Bargaining at Retail Stores: Evidence from Vienna*

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Abstract

The optimality and efficiency of trading mechanisms has long been a subject of great interest in economics, yet there exists relatively little empirical evidence regarding the factors that influence the firm's preferred mechanism of trade. In this paper, we conduct a field study at nearly 300 stores throughout Vienna, Austria in order to understand how price and firm characteristics influence the decision to engage in bargaining with hypothetical consumers who seek a discount. We find that the likelihood of obtaining a discount is greater for higher-priced products, for non-sale items, and for products sold by small-scale firms. Our findings are consistent with the predictions of a theoretical model in which a firm decides whether to augment posted prices with bargaining concessions.

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1 Introduction

Given the prevalence of posted prices in the Western world, it is easy to forget that they are a relatively recent phenomenon in the history of commerce. The first documented instance in the world occurred in Tokyo in 1673 and the first documented instance in the West occurred in New York in 1823 (Mahoney and Sloane (1966)). Since then, posted prices have become the norm for retail goods sold in developed countries.

Naturally, economists have been interested in understanding trading mechanisms in general, and in particular, explaining why and how posted prices have emerged as the dominant mechanism. Riley and Zeckhauser (1983) showed that a firm that sells a single unit to a sequence of buyers prefers committing to a take-it-or-leave-it posted price for all buyers to any alternative selling mechanism, including bargaining.[1] Several studies have examined the more specific question of whether firms prefer bargaining with alternating offers to a posted price and have found that a posted price may emerge in equilibrium, even if bargaining is also possible.[2]

In a world in which posted prices are prevalent, however, the firm's choice of trading mechanism is not necessarily a question of *either/or.* Even though posted prices are the norm in retail, there is recent evidence that some retailers grant requests to consumers who ask for discounts below the posted price, at least for some products.[3] Furthermore, in a survey that we conducted in Vienna of nearly 400 consumers who had just visited retail stores examined in our study, 6% said that they had just asked for a discount below the product's posted price. Therefore, we are interested in a somewhat different question. Namely, under which circumstances does a firm choose to bargain with some consumers *in addition* to posting a unit price for all others? While a small collection of recent theoretical literature has begun to address this question, very little on the subject is known empirically.[4] In particular, we would like to understand which price and firm characteristics induce firms to augment their posted prices with personalized discounts upon a consumer's request.

[1]In related settings, similar results were obtained by Myerson (1981), Sobel and Takahashi (1983), and Perry (1986).

[2]For example, Bester (1993) considers a market for an experience good and shows that the posted price mechanism increases the probability of trade but reduces sellers' incentives to provide high quality relative to bargaining. Other studies that compare posted prices with bargaining include Wang (1995) and Arnold and Lippman (1998), who both study a monopoly seller which sells one unit of an indivisible good to many potential buyers. Other related studies include Camera and Delacroix (2004) and Raskovich (2007).

[3]The New York Times (December 15, 2013), The Independent (March 29, 2015) and other news outlets have recently addressed the phenomenon of haggling at retail stores in a casual, anecdotal manner and found that retail stores such as Best Buy, Home Depot, Nordstrom, and Bloomingdales were willing to give a discount when asked.

[4]See Footnote 6 for a summary of the related theoretical literature.

To address this question we first write down a simple theoretical model in which we interpret bargaining as a tool used by a firm in conjunction with a posted price in order to discriminate between consumers with different valuations for a product.[5] In particular, we consider a firm selling many units of a particular good that chooses a posted price and then decides whether or not to bargain with consumers who ask for a discount (to whom we will refer as *hagglers*). In this simple environment, the firm's decision to bargain for a particular product will depend on a number of factors, including the price of the good, the salesperson's ability to determine the true valuation of a consumer who bargains, and the firm's cost of bargaining.[6]

It is easy to show that if a large enough percentage of consumers were known to ask for discounts, the posted price (as well as other firm characteristics, such as its number of employees) would be influenced by the existence of these consumers.[7] Given our interest in the determinants of bargaining propensity from the firm's perspective in posted-price settings, it is therefore advantageous that in practice a small percentage of retail consumers ask for discounts because this simplifies the task of isolating factors that influence a firm's propensity to bargain from the firm's pricing decision.[8] Also note that our model examines the bargaining decision at the firm$\times$product level rather than at the firm level, and thus it may well be the case that a firm bargains for some products but not for others.

Outside of studies of trade via the internet, we are unaware of any existing empirical work examining the firm-side factors that influence the trading mechanism decision in a retail setting.[9] In order to analyze the drivers of a firm's propensity

[5]Even though we employ the term *bargaining* to describe interactions in our theoretical model as well as in our empirical study, one may also contextualize such interactions as a form of price discrimination upon a consumer's request.

[6]Perhaps the closest theoretical papers are Desai and Purohit (2004), Gill and Thanassoulis (2009) and Gill and Thanassoulis (2015), who consider an oligopoly with two types of consumers, hagglers and non-hagglers. In Desai and Purohit (2004), two firms can choose to bargain with hagglers while they charge a (higher) posted price to non-hagglers. Our monopoly model is similar with the crucial difference that if no agreement is reached with a haggler, the haggler may still purchase at the posted price. Gill and Thanassoulis (2009) study an oligopoly where the price for non-hagglers is determined via Cournot competition. Hagglers may request discounts from multiple firms simultaneously while taking the best offer, and as a result discounts are randomized in equilibrium. In Gill and Thanassoulis (2015) firms post prices to non-hagglers and give random discounts to hagglers. They show that the presence of hagglers raises all prices and facilitates collusion. Finally, Raskovich (2007) studies a related model where firms with homogeneous goods post price and negotiate with hagglers.

