spatially substitutable. This changes the equilibrium price which arises out of a balance between the increased margin and the consequences of lower, more variable demand on profits and safety stocks (Equation (2)). The effect of a density change on these elements determines how the equilibrium price will shift.

The forces pushing the equilibrium price can be viewed as those coming from the (first-order) changes in mean and variability of demand due to *density* increases (first two terms of Equation (8)), and those that come from the (second-order) changes in the *sensitivity* of demand to prices due to *density* increases (last two terms in Equation (8)).

Higher density directly means lower, more variable demand, as more stores implies that each store has fewer, closer (less wasteful) customers, which leads to lower mean demand. Fewer, closer customers means less demand pooling and more variable household cycle times (cycle truncation) leading to higher variability. Higher density also means a lower *sensitivity* of mean and standard deviation of demand to higher prices, as the mechanisms relating prices to mean and standard deviation (Lemmas 2 and 3), now affect fewer and closer (less sensitive) customer-households.

The lower, more variable demand and the lower sensitivity of standard deviation of demand in denser markets instigates a lower equilibrium price, whereas the lower sensitivity of mean demand to price in these markets instigates a higher equilibrium price. Condition 8 in the theorem encapsulates this trade-off in a necessary and sufficient condition: equilibrium prices are lower if and only if $\mathcal{P}(p^*) > 0$. Part (ii) of the theorem now follows.

Observation 1. *For all plausible urban, demographic and economic parameters, denser markets have lower equilibrium prices (which increases consumer waste).*

We find that for all plausible parameters (see Table 1) equilibrium prices are lower in denser markets ($\mathcal{P}(p^*) > 0$). The RHS of Equation 7 captures the magnitude of this increase: $\wp\mathcal{P}(p^*)$ captures the magnitude of price decrease and $\xi^{wc}_{p^*}$ the customer waste increase in response to the price decrease.

Access and Strategic Effects. The access effect reduces consumer waste, while the strategic effect increases it (for plausible parameters). The LHS and RHS of Condition 7 captures the magnitude of these effects on waste, and the equation itself, then captures the trade-off.

Observation 2. *For all plausible parameters, the direct-access effect dominates the strategic effect: denser markets have lower consumer waste.*

Interestingly, extensive numerical examination reveals that for all plausible parameters (Table 1), the access effect dominates. The access effect is a direct result of lower waste by closer households. On the other hand, the strategic effect arises from the households' response to the equilibrium price change by stores in response to the change in households' behavior (closer households with lower waste) and intensified competition. In general, the indirect relationship through the equilibrium actions underlying the strategic effect could lead to an amplification or attenuation of the original change in households' behavior; making the strategic effect more or less important. Our results suggest that for all plausible urban areas, the strategic response attenuates the original effect, and overall the direct-access effects dominate strategic effects. The dominance of the access effect has an important implication. We can now unambiguously say that for all typical urban areas, denser markets lead to lower consumer waste.

6.2 Retail Food Waste

The waste generated by a store in any period is the amount purchased S_n minus amount sold $S_n - \min\{S_n, D_n\}$. We can rewrite the store's stocking quantity S_n as $S_n = m_n + s_n\sigma_n$ (mean demand plus a safety stock). Further, because we use the type 2 service level or fill rate (Wikipedia 2018), we have $\beta_n = m_n^{-1}E[\min\{S_n, D_n\}]$. Thus, the expected waste at a store in a replenishment cycle is then $S_n - E[\min\{S_n, D_n\}] = m_n\bar{\beta}_n + s_n\sigma_n$. Aggregating the waste across all stores in the market implies that the expected waste rate of all stores in equilibrium or the *equilibrium retail* waste is

$$W_r(N, p^*(N)) \equiv \tau^{-1}(Nm_n\bar{\beta}_n + N\sigma_n s_n). \tag{9}$$

This waste level depends on the demand mean and standard deviation. More variable demand requires a higher safety stock leading to more waste; as discussed in Section 5.2, a unit increase in demand standard deviation leads to an increase of ξ^{ss}_{σ} in the safety stock and the waste. A unit reduction in the mean demand increases the safety stock required by ξ^{ss}_{m} but decreases the first component of waste by $\bar{\beta}_n$.