[7]Along these lines, while this study will not be able to answer the question of why a majority of consumers do not attempt to bargain at the types of retail stores which we examine, it is remotely possible that knowledge of the way in which firms would respond to discount requests might induce some consumers to alter their behavior (whereas some consumers might always find the social cost or effort associated with asking for a discount to be too high).

[8]In contrast, Backus et al. (2014) find that the seller's price signals its bargaining power (patience) on eBay, where 91% of transactions are made via bargaining.

[9]We should note that the choice of auction formats by sellers has been studied in timber markets (Athey et al. (2011)), on eBay (Wang et al. (2008), Hammond (2010), and Bauner (2015)) and for online advertisements (Ostrovsky and Schwarz (2011)).

to bargain, we assigned 12 research assistants to pose as consumers at nearly 300 diverse retail stores in four different commercial areas of Vienna and ask for discounts off of posted prices. Research assistants were assigned specific stores to visit, find a product in a pre-specified price range, feign credible interest in that product and then ask for a discount. Products surveyed ranged from a posted price of 30 EUR to 999.99 EUR, with a median posted price in the data of 135 EUR. As a result, we were able to collect observations that pertain to a diverse pool of price and firm characteristics and use this information in order to analyze the determinants of a firm's propensity to bargain.

Before we proceed to describe our empirical findings, it is useful to place our work in the context of a wider empirical literature. Our paper is closest to a growing literature on bargaining in product markets, however, there are important differences.[10] The early focus of this literature is on the automobile market, where bargaining is widespread. In their pioneering work, Ayres (1991) and Ayres and Siegelman (1995) conducted a series of field studies by sending hypothetical consumers to car dealerships in Chicago. They found that blacks and females received significantly worse price quotes than white males, whereas in an empirical analysis of automobile purchase data Goldberg (1996) did not find clear evidence of discrimination.[11] List (2004) examined bargaining in a sportscard market and found that minorities receive considerably worse offers but that discrimination is statistical in nature. Other field studies that have focused on bargaining include Keniston (2011) (autorickshaw rides in Jaipur, India), Zussman (2013) (cars), Castillo et al. (2013) (taxi rides in Lima, Peru), and Bengtsson (2015) (taxi rides in Cape Town, South Africa).[12] Finally, Jindal and Newberry (2014) study bargaining outcomes for refrigerators at an appliance retailer. In their sample, 92% of consumers bargain the posted price down, whereas the remaining consumers pay the posted price. Jindal and Newberry (2014) use this variation to estimate consumers' bargaining costs and bargaining power. Therefore, while previous studies have analyzed firm bargaining behavior in individual markets where bargaining is the norm and most have focused on consumer variation, we study a large collection of diverse firms in markets where a majority of transactions take place at the posted price, focusing on how price and firm variation influences the likelihood of a discount being granted.

[10]There is a large body of work that focuses on discrimination in labor and real estate markets. See Riach and Rich (2002) for a comprehensive survey.

[11]Several other authors have studied car negotiation outcomes. Scott Morton et al. (2011) find that buyer search cost and bargaining disutility have significant effects on the purchasing price and Huang (2010) estimates the profitability of no-haggle prices vs haggling for car dealerships. Huang (2010) does not observe transaction prices for haggling dealers and does not model bargaining explicitly.

[12]The latter is different from the literature in that rather than focusing on discrimination, the authors examine how regulation affects bargaining outcomes and consider welfare properties of bargaining.

This brings us to a summary of our findings. We were quite uncertain a priori with regards to the extent to which firms would grant a discount overall. Nevertheless, we were largely surprised to learn that a discount was offered approximately 40% of the time overall (303 of 751 products). In order to get a sense for the types of products for which a discount was granted, here we provide a list of 10 products taken from 303 such instances: a backpack, a blanket, a cordless screwdriver, a kite, a manicure set, a bottle of perfume, a scarf, a stuffed animal, a surveillance camera for babies, and a sweater.[13] Including instances in which no discount was granted, the average discount was approximately 10 EUR (7,715 EUR off of 159,516 EUR, or 4.8%). Conditional on a discount being granted, the average discount size was approximately 25 EUR (7,715 EUR off of 80,725 EUR, or 9.5%) and the simple average discount percentage (and median discount percentage) was approximately 10%.[14]

Turning to our main empirical findings, we estimate that the probability of a discount increases with the price of the good, is lower for sale items, and is lower at large-scale firms (firms with many branches or firms with multinational reach). The first finding is consistent with our model under the plausible assumption that in a cross-section of products, a higher price is associated with a higher (absolute) margin.[15] The second finding suggests that products on sale have lower margins than identically priced goods that are not on sale.[16] Such an inference would be consistent with several possible interpretations of sales, including the possibility that sales reflect discrepancies in demand rather than costs. The third finding is consistent with a presumption that large-scale firms tend to organize themselves in a way such that their salespeople cannot or would not estimate a bargainer's valuation for a good with the same accuracy as the owner or salesperson at a small-scale firm. Along these lines, we find that a discount is more likely to be granted at a firm with few visible employees. In addition, we find that the difference in probability of earning a discount at a small-scale firm vs. a large-scale firm tends to be larger at higher price levels, in line with our theory, which predicts that a bargainer is more likely to receive discounts on higher-priced products, and more so at small-scale firms.

We also find that it is less likely to receive a discount for non-sale items after

[13]A complete list of every product observed is available from the authors upon request.

[14]Given an average unconditional discount of 10 EUR and an average conditional discount of 25 EUR, it is interesting to note that Jindal and Newberry (2014) estimate that the average consumer bargaining cost for refrigerators amounts to 28 USD (about 20 EUR at the exchange rates for the relevant period).

[15]For example, see evidence of the relationship between prices and margins in Berry et al. (1995). We shall address this relationship in further detail later in the study.

[16]Note that this statement does not concern a comparison of margins on the same product before and after a sale, but rather two products currently priced at the same level, one on sale from a previously higher price and one not on sale.

Christmas, whereas we do not find a difference in discount probabilities for sale items before and after Christmas, suggesting that sales immediately after Christmas are unlikely to be inventory-related. When a discount is granted, the amount of a discount increases with the price of the good; we estimate that the elasticity of discount size with respect to price is approximately unitary. Interestingly, stores which were observed with no customers for a three minute period prior to the data collection stage give substantially larger discounts. Generally speaking, firms did not decide to grant a discount on the basis of RA identity or RA gender.

The paper is structured as follows. Section 2 offers a theoretical framework for purposes of understanding the incentives of a firm to agree to grant a discount. Section 3 introduces the study design and Section 4 discusses the empirical analysis and results. Section 5 concludes.

2 Theory

We begin by providing a concise description of our empirical setting. Then we shall introduce a theoretical framework that we believe captures the main firm-related factors that influence the decision regarding whether to grant a discount.

A consumer enters a retail store with an interest to purchase a particular product. Upon noting the posted price of the product, the consumer approaches the nearest salesperson and engages in a brief interaction in order to request a discount off of the posted price. The salesperson then either denies the consumer's request or approves it with a lower price offer. Empirically, we observe a wide variety of retail stores selling a diverse range of products at various price levels. Therefore, we need to formulate a flexible theoretical model in which a firm chooses a posted price and decides how its salespeople should respond to discount requests. In particular, a given firm may prefer to bargain for certain products but not for others.

It is important to note outright that in our setting, we consider bargaining as a firm's attempt to price discriminate among heterogeneous consumers. This view is shared in the theoretical literature on endogenous choice of pricing mechanisms, where bargaining is studied as a costly discrimination tool because it allows a firm to obtain additional information (via interaction with the consumer) about the consumer's willingness to pay.[17] Based on this tradition, and given that it closely corresponds to our empirical setting, we will assume away any issues related to delays and the consumer's discount factor.

In addition, while retailers in our sample face varying degrees of competition, for simplicity we shall only consider a monopolist. It shall become evident from the model that competition affects bargaining decisions insofar as it reduces margins,

[17] E.g. see Bester (1994), Wang (1995), and Arnold and Lippman (1998).

and therefore, controlling for competition, qualitative predictions of the monopoly model can be extended to an oligopolistic environment. Furthermore, we shall study a monopolist that sells a single good rather than multiple goods both for simplicity and because we believe (and observe empirically) that pricing and bargaining decisions are product-specific.[18]

2.1 Simple model

We now introduce a simple theoretical model that will allow us to contextualize our empirical analysis.

We envision a firm that sells a good to many consumers. Most consumers do not haggle and take the price of the good, p, as given. In this study we model p as exogenous to the firm's bargaining decision because consumers who bargain constitute a small fraction of the population in our empirical environment.[19] In our model we will normalize the firm's marginal cost of production to zero, and therefore p is also the firm's margin.

Even though hagglers are a small proportion of the population, they are numerous enough such that the firm's owner must determine how to respond to their requests for a discount. We assume that hagglers always attempt to bargain, regardless of the firm's policy regarding haggling. Hagglers' valuation for the good, denoted by v, is distributed in the following way. With probability h their valuation exceeds p.[20] With probability $1-h$ their valuations are distributed uniformly on the interval $[0, p]$.[21] Here, h is the probability that the price p is acceptable to a haggler, or in other words h captures how mispriced the good is for the haggler population (where the extent of how mispriced the good is increases as h decreases). We shall assume that $h < \frac{1}{2}$ so that the optimal price for hagglers, given by $\frac{p}{2(1-h)}$, is below p and thus the firm is inherently interested in price discriminating between hagglers and non-hagglers. Note that we implicitly assume that hagglers' valuations are never below the marginal cost (zero by assumption).[22]

The owner employs a clerk who has to deal with hagglers. When a haggler with a valuation v approaches the clerk, we assume that the clerk receives a noisy signal s that is related to the true v in the following way. With probability λ, it is equal to v. With probability $1-\lambda$, s is completely unrelated to v and is randomly

[18]Of course, in our empirical analysis we will account for within-store correlation across observations, which we will address in further detail in Section 4.

[19]It is easy to show that the firm's pricing decision is made essentially without taking hagglers into consideration when the proportion of non-hagglers is high.

[20]As it becomes clear below, the exact distribution of valuations above p is inconsequential for the model. Alternatively, we could have assumed that valuations are uniformly distributed on the interval $[0, \frac{p}{(1-h)}]$.

[21]Our assumption of a uniform distribution is made for simplicity and may be relaxed.