Table 1. Retailer, Household, and Product Parameters

Parameter	Baseline value	Range	Sources
Area	$A = 40$ sq km	$A \in [2; 500]$	Typical urban area (Wikipedia: List of U.S. cities by area, 2016)
Store density per 10 km^2	$N \in [5; 250]$	$N \in [5; 750]$	City licensing data
Households' density	$\rho = 12{,}000$ hh/km^2	$\rho \in [1{,}000, 24{,}000]$	Median household density in 200 biggest cities (citymayors.com)
Househ. consumpt. rate	$\mu = 90$ units/wk	$\mu \in [40, 140]$	Consumer Expenditure Survey (2015)
Product life	$T = 1$ week	$T \in [0.5, 2]$	Donselaar et al. (2006)
Fixed costs of store visit	$\Gamma = \$10$	$\Gamma \in [0, 20]$	2 x *online* ordering cost of $5 (est. by Hann and Terwiesch 2003)
Distance cost	$c = \$10$ per km	$c \in [1, 60]$	Incl. cost of time & dist. traveled (Brown and Borisova 2007)
Store replenish. freq.	$\tau = 1$ days	$\tau \in [1, 5]$	Most stores have daily grocery deliveries (Holmes 2011)
Service level	$\beta = 0.95$	$\beta \in [.75, .9999]$	Industry standard (Food Marketing Institute 2015)
Grocery sourcing cost	$\zeta = \$0.9$/unit	$\zeta \in [0.7, 1.2]$	The Reinvestment Fund (2011)
Selling price	$p = \$1.2$/unit	$p \in [\zeta, 2\zeta]$	Based on typical gross margins (The Reinvestment Fund 2011)
Price of outside option	$p_o = \$5$/unit	$p_o \in [2, 10]$	4.16 times more expensive than home (Flannel Guy ROI 2011)
Units throughout. opt.	$q = 5$ units	$q \in [1, Q_n]$	Author Estimate
Food-waste emis. coeff.	$e_f = 1$/unit	$e_f \in [0.36, 1.67]$	Belavina et al. (2017) (e-companion, Section 1, in kg of CO_2Eq)

The overall impact on waste of retailers is then $\xi^{wr}_m = \xi^{ss}_m - \bar{\beta}_n = \bar{\beta}_n \bar{\Phi}(s_n)^{-1}\Phi(s_n)$, which is positive. That is, the impact of the higher safety stock dominates, and, in aggregate, a unit decrease in mean demand increases waste by ξ^{wr}_m. Put differently, lowering mean while keeping the standard deviation the same leads to more variable demand and, thus, higher waste.

As with consumer waste, the impact of higher density on retail waste can be decomposed into direct and strategic effects: $\frac{dW_r(N,p^*(N))}{dN} = \frac{\partial W_r}{\partial N} + \frac{dW_r}{dp^*}\frac{dp^*}{dN}$.

Theorem 2. *An increase in store density leads to* (i) *an increase in retail waste due to changes in the scale of stores (direct effect, $\frac{\partial W_r}{\partial N} < 0$),* (ii) *a decrease in retail waste, on account of lower equilibrium prices, iff $\xi^{wr}_{p^*} \cdot \mathcal{P}(p^*) > 0$ (strategic effect, $\frac{dW_r}{dp^*}\frac{dp^*}{dN} < 0$). Overall, retail waste is higher (direct-scale effect dominates strategic effect) iff*

$$\xi^{ss}_\sigma \partial_N(N\sigma_n) - \xi^{wr}_m \partial_N(Nm_n > \wp\mathcal{P}(p^*)\xi^{wr}_{p^*},$$
$$\xi^{wr}_{p^*} \equiv \xi^{ss}_\sigma \frac{d}{dp^*}(N\sigma_n) - \xi^{wr}_m \frac{d}{dp^*}(Nm_n). \tag{10}$$

Direct-Scale Effect. Higher density lowers the mean retail demand Nm_n—customers are closer to the grocery stores, they waste less and, thus, they buy less (see Lemma 1). At the same time, with higher density, inventories in the retail network are more decentralized: each store now serves a smaller portion of demand and thus enjoys lower benefits of pooling. Further, as customers are closer to the store their basket-sizes are smaller which leads to more variable demand due to the *cycle-truncation effect*. Both inventory decentralization and cycle truncation lead to higher total standard deviation $N\sigma_n$.

Overall, higher density leads to lower mean retail demand ($Nm_n \downarrow$) and higher total standard deviation ($N\sigma_n \uparrow$). As discussed before the theorem, both result in higher waste, part (i) of Theorem 2 now follows. This is the direct effect: *higher density increases retail waste*. Because it arises from the smaller scale of the stores, and smaller, irregular replenishments by households, we call this direct effect of density on stores, the *scale effect*. The LHS of Equation (10) captures the magnitude of this effect; the first term is the impact of higher standard deviation and the second of lower mean.

Strategic Effect. From Section 6.1, we know that equilibrium prices are lower with higher density iff $\mathcal{P}(p^*) > 0$, which is always the case in practice. A lower equilibrium price leads to both higher total standard deviation and *higher* mean retail demand, as households now waste more of the cheaper food ($-\frac{d}{dp^*}(Nm_n), -\frac{d}{dp^*}(N\sigma_n) > 0$). Unlike the case with the direct effect, where the changes in both the mean and standard deviation led to higher waste, here the *higher* mean decreases waste, whereas the higher standard deviation increases waste. That is, the impact via the mean and the standard deviation are competing. The net impact of these competing effects is captured by $\xi^{wr}_{p^*}$. Iff $\xi^{wr}_{p^*} > 0$, the mean effect dominates the standard deviation effect, and a lower equilibrium price lowers the retail waste. On the other hand, when $\xi^{wr}_{p^*} < 0$, the lower equilibrium price increases retail waste. The RHS of Equation (10), mathematically captures these effects.

Direct and Strategic Effects

The LHS of Equation (10) captures the direct-scale effect that increases waste, whereas the RHS captures the strategic effects that arise from lower prices but can increase or decrease waste depending on $\xi^{wr}_{p^*}$. The tradeoff between the two is captured by Condition 10.