[22]This assumption may also be relaxed, but precluding this possibility simplifies our analysis.

drawn from the same distribution as v. In the industrial organization literature this signal technology is referred to as "truth or noise" (see, for example, Lewis and Sappington (1994) and Johnson and Myatt (2006)) and will prove to be very convenient for this model. In particular, the distribution of s is identical to the distribution of v for any level of λ. Thus, while clerks with different levels of λ differ in how well they are able to judge v, on average their perception of consumers is correct. The parameter λ, therefore, measures how well the clerk can estimate v, which in a more evolved model may depend on the clerk's skills, his effort, the owner's monitoring technology, the contract between the clerk and the owner, as well as other factors. One useful interpretation of this model is that λ measures the probability the clerk pays attention, in which case he gets v exactly right, whereas he formulates a random estimate if he does not pay attention.

In order to introduce tension between the clerk and the owner, we shall assume that if the clerk is allowed to grant discounts, he bases his decision on s as if it were a perfectly informative signal of v. This implies that the clerk does not use Bayesian updating. As a consequence, the clerk may grant a discount when it is not profitable for the firm.[23] On top of this agency issue, we shall also introduce a fixed bargaining cost b that the firm (i.e. the owner) suffers every time a clerk agrees to grant a discount and a consumer purchases. One can think of this cost in several ways. Namely, granting an individualized discount may be more time-consuming for the salesperson than selling a product at a posted price. Therefore, it will be the case that an owner is more likely to agree to bargain for higher-priced (higher-margin) items because the per-product profit for such items after bargaining will be more likely to exceed the fixed bargaining cost b. We assume that the clerk does not take into account the cost b when dealing with hagglers, and thus bargains even if $s < b$. In such a case, the owner would lose money on the transaction even if $v = s$. Given the clerk's behavior, the owner therefore has two choices: either allow the clerk to grant discounts in the way specified above, or to prohibit giving discounts altogether.

[23] A fully Bayesian clerk would take into account the noisiness of the signal and use it to form a posterior distribution of v conditional on s. Using this, the clerk then would charge different prices depending on the realization of s and the parameters of the model. For example, if $\lambda = 0$, then the Bayesian clerk would discard his signal and charge $\frac{p}{2(1-h)}$ to all hagglers. In contrast, our clerk will interpret s as a perfect signal regardless of the value of λ, and such an approach is not profit-maximizing.

2.1.1 The firm's bargaining policy

We now proceed to solving the firm's problem. If the firm never allows the clerk to bargain, the profit per haggler is simply

$$\pi_0 = ph, \tag{1}$$

which is the price times the probability that a haggler is willing to pay the posted price.

Now let us consider the profit per haggler when the firm allows the salesperson to bargain with consumers whom the salesperson judges to have a valuation below the posted price. In this case, let us first consider the case when the haggler's valuation is above p. With probability λ the clerk will correctly assess v and will not grant a discount. With probability $1-\lambda$ the clerk perceives a random haggler, which means that with probability h he still judges the consumer's valuation to be above p and (correctly) declines the request. However, with probability $1-h$ he mistakenly determines that $v < p$ and grants a discount, the magnitude of which depends on a specific realization of s. Therefore, the frequency with which the clerk will grant discounts to hagglers with $v > p$ will decrease with the values of λ and h.

Now let us consider the case in which the haggler's valuation is below p. With probability λ the clerk assesses v accurately, grants a discount, and charges the consumer a price equal to v. With probability $1-\lambda$, the clerk's signal is random. In such a case, with probability h he declines to grant a discount, in which case the consumer walks away. With probability $1-h$, the salesperson offers a discount. However, the consumer will only accept this offer if $s < v$.

In any case in which a discount is granted and accepted by the consumer, the firm must pay b.[24] Therefore, given all the above, the profit per haggler when the owner allows for haggling is

$$\begin{aligned}\pi_1 &= h\left[\lambda p + (1-\lambda)\left(\int_0^p \frac{(1-h)}{p}(s-b)\,ds + hp\right)\right] \\ &+ \int_0^p \left[\lambda(v-b) + (1-\lambda)\int_0^v \frac{(1-h)}{p}(s-b)\,ds\right]\frac{(1-h)}{p}\,dv. \end{aligned}\tag{2}$$

The owner will allow its salespeople to grant discounts to consumers who are judged to possess a valuation that is lower than the posted price only if the profit per haggler from haggling is higher than the profit from not haggling, or $\pi_1 - \pi_0 > 0$,

[24] Alternatively we could have assumed that b is paid by the firm even when a discount offer is declined by a consumer, which would be consistent with some interpretations of b. This is ultimately of little qualitative importance for the model, which is deliberately stylized.

which can be rewritten as

$$p(1 + 2\lambda - 4h(1 - \lambda)) - 3b(1 + \lambda + h(1 - \lambda)) > 0. \tag{3}$$

It is easy to see that the LHS of the above inequality is decreasing in h and b. Intuitively, if a large percentage of hagglers would be willing to pay the posted price (high h) and the bargaining cost is high, then bargaining is less attractive relative to the posted price. When b exceeds $\frac{p}{2}$, the owner will not allow bargaining regardless of the clerk's attentiveness or how mispriced the product is for hagglers. This is because the most the owner can earn per haggler by allowing the clerk to discriminate between hagglers and non-hagglers is $\frac{p}{2}$, so if the per-haggler cost exceeds this benefit, the owner will forbid haggling. When $b < p/2$, haggling is potentially profitable, and the more so the lower is b. In particular, the LHS of (3) is increasing in λ when $b < p/2$. Therefore, in the range of b that is relevant for the firm's bargaining decision, it is more likely that the inequality will be satisfied for a high value of λ. Likewise, when $h < 0.25$, the LHS of (3) is always increasing in p. Conversely, note that when $b = 0$ and $\lambda < 0.5$, the owner will find it unprofitable to allow haggling when $h > \frac{2\lambda+1}{4(1-\lambda)}$ because a sufficiently high proportion of customers who haggle would have been willing to pay the posted price. To summarize, the owner will allow the clerk to offer a discount to a consumer whose valuation is judged to be below the posted price when p is high, b is low, λ is high and h is low.

These considerations are illustrated in Figure 1 for $p = 1$ and $h = 1/3$. In the shaded area (high λ and low b) the owner will not forbid haggling. The upward-sloping curve corresponds to $\bar{\lambda}$, the critical threshold for λ above which discounts are given to consumers whose valuations are judged to be below the posted price. This threshold is increasing in b, and therefore the more costly is bargaining, the more attentive the clerk must be to induce the owner to allow haggling. However, if $b > 0.5$, $\bar{\lambda} = 1$, so even if the clerk can perfectly assess the customer's valuation, the owner will not allow haggling. Horizontal lines in the shaded area correspond to equal probability of a discount being given, with higher lines associated with higher probability, assuming $v < p$ (see below for a detailed discussion).

2.1.2 The salesperson's bargaining decision

Even if the firm allows for its salespeople to bargain, the salesperson may decline a consumer's request for a discount based on the signal she receives regarding the consumer's valuation. Given that in our empirical study we do not observe firm bargaining policies but only whether a discount was granted in the context of a particular interaction, it is therefore also useful to derive the probability of a salesperson granting a discount.

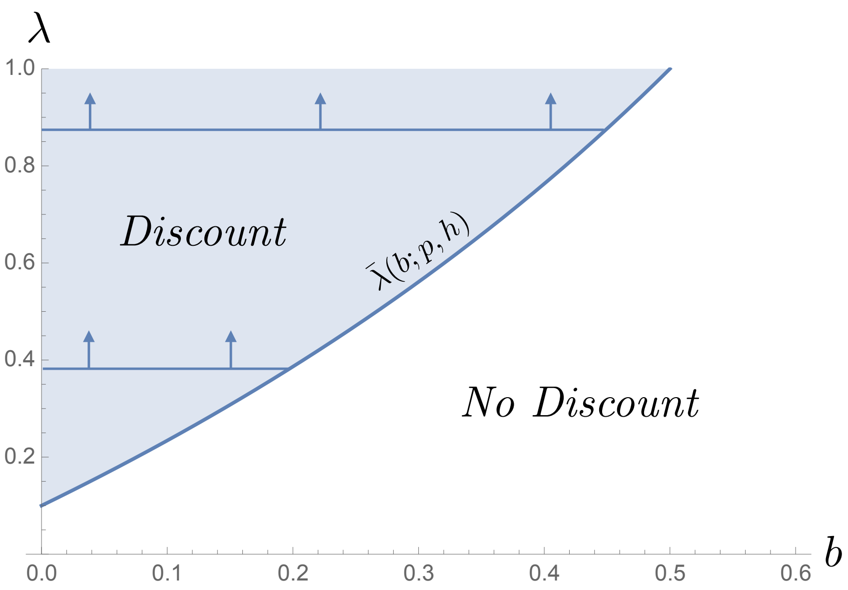

Figure 1

We now examine how λ affects the discount probability (alternatively, we could have chosen any of the other three parameters). When λ is low, the owner will forbid discounts to be granted to any customers. However, when λ exceeds a certain threshold, to be given below, the owner permits discounts to be granted, although a salesperson may nevertheless decline a particular consumer's request. The probability that this will occur depends on the consumer's true valuation v, and in particular, whether v is above or below p. In our empirical analysis it is natural to presume that the "true" valuations of our RAs were below p. This is because they were specifically instructed to imitate a situation in which they are interested in buying a product, but were not willing to pay the posted price. Therefore, for the remainder of our theoretical analysis we assume that $v < p$, and let us further assume that $b < p/2$ so that the owner does not necessarily forbid the salesperson to haggle.

The probability of receiving a discount when a consumer has valuation v, denoted by ω, is given by

$$\omega = \begin{cases} 0 & \textit{if } \lambda \leq \bar{\lambda}(p,b,h) \\ \lambda + (1-\lambda)(1-h) & \textit{if } \lambda > \bar{\lambda}(p,b,h), \end{cases}$$

where $\bar{\lambda}(p,b,h) \equiv \frac{3b(h+1)+(4h-1)p}{2(2h+1)p-3b(1-h)}$ is the solution to (3). The last line follows from $v < p$ and from the fact that in this case, a discount is granted either when the clerk's signal is correct or when the signal is random and below p. As is clear, the probability of granting a discount is (weakly) increasing in λ because it is independent of λ when $\lambda \leq \bar{\lambda}(p,b,h)$ and it is increasing in λ when $\lambda > \bar{\lambda}(p,b,h)$.[25] Going back to Figure

[25] We note here that due to the convenient form of the signaling technology, once λ exceeds $\bar{\lambda}$, the probability that a discount is given does not depend on v, which is because if it is below p, the

1, horizontal lines in the shaded area show where ω is constant. As λ increases, so does ω in the shaded area (outside $\omega = 0$).

Furthermore, the probability that a discount will be granted is increasing in p because an increase in p will result in a decrease in $\bar{\lambda}$, leading to an increase in ω from zero to the positive value $\lambda + (1-\lambda)(1-h)$ for products and firms associated with a given set of parameters. Likewise, the probability that a discount will be granted is decreasing in b and h for analogous reasons, noting further that an increase in h also enters directly into the determination of ω whenever $\lambda > \bar{\lambda}(p, b, h)$.