Observation 3. *For all plausible parameters, direct-scale effects dominate strategic effects: denser markets have higher equilibrium retail waste.*

Interestingly, as in the case of consumer waste, we again find that for all plausible parameters (Table 1), the direct-scale effect dominates. The direct effect arises from decentralization of inventory, less demand (on account of lower consumer waste) and diminished cycle truncation by customers. The strategic effect, on the other hand, arises from the retail-tier inventory response to the changes in market prices, which arises in response to the above effects and intensified competition. The indirect relationship through the equilibrium could attenuate or amplify the direct effects. Our results suggest that for plausible types of urban areas, the strategic effect attenuates the direct effect, and overall the direct effect prevails. Thus, we can unambiguously say that *denser markets have higher retail waste*.

We make two important comments here. First, our results show that the same strategic effect that has been the focus of the vast majority of thinking regarding grocery store competition is dominated by the hitherto ignored direct effect. The direct effect which captures inventory responses by consumers and stores, are almost always ignored in comparison with the more economics style discussion on the competitive dynamics, possibly leading to erroneous prescriptions.

Second, the direct effects dominate and determine the overall impact of density on waste, both for the consumer and for the retail tier, but these effects actually act in the opposite directions. Higher density *decreases* consumer waste but *increases* retail waste. This opposite effect implies an important trade-off to be characterized in so far as the market waste is concerned and is the focus of our next section.

6.3. Market Food Waste

We now explore the waste generated in the market, that is the sum of the consumer and retail-tier wastes, $W \equiv W_c + W_r$. As with consumer and retail waste, it is instructive to decompose it into direct and strategic effects: $\frac{dW(N,p^*(N))}{dN} = \frac{\partial W}{\partial N} + \frac{dW}{dp^*}\frac{dp^*}{dN}$. Recall that direct effects dominate strategic effects for both tiers, but they act in opposite directions. We, thus, start our examination studying the change in market waste only on account of direct effects. We then bring in the strategic effects to see if and how they alter the insights obtained from the dominant direct effects.

Theorem 3. *Store Density and Equilibrium Market Food Waste*

i. *Direct effect: Higher density leads to **lower** market waste iff the store density is below a threshold-level. Formally, $\partial_N W < 0$ iff $N \le \hat{N}$, here $\hat{N}$ is a solution to*

$$\begin{aligned}[w(\bar{d}) - w(\underline{d})]A\rho N^{-1} = N^{-1}[R(\bar{d}) - R(\underline{d}_R)]\xi_m^{wr} A\rho \\ + \sqrt{N^{-1}}\aleph(N)\sqrt{A\rho}\xi_\sigma^{ss}.\end{aligned} \tag{11}$$

ii. *Strategic effect: Lower prices, that result from higher density, lead to higher market waste. Formally, $\frac{dp^*}{dN}\frac{dW}{dp^*} > 0$.*

iii. *Higher density leads to **lower** market waste iff density is below a threshold-level, this level is lower than the level in (i). Formally, $\frac{dW}{dN} < 0$ iff $N \le \bar{N}$, $\bar{N} < \hat{N}$. Here, $\bar{N}$ is a solution to*

$$\begin{aligned}[w(\bar{d}) - w(\underline{d})]A\rho N^{-1} = N^{-1}[R(\bar{d}) - R(\underline{d}_R)]\xi_m^{wr} A\rho \\ + \sqrt{N^{-1}}\aleph(N)\sqrt{A\rho}\xi_\sigma^{ss} + A\rho\mathcal{P}(p^*)\xi_{p^*}^{w}\wp,\end{aligned} \tag{12}$$

$\xi_{p^*}^{w} = \partial_{p^*}Q^*(\underline{d}_\xi)(\partial_Q A_\xi(\underline{d}_\xi) + y(2\sigma_n)^{-1}\partial_Q\delta_n(\underline{d}_\xi))$, $\aleph(N)$, $A_\xi(z)$, δ_n, $\underline{d}_\xi$, $\underline{d}_R$ are defined in Section D.7.

Direct Effects. Recall that the direct effect of an increase in density is the decrease of consumer waste and the increase of retail waste, as per Theorems 1(i) and 2(i). Thus, the effects on consumer tier and those on the retail tier compete. Part (i) of Theorem 3 arises from the observation that at low densities, the consumer waste reductions are higher than the retail waste increases; this reverses at higher densities. Equation (11) characterizes the density at which this reversal happens.

The LHS of the equation captures the rate of decrease of consumer waste. Recall that this decrease arises out of the shorter distances that the average customer-household has to travel to access groceries. This average distance decreases as $A\rho N^{-1}$. Our analysis shows that this hyperbolic distance decrease also translates into a hyperbolic waste decrease (along with a small technical adjustment, captured by the term $w(\bar{d}) - w(\underline{d})$ which depends on N).

The RHS of the Equation (11) captures the rate of increase of retail waste. This increase arises out of lower mean store demand, decentralization of inventories, and higher demand variability (due to less cycle truncation). Mean store demand changes due to the change in the consumer waste, and, thus, also has a hyperbolic rate (first term of the RHS). The effects of inventory decentralization and cycle truncation are captured via changes in standard deviation and represented by second term of the RHS.

The rate of losses from decentralization is well known in single-echelon inventory theory: decentralization leads to an increase in inventory/costs/waste at a rate of $N^{-1/2}$ (Cachon 2014). In our two-echelon model, in addition to the decentralization we have cycle truncation, and the increase in inventories in our two-echelon model is in fact proportional to $\aleph(N) \cdot (A\rho N)^{-1/2}$, where the function $\aleph(N)$ comes from the variability propagation in the supply chain via the cycle-truncation effect. Together, the decentralization and cycle-truncation effects induce a rate of increase in market inventories (and thus retail waste) that is even faster than the rate from single-echelon models of $N^{-1/2}$.

The comparisons of the rates of increase and decrease thus (roughly) comes down to a comparison of the factor $A\rho N^{-1}$ (decrease in consumer waste) vs. the factor $\aleph(N) \cdot (A\rho N)^{-1/2}$ (increase in retail waste). This implies that for low density levels, the decrease in consumer waste dominates, while at higher density levels the increase in retail waste dominates. In turn, this implies that there exists a threshold level of density at which the effects of density increase changes. In particular, for markets with density lower than this threshold, density increases are beneficial. For markets with density higher than this threshold density increases are harmful as far as waste is concerned.

Strategic Effects. The strategic effects lead to an increase in consumer waste due to lower prices associated with higher density, and ambiguous effects on retail waste (decrease iff $\xi_{p^*}^{wr} > 0$). Thus, there should be a trade-off or ambiguity in the impact of the strategic effect on market waste. Yet, our result shows that in so far as strategic effects are concerned an increase in density always increases the market waste. That is, the consumer-tier increase always dominates retail-tier decrease (if any).

Higher density intensifies competition and lowers prices. This increases consumer waste as consumers waste more of the cheaper groceries. This higher consumer waste translates into higher market demand, which decreases retail waste on account of the smaller safety stocks. Our analysis reveals that this decrease in retail waste is always smaller than the increase in consumer waste, because a unit increase in market demand (consumer waste) leads to

$\xi_m^{wr} = \bar{\beta}_n \bar{\Phi}(s_n)^{-1}\Phi(s_n) < 1$ units decrease in retail waste. That is the stores' reduction in inventory can never fully compensate for the consumers' increase. Thus, the increase in consumer waste plus the decrease in retail waste leads to an overall increase in waste. On top of this, there is an additional increase in retail waste due to the higher standard deviation. This implies that strategic effects increase market waste, and part (ii) of the theorem now follows.

Combining Direct and Strategic Effects. The direct effects led to the threshold density $\hat{N}$, below which higher density reduces waste, and above which it increases waste. The strategic effect increases waste at all density levels. Thus, when we combine the strategic and direct effects, we again obtain a threshold density level $\bar{N}$, but this density level is lower, that is, $\bar{N} < \hat{N}$ (the strategic effects pushes down the threshold). Therefore, taking all effects into account, an increase in store density decreases food waste, if the density is less than $\bar{N}$, but increase waste if the density is higher than $\bar{N}$. Put differently, the optimal number of stores in a market (as far as food waste is concerned) is this threshold level $\bar{N}$.

6.4. Summary

Our analysis revealed that direct effects of density decrease consumer waste due to improved *access* to groceries, while increasing retail waste due to decentralization of inventory, diminished cycle truncation and demand by customers. Strategic effects, that capture the effects of density induced changes in prices on waste, increase consumer waste, their effect on the retail tier is ambiguous, but strategic effects increase the market (combined consumer and retail) waste. All effects put together, lead to a threshold density below which density increases are beneficial, and beyond which they are harmful. We will calibrate our model and identify this important threshold density for a number of cities in Section 8.

Our findings are in contrast with simplistic analysis that looks at higher density as just increasing competition (strategic effect) and misses the key phenomenon (the direct effect). Such an analysis would simply prescribe decreasing density to reduce competition, increase prices and reduce waste. Not only would this prediction be incorrect, but it also (incorrectly) implies that food waste reduction and food affordability are competing goals, which adversely affects the policy discussion on food waste. We estimate the impact of density on affordability in Section 8.2, but note here that as per the above analysis, for urban areas with density less than $\bar{N}$, higher density leads to lower prices *and* lower waste.

Next, note that even though strategic effects are dominated by direct effects (Observations 2 and 3), ignoring them would lead us to overestimate the optimal density for the market, as $\hat{N}$ instead of $\bar{N}$. Also, looking at simply the retail or the consumer tier would lead to incorrect predictions as well, because one would then predict monotonic reductions in waste on decreasing density (if only stores were considered) or monotonic reductions in waste on increasing density (if only consumers were considered), both of which are incorrect and conflicting observations.

Finally, note that the accounting for the variability of demand and how it changes with density is critical for each of these above discussed effects. Overall, each piece of our model—the two echelons; the direct and strategic effects; and the mean and variance of demand—is essential for arriving at precise predictions about the impact of density.