2.1.3 Discount size

We now turn from the issue of the discount probability to the issue of the average observed discount size, conditional on the discount being granted. If $v < p$ and the discount is granted, the average price paid is

$$\frac{1}{(1-h)(1-\lambda)+\lambda}\left(\lambda v + (1-\lambda)\int_0^p s\frac{(1-h)}{p}\,ds\right) = \frac{(1-h)(1-\lambda)p + 2\lambda v}{2(1-h(1-\lambda))},$$

which yields an average discount of

$$d = \frac{p(1+\lambda-h(1-\lambda)) - 2\lambda v}{2(1-h(1-\lambda))}. \tag{4}$$

To better understand d, let r stand for the percentile a consumer occupies in the distribution of consumers between 0 and p ($r = v/p$ so that, e.g., $r = 0.5$ implies that a consumer's true valuation is at the 50th percentile of consumers whose valuation is below p), and let r be independent of p, i.e. a given consumer occupies the same percentile regardless of the price. Then we can write

$$d = p\left[\frac{1}{2} + \frac{\lambda}{(1-h(1-\lambda))}(1/2 - r)\right] \tag{5}$$

which shows that the discount amount is proportional to the price (margin), and is equal to exactly half the price for the consumer at the 50th percentile, but is lower for consumers whose valuations are above the median, and higher for those whose valuations are below the median. As expected, the average discount size is increasing in p, and therefore a firm with a higher price will offer a larger discount. With regards to λ, the comparative statics are more nuanced. Namely,

$$\frac{\partial d}{\partial \lambda} = \frac{p(1-h)(1/2-r)}{(1-h(1-\lambda))^2}.$$

signal is either exactly equal to v, in which case the discount is granted, or it is random, in which case the signal, and thus the probability of a discount being granted, does not depend on v.

This expression is zero for the median consumer ($r = 1/2$), is positive for the consumer above the median, and negative otherwise. This means that if the RA's true valuation is equal to the median valuation of hagglers, then the average discount amount is independent of the clerk's signal precision. If the true valuation is above this median, then the more precise the clerk is, the lower is the discount amount. This is intuitive given that under full information ($\lambda = 1$), the discount is equal to $p - v$, whereas without any information ($\lambda = 0$), it is $p/2$.

In the less realistic case when the RA's true valuation $v > p$, the relationship between ω and λ is non-monotonic, where for $\lambda \leq \bar{\lambda}(p, b, h)$ it is the case that $\omega = 0$, and for $\lambda > \bar{\lambda}(p, b, h)$ it is the case that ω is positive but decreasing in λ. The average observed discount d is given simply by $d = p/2$ because when $v > p$, a discount is only given when the clerk makes a mistake, and in that case s is uniformly distributed on $[0, p]$, which implies that the average discount is $p/2$.

3 Study design

First and foremost, Vienna served as a reasonable location for purposes of conducting this study because it was the authors' place of residence prior to and during the data collection and because the authors are well-acquainted with the retail areas of the city. In addition, the retail shopping environment in Vienna is comparable to many large Western European and North American cities in that it consists of thousands of retail stores, from small independently owned stores to large multinational chains. The retail shopping culture in Vienna is also comparable to other Western cities in that most consumers in Vienna do not ask retailers for discounts. Therefore we considered Vienna to be an appropriate venue for purposes of studying how price and firm and characteristics influence a retailer's propensity to bargain.

The study design proceeded in several stages. First, we selected the geographic areas of Vienna to be studied. Vienna is comprised of 23 districts. We chose four distinct geographic areas that vary in average annual net income per person: the 1st district (34,333 EUR, the wealthiest district), the 2nd (18,838 EUR, the 17th wealthiest district) and 20th (17,334 EUR, the 22nd wealthiest district) districts, the 18th (23,771 EUR, the 4th wealthiest district) and 19th (25,372 EUR, the 3rd wealthiest district) districts, and the 6th (21,989 EUR, the 12th wealthiest district) and 7th (22,659 EUR, the 8th wealthiest district) districts.[26] The city's main shopping thoroughfare, Mariahilferstrasse, is located on the border between the 6th and 7th districts. Not only does the area around Mariahilferstrasse feature more stores than the other three areas, it is arguably the heart of commercial Vienna.

In order to construct a sample of stores to observe in each district, RAs were

[26]Statistics obtained from Statistik Austria.

instructed to record the name of every retail store on the main thoroughfares of these areas that met certain criteria. That is, stores that were service-focused (e.g. restaurants, salons, etc.), stores that primarily sell food or beverages, pharmacies, and highly specialized stores (e.g. hearing aids, orthopedic shoes) were not considered. Furthermore, the second highest price of a store was required to be at least 120 EUR; this would rule out stores such as "Tabak" shops, for example. Approximately 750 stores were recorded in total; approximately 300 stores were recorded in the 6th and 7th districts due to its commerical importance in Vienna, and approximately 150 stores were recorded in each of the remaining three areas. The RAs assigned to this task were not subsequently assigned to ask for discounts at stores. Then, from each geographic area, a sample of 40% of the stores was selected at random for purposes of observation. Therefore the final sample consisted of 300 stores, although several stores needed to be discarded during the data collection phase for reasons to be noted later in the study.