7. Store Density and Food Waste: Service Setting

First, the direct effects in Theorems 1, 2, and 3 are agnostic to the dimension of competition, price or service. Thus, direct effects in the service-setting case are identical to those described in the price-setting case. The strategic effects on the other hand are different, we next highlight the major differences in strategic effects between the service and price settings.

To understand the strategic effects, it is important to understand how the equilibrium service levels change with increase in density.

The equilibrium service levels decrease with higher density iff $\mathscr{A}(\beta^*) > 0$,

$$\begin{aligned}\mathscr{A}(\beta^*) \equiv & \left(\zeta\xi_\beta^{ss} - p_n\right)\partial_N m_n + \xi_{c_v}^{ss}\partial_N c_{vn}\frac{dc_{vn}}{d\beta_n} \\ & - \left[\beta_n p_n - \zeta + \zeta\xi_m^{ss}\right]\frac{\partial}{\partial N}\frac{dm_n}{d\beta_n} + \xi_\sigma^{ss}\frac{\partial}{\partial N}\frac{d\sigma_n}{d\beta_n} \\ & + \zeta\dot{\xi}_\beta^{ss}\partial_N c_{vn}. \end{aligned} \tag{13}$$

This condition (the counterpart of Condition 8 for the price-setting case) arises by examining how the factors determining equilibrium availability (Equation (4)) change with density. The first four terms are just as in price setting and arise from the changes in mean and variability of demand and from the changes in the *sensitivity* of demand to service. However, there is an additional (last) term here that arises as safety stock is now influenced by the change in equilibrium service level.

Observation 4. *For all plausible parameters, equilibrium service levels are lower in denser markets.*

Although we are not aware of any careful studies of the impact of density under service competition of spatially differentiated stores, intuition based on typical competitive models would suggest an increase in service levels due to intensified competition, in contrast to our finding of reduced service levels. The contrast stems from accounting for *endogenous demand* formation and changes in *demand variability*.

Two effects arise in addition to the conventional reasoning that more competition increases the need for better service. First, because of improved access, a firm with lower service can still obtain the same market size (households closer to the store will choose to visit the store even with lower service). Second, stores experience higher demand variability (as stores are smaller, and they enjoy less pooling benefits), which forces the retailer to decrease service (the costs of achieving the target service level are higher with more variable demand). This effect overcomes the usual competitive effect and leads to lower service with higher density. Accounting for endogenous demand formation from the downstream tier and its variability is thus critical to studying the effect of density in service competition.

7.1. Strategic Effects: Consumer and Retail Tiers

A lower service level induces households to buy bigger basket sizes when they find groceries in stock which leads to more waste, but it is also associated with higher use of the outside option. Overall the strategic effect on consumer waste is ambiguous. Stores providing lower service levels need lower safety stocks (reducing waste), but they also have higher unmet demand—the demand m_n is higher and a lower fraction of it is met—increasing waste (see Equation (9)). The strategic effect on retail waste is also ambiguous.

Observation 5. *For all plausible parameters, higher density decreases the equilibrium consumer waste but increases the equilibrium retail waste (like in the price-setting case).*

The above is based on observing that for all for plausible parameters, strategic effects oppose direct effects, yet they are dominated by direct effects. Thus, as a practical matter, the implications on the service-setting case and price-setting case are the same when examining consumer and retail waste independently. However, this is not (fully) the case when we examine the overall market waste.

7.2. Market Waste

The direct effects are naturally the same: density increase is beneficial below the threshold density $\hat{N}_s$, and harmful otherwise. In the price case, the strategic effects when combined for the two tiers unambiguously led to *more* waste in denser markets: the reduction in retail waste on account of lower prices, where not enough to overcome the accompanying consumer waste increase. In the service case, the *strategic effects leads to less waste* in denser markets. The waste gains from the lower safety stock that stores carry to deliver lower service levels are more than the losses from the increased consumer inventories and waste. That is, at the supply chain level, the results for the strategic effects are opposite in the service and in the price case. The difference stems from the fact that *price impacts consumer waste more directly, while service is more directly linked to retail waste.*

Combining the direct and strategic effects, we still see the threshold pattern–density increases are beneficial below a threshold density $\bar{N}_s$, but are harmful above it. Interestingly, the threshold comparison, $\bar{N}_s > \hat{N}_s$, is opposite to that in the price case, where $\bar{N} < \hat{N}$. In the service case, the strategic effects contribute to decreasing waste, rather than increasing waste as in price case.

8. Model Calibration

We calibrate our model using data from the grocery industry, the census bureau and other academic studies. Table 1 provides the parameter estimates and sources. To account for the wide heterogeneity in demographics and economics of grocery markets, for each parameter, we consider a wide range of values around the baseline to obtain the widest plausible range of values; these ranges are reported in the third column of the table.