We searched for RAs who would be asked to seek discounts at stores by posting an advertisement in the building of the Faculty of Business, Economics, and Statistics at the University of Vienna and by sending an email with the same advertisement to the co-authors' former students. We hired the first six male and first six female German-fluent RAs for which we were able to schedule an interview. In order to prevent intra-RA communication during the project, RAs were not told the names of the other students who were hired nor were their names ever displayed on group e-mails. These RAs' first task was to visit approximately 20 stores each in order to record several pieces of information about each store; we refer to this as the "Information Gathering" stage and an RA who recorded information from a particular store was referred to as an "Information Gatherer" (IG). These observations are summarized in the next section.

The study was conducted starting in late 2013 and continued into the first week of 2014 for administrative reasons, and we split the study into two separate periods for two reasons. First, since the same stores were visited repeatedly, we wanted to allow for a break in between observations. The pre-Christmas and post-Christmas periods allowed for a natural pause in the data collection, and it also allowed us to the opportunity to examine whether a firm's bargaining behavior could provide an indication regarding the nature of post-Christmas sales.[27]

Three separate RAs were randomly assigned to each store in the sample using a stratified approach. More specifically, a random assignment was made with the following restrictions: each store was assigned a visit by at least one RA of each

[27]In particular, if post-Christmas sales were inventory-related, we would have expected firms to agree to grant discounts more frequently post-Christmas. We shall return to this question in Section 4.

gender, each store was assigned to be visited at least once both before and after Christmas, an IG associated with a particular store was forbidden from visiting the same store as a bargainer, the observations of a given RA were divided roughly evenly across the four geographic areas, and each RA was assigned roughly the same number of observations before and after Christmas. Roughly half of the stores were assigned to be visited twice before Christmas and once following Christmas, and roughly half of the stores were assigned to be visited once before Christmas and twice following Christmas.

If a store was assigned to be visited twice during the same shopping period, then arrangements were made in order to ensure that no store would be visited twice on the same day. The size of the price range observed, the number of stores visited, the number of visits per store, the areas of the city observed, and the number of RAs employed were dictated by budgetary constraints. RAs were paid 12 EUR per hour. Along these lines, it is important to note that RAs were not incentivized monetarily according to the number of successful bargaining interactions as such an incentive would have created an incentive for RAs to fabricate their results. While incentivizing RAs based on successful bargaining interactions may have resulted in a higher number of discounts granted overall, the credibility of such data could be easily called into question.

4 Empirical analysis

4.1 Summary statistics

In Table 2 we report summary statistics for the quantitative variables of primary interest in our analysis: list price, posted price, discount amount, and discount percentage. The posted price is the price that the consumer would pay without explicitly asking for a discount. If the product is on sale, the posted price will be below the list price. Otherwise, the posted price is identical to the list price. Note that the maximum list price of 5,900 EUR was recorded for a carpet, which was associated with the maximum sale amount and sale percentage of 5,240 EUR and 89%, respectively. The next highest list price was 1,299 EUR. Removing this observation has very little effect on our forthcoming results. The third and fourth row of Table 2 report summary statistics of discounts granted due to bargaining; these cases are conditional on a discount being granted and are calculated off of the current price. One may infer from the table that 303 of 751 observations entailed a discount being granted due to bargaining and that 169 of 751 items in the data were on sale.

Figure 2 illustrates the distribution of discounts in absolute and relative size.

There were no discounts granted in approximately 60 percent of the observations, as can be seen in Figures 2A and 2C. Furthermore, note that Figure 2B only uses strictly positive discounts as the horizontal axis measures the log of discount amounts. In Figure 2C, horizontal lines were added to show the relatively higher frequency of 3 percent, 5 percent, and 10 percent discounts. Figure 3 illustrates the distribution of list prices observed in absolute and relative sizes, and Figure 4 does the same for posted prices (after any sale reductions).

We can generally divide our variables into two categories - store-specific variables and observation-specific variables. Store-specific data that relate to characteristics observed at the store itself were recorded approximately 1-2 weeks prior to the bargaining interactions. Store-specific data that relate to institutional characteristics of the store, such as multinational presence and the existence of additional branches of the same store, were recorded during the months following the bargaining interactions. Of course, observation-specific variables pertain to the bargaining interaction itself, and these data were recorded immediately following an interaction. In Table 3 we report summary statistics for our store-specific variables. Near the bottom of Table 3, the store category designations for each store were constructed by the authors in the absence of any preferable, more objective available designation.

In addition, the nature of the discounts offered serves as interesting evidence of how small-scale firms are organized differently from large-scale firms. In principle, a discount may be offered as a round percentage (e.g., 3%, 5%, 10%) or in a euro amount that clearly would not have been offered by the salesperson as a percentage.[28] Table 4 illustrates how large-scale firms offer a substantially higher ratio of discounts in round percentage terms than small-scale firms. This is informative for our purposes because it provides support for the notion that salespeople at large-scale firms are less likely to be given discretion to assess a haggler's true valuation for a good.

Table 5 lists all of the multinational stores in our dataset and the incidence with which a discount was granted at each firm. We define a store as multinational either if its owner owns the same store outside of Austria or if it is a franchise store whose franchisor is a multinational firm. Whereas the names of domestic firms may not carry much meaning for readers outside of Austria, the recognizable names of many of the multinational firms should assist the reader to understand the types of large-scale firms that were observed in our study.[29]

[28]For purposes of Table 4, we classify a discount as a round percentage if the percentage itself is an integer. Of course, there may have been a small number of observations in which a discount was quoted by the salesperson in euros which coincidentally also can be computed as a round percentage.