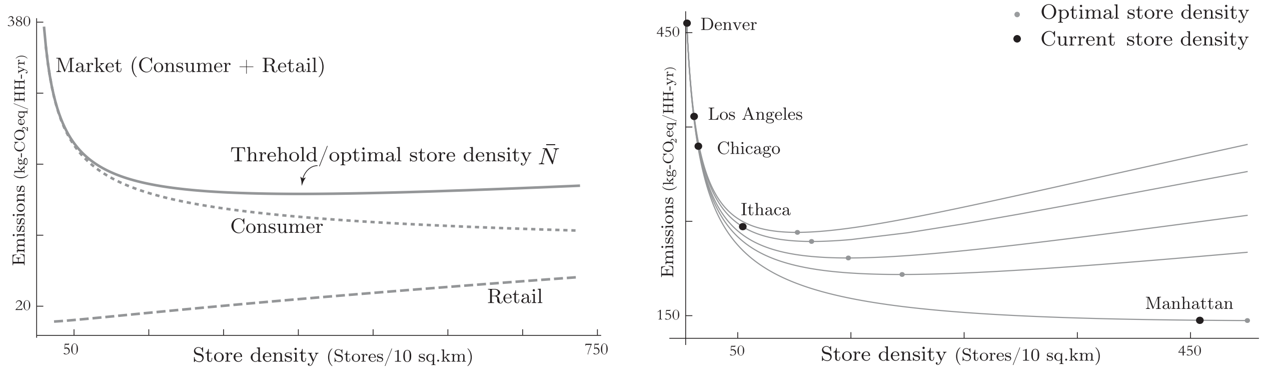
Although we attempt to test our findings for all combinations of the widest plausible ranges of parameter values, the following analysis should be considered indicative of the relative magnitudes of the effects discussed above, rather than a precise prediction of outcomes. Like all models, ours is meant to provide a simplified representation of reality that is amenable to study, and as such, it necessarily leaves out some other phenomena (less important in our assessment, see the discussion in Section 9 and online appendix). The material presented next is thus no substitute for a rigorous empirical analysis, which remains a fruitful prospect for future research.

8.1. Food Waste Emissions and Store Density

Drawn for baseline value of all parameters (Table 1), unless stated otherwise. In the right panel, lines represent areas with different *population* densities (top to bottom: 1,550 [Denver], 1,900 [Ithaca], 2,836 [Los Angeles], 4,447 [Chicago], and 24,137 [New York] sq km).

Threshold Density. Figure 2 shows the per capita annual carbon emissions associated with food waste for varying levels of store density in the price-setting case (the service setting leads to the same conclusions as those reported next). The emissions predicted by our model are within the ranges reported by the previous

Figure 2. Emissions Associated with Food Waste: Price Setting



Note. Drawn for baseline value of all parameters (Table 1), unless stated otherwise. Right Panel: lines represent areas with different *population* densities (top to bott.: 1550 (Denver), 1900 (Ithaca), 2836 (Los Angeles), 4447 (Chicago), 24137 (New York) /sq. km).

studies (Food and Agriculture Organization 2015), validating our analysis. We also compared the estimates of the influence of distance on shopping frequency with those in empirical studies on this subject (e.g., Gustat et al. 2015). Our effects are very close (slightly on the conservative side), validating a key influential metric in our analysis.

The left panel shows the contributions to market waste of the consumer and retail tiers (for baseline parameters). Note that consumer waste is decreasing with higher store density, while the retail waste is increasing (as per observations 2 and 3). As for the market waste, there exists a threshold/optimal density (as predicted by the Theorem 3).

Next, we calibrate our model using data from different markets representative of various kinds of cities: dense urban areas like Manhattan, more sprawling cities like Los Angeles, Chicago and Denver, and college towns, like Ithaca. Table 2 shows the major differentiating characteristic of these cities (population and store density), all other characteristics are close to our baseline parameters. The results are illustrated on the right panel of Figure 2, the lines correspond to different cities, the current and optimal store densities are indicated.

Note that *for all kinds of urban areas we studied, an increase in store density is beneficial*. Even though our analysis predicts the existence of a threshold, it turns out that as a practical matter, the current store densities in all urban areas are below their respective thresholds. That said, there are important distinctions between cities. First, the higher population density cities have a higher threshold $\bar{N}$. With higher population density, stores experience less losses from decentralization of inventory and thus the gains from store density increases continue to be available even at higher store densities.

Manhattan is the only area where the store density is close to the optimal store density, as such there are very limited gains (or losses) from adding more stores. The optimal density is about 495 stores/10 sq km, whereas the actual density is 458 stores/10 sq km Adding significantly more stores here might even lead to an increase in waste.

For most cities (Los Angeles, Chicago, Denver, etc.) small additions to store density, or a handful more stores in these cities, can lead to substantial reductions in waste and large environmental gains. For example, in Chicago, an *increase of density corresponding to just 3–4 new stores in a 10-sq-km area would lead to a 6%–9% decrease in food waste* (for various scenarios and parameter combinations). This would be equivalent to converting over 20,000 cars from fossil fuel to electric power-trains, which is far more than what has been achieved by the substantial subsidies offered for the purchase of electric cars. This outsize impact of store density also highlights the large environmental consequence of the widespread disappearance of the corner grocery shops.

Further analysis (not reported in the figure) shows that higher fixed and variable costs of visiting the store also increase $\bar{N}$ as both these costs increase consumer waste. This has implications for the above analysis: decreasing the costs and inconveniences of

Table 2. Differentiating Characteristics

Parameter	Manhattan	Chicago	Los Angeles	Ithaca	Denver
Population density, ρ, per sq km	24,137	4,447	2,836	1,900	1,550
Current store density (stores/10 sq km)	458$^{(1)}$	15$^{(2)}$	11.5$^{(3)}$	53.5$^{(1)}$	5$^{(4)}$

Note. City license data: (1) data.ny.gov, (2) data.cityofchicago.org, (3) superpages.com, and (4) denvergov.org.

visiting stores (by providing better transit, etc.) can also bring some cities closer to optimal.

Importance of Studying Consumers. Note that for all scenarios studied (including the subset shown in Figure 2), consumer waste is higher than retail waste; for typical urban store densities (5–250 stores/10 sq. km), consumer waste is ten times the retail waste. Previous studies (Food and Agriculture Organization 2013) also report an order-of-magnitude gap between consumer and retail waste, which provides another external validation for our results.

Note that while consumer waste much dominates retail waste for all plausible parameters, most literature, governmental organizations, and press currently focus on retail waste. Per our results, this focus actually might be misplaced and misleading, at the very least regarding the impact of store density on food waste, because consumer waste is the main source of emissions and the effects on consumer and retail waste are *opposite*. Future academic work and study of waste reduction actions should carefully weigh the impacts on consumer and retail waste.

Role of Strategic Effects. The above results imply that the strategic effects are dominated by the direct effects. Yet, as predicted by Theorem 3, we find that ignoring strategic effects would lead to inaccurate estimates of the threshold densities, numerical calibration shows the estimates are off by about 25% for the price case and 35% for the service case.

8.2 Grocery-Acquisition Costs and Retail Profits

In addition to the impact on waste, a full analysis must also consider the impact on consumer costs of buying groceries, industry profits and welfare (Figure 3). Our estimated consumer costs and grocery-store profits are within the ranges reported by households about their expenditures and in industry statistics (Consumer Expenditure Survey 2015, Food Marketing Institute 2015). Panel (a) shows the combined consumer grocery-acquisition cost $\mathbb{C}_c^v$, $v \in \{\beta, p\}$; Panel (b) shows the total retail profits $N\pi_n^v$, $\pi_n^v = \pi_n(p, \beta, \{p\}, \{\beta\})|_{v=v^*}$, the exogenous variables p/β are set as per Table 1. Note, consumer utility is *Consumption Utility* $- \mathbb{C}_c^v$, because consumption utility is always the same in all cases, we simply refer to the sum of costs and retail profits $-\mathbb{C}_c^v + N\pi_n^v$ as the welfare. It is shown on Panel (c).

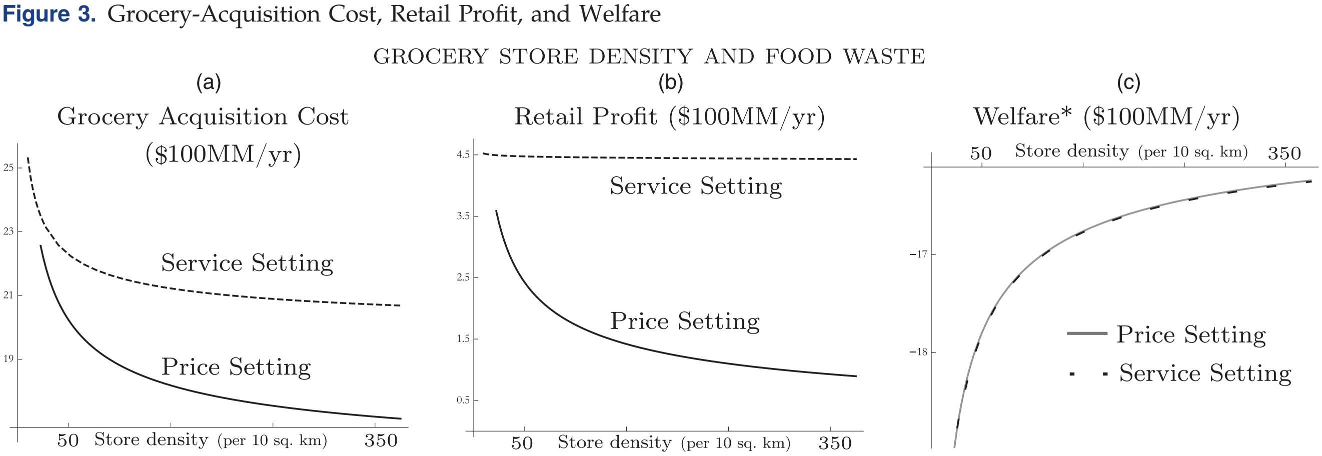
Higher density increases welfare, decreases industry profits (due to effects considered, plus due to the fixed costs of opening and operating grocery stores) and the household-grocery-acquisition cost. In particular, a small increase in store density, the same 3–4 additional stores discussed above, would decrease households' grocery expenses by 1%–4.26%. This implies that for most typical cities, a reduction in density leads to *both a reduction in waste and an increase in grocery affordability.* That is, the commonly held belief (based on logic which only thinks about the strategic effect) that food waste reduction and affordability are competing goals is not true, it is just an artifact of ignoring the all-important direct effects. As such, decision makers should strive for grocery density increases without hesitation, as these are a win-win: a win for the environment and a win for consumers.

9. Alternate Model Formulations and Discussion

9.1. Basket Variety

Our analysis is built around a representative perishable grocery good. Even with an assortment of fresh goods, our analysis applies if the goods are highly substitutable (e.g., if one vegetable could be substituted for another, likely to be true in many case)

Figure 3. Grocery-Acquisition Cost, Retail Profit, and Welfare



Note. The figures are drawn for an urban neighborhood/market area with the baseline value of all parameters as per Table 1.
*Welfare expression omit positive consumption utility, which is the same in all cases

and have similar shelf life. In the case in which the assortment of fresh goods is not fully substitutable and there is significant difference in the shelf life of different goods, both the store and households' inventory-management problem is harder and in general will lead to more retail and consumer waste, even though the direction and dominance of the discussed effects is the same as in the original analysis.

First, empirical evidence (which is indeed for the multi-item case) shows the same direct effect of increased store density on households (direct-access effect) as that predicted in our model, with a slightly enhanced magnitude (Gustat et al. 2015, Jiao et al. 2016). This is expected as with more variety, higher access is even more consequential; the demand for specific items (as opposed to one fully substitutable good) will likely require the households to visit the grocery store even more often, enhancing the density effect.

Similarly, the counterbalancing force to the access effect—the scale effect—persists and is intensified, as decentralization is more harmful for multi-item inventory management. Nevertheless, given that the store continues to enjoy benefits of demand pooling from a large number of households for each item in the inventory, retail waste will remain significantly lower than consumer waste, and the gap is likely to be even greater. In so far as the strategic effect is concerned, the lowering of prices due to intensified competition is directionally unaffected by the level of variety. Overall, as in the original analysis, we expect there to be a threshold density (even higher than the one in the original analysis), that arises out of the competing effects of density on households and stores. Practically, most markets will be below this threshold and increasing density will lead to substantial reductions in food waste.

9.2. Other Heterogeneous Characteristics

Our model captures heterogenous location of households; households also may be heterogenous in size, wealth (cost of time), age, environmental attitudes, levels of consumption uncertainty (typically highest for the single member households), and so forth. The household direct-access effects arise at each individual level and a higher store density decreases each household's basket size and waste, compared with its own past level, leading to overall lower waste. Similarly, at the store level, direct-scale effects are unaffected by customer heterogeneity, smaller stores in denser market produce more waste. The strategic effects arise out of lower prices, and, even with heterogenous customers, more stores lead to more competition, lower prices, and higher waste. Overall, like in the original analysis, there is a threshold density.

9.3. Periodic Review Policy

Our key effect, that is, the household access effect, may be enhanced or diminished if households followed a periodic review policy instead of a continuous review policy. On the one hand, constraining the order times for households will limit the changes in households' behavior in response to changed density. On the other hand, periodic review increases the consequences of running out of groceries as the expensive outside option must be used until the next review period, which would lead to more safety stock and every marginal increase in distance would be even more consequential for the households—fixed order costs and underage costs have complimentary effects in our model. Comparing the magnitude of the access effect from our (calibrated) model's predictions with those from external empirical evidence (Gustat et al. 2015) shows that actual access effects are even stronger than those predicted by our model.

9.4. Grocery Chains and Monopolies

Our analysis assumes that all stores are independently owned and operated. Our results would also closely apply in markets where grocery chains operate multiple stores, as the direct effects (principal drivers) are unaffected, and the strategic effects only use the fact that each household has independently operated stores in its local neighborhood. This is often the case as chain networks are designed with such local competition in mind. In the extreme case in which households have access to stores operated by just one entity (a monopoly), the strategic effect would operate differently leading to higher prices (the monopolist extracts consumer convenience gains from higher density via higher prices), which lead to lower waste. This pushes the optimal density to be higher than the one from direct effects, $\bar{N} > \hat{N}$ (original analysis was lower).

Discussion on further alternative model formulations is provided in online appendix. We examine the case of joint price and service competition (B.1), nonperishable purchases that accompany fresh good purchases (B.3), nonuniform store and household densities (B.5), endogenous market entry (B.6), store substitution on stockout (B.7). We also study the role of travel emissions (B.8), the effects of cost of sourcing that depends on store size (B.4), and the effect of our technical assumptions on the lifetime of households' and store inventory (B.2). In each of these cases, we find that our key findings persist.

Food waste arises at two levels in the households. First is the expiration of purchased but *unprepared* food (the focus of this paper, about two-thirds of the total), and second is the expiration of *prepared*, but not consumed, food (the rest, Gunders et al. 2012). Examining the impact of store density (and other aspects) on waste resulting from the food production process is an exciting subject for future study.

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Endnote
[1] The bullwhip effect stems from the nonstationarity of the demand distribution (as demand forecasts have to be updated based on the demand observed in the previous period). The settings where bullwhip has been shown to operate consider nonperishable products. Our analysis considers stationary demand (thus, bullwhip effect does not arise) and *perishable* products. As we illustrate above, it is the *perishability* that *leads to* the cycle-truncation effect.

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