[29]Data regarding a firm's scale (the number of stores owned by the same firm) and its multinational status were verified via subscription to the Aurelia database offered by Bureau Van Dijk and via information provided by firm websites. When firm-scale and multinational status could

4.2 The empirical model

Recall once again that we recorded two primary outcomes - whether or not a firm granted a discount for a particular product, and if a discount was granted, the size of the discount. The first outcome is essentially a participation decision - whether or not to grant a discount, and the second outcome is an amount decision that is bounded below at zero. Since our theoretical predictions do not imply that every variable of interest will influence the participation decision and the amount decision in the same direction, we utilize a flexible model whereby separate mechanisms are allowed to determine the participation decision and the amount decision.

Let d be a binary variable that indicates whether the observed discount size z is zero or strictly positive, and let z^* be a nonnegative, continuously distributed latent variable that represents the size of the discount that the salesperson will offer. Then we may write:

$$z = dz^* \tag{6}$$

When a discount is strictly positive, $d = 1$ and $z = z^*$; otherwise $d = z = 0$. The appropriate model for analysis depends in part on our assumptions regarding the relationship between d and z^*. If they are independent conditional on a set of explanatory variables, then we may analyze the firm's decision using what is commonly referred to as a two-part model. However, if some common unobserved factors affect both d and z^*, then one should consider analyzing the firm's decision using what Wooldridge (2010) refers to as an exponential type II (ET2T) model. Here, we shall investigate both possibilities and compare our results.[30]

First, let us suppose that d and z^* are independent conditional on a set of explanatory variables, and the participation decision is modeled in terms of the probit model, where we denote r as a vector of covariates affecting whether or not a particular firm will choose to bargain for a particular product if $\omega = r\alpha + v > 0$:

$$P(d = 1|r) = \Phi(r\alpha) \tag{7}$$

Note that the model cannot predict negative outcomes for z because the support of z^* is $(0, \infty)$. One possibility is to define the amount equation as:

$$z^* = x\beta + u \tag{8}$$

where u given x follows a truncated normal distribution with lower truncation point $-x\beta$. This equation, together with (7), is commonly referred to as the truncated

not be confirmed via either of these two sources of information, the authors called the stores in the dataset directly in order to retrieve this information.

[30] For a thorough treatment of two-part models and Type II Tobit for corner solutions, see Wooldridge (2010).

normal hurdle (TNH) model and was first proposed by Cragg (1971). Another possibility is to define

$$z^* = e^{(x\beta+u)} \tag{9}$$

where u given x follows a normal distribution with mean zero and variance σ^2. Also proposed by Cragg (1971), this equation together with (7) is commonly referred to as the lognormal hurdle (LNH) model. Here, we may express z as:

$$z = dz^* = 1[r\alpha + v > 0]e^{(x\beta+u)} \tag{10}$$

where v is unobservable with a standard normal distribution, u and v are independent, and (u, v) is independent of x with a bivariate normal distribution. In this case, due to our previous assumption on the distribution of u, we may say that $z^* = e^{(x\beta+u)}$ has a lognormal distribution and z conditional on $(x, z > 0)$ has a lognormal distribution as well because we assume that the errors of the participation and amount equations are independent of each other. Whether the amount equation is modeled according to (8) or (9), the participation equation and the amount equation may be modeled independently from one another.

If, however, we relax the assumption that $Cov(u, v) = 0$, then we may modify the lognormal hurdle model in order to obtain the ET2T model. In this case, note that we may not use (8) as the amount equation because the ET2T allows for negative outcomes on z; this would be a particular concern if $Corr(u, v) = \rho$ is estimated to be negative, as $E[log(z)|x, z > 0] = x\beta + \rho\sigma\lambda(r\alpha)$, where $\lambda(\cdot)$ is the inverse Mills ratio, $Corr(u, v) = \rho$, and $Var(u) = \sigma^2$. Therefore we may only apply the type II model to $ln(z)$. Of course, this is only a potential problem if the amount equation is expressed as (8) rather than (9). However, the literature has noted that the more general ET2T model also carries a potential risk of poor identification, particularly if $r \equiv x$.

4.3 Empirical results

We specify the participation equation using (7). The right-hand-side variables of the participation equation, to be discussed in more detail below, are listed in Table 6. We also include three interactions in the participation equation that are not shown in Table 6 but which we will report separately: list price with firm scale, firm scale with sale size, and sale size with observation period (pre-Christmas or post-Christmas). In our forthcoming discussion of the results we shall explain our interest in these interactions. The amount equations analyzed and reported in the paper contain all of the variables contained in the participation equation but without these three interactions, primarily for reasons related to sample size.

We analyze the participation and amount equations using the TNH model, the LNH model, and ET2T model. Because these models are non-nested, we apply Vuong's (1989) test to check whether the difference in log-likelihoods between the TNH model and the LNH model is statistically significant. The test finds that the average difference in the log likelihood between the LNH model and the TNH model is 0.163 and statistically significant at the .01 level. Therefore, because we have strong evidence that the TNH model is inappropriate for our empirical application, we only report the results of the LNH model and ET2T model in Table 6. It is also interesting to note that a Type I tobit using discount amount as the dependent variable yields a log-likelihood value that is significantly lower than the TNH model, further evidence that a flexible two-part specification is most appropriate in our setting.[31]

The results of the two specifications in Table 6 are qualitatively quite similar. First, note that we obtain a negative and significant estimate for ρ in the ET2T specification. This estimate is somewhat dubious because upon removal of variables in the amount equation for which we have no theoretical predictions in terms of discount size (not reported), we do not reject the null hypothesis that $\rho = 0$.

Given that the LNH model offers a better fit than the TNH model, and given that we cannot make a strong statistical claim that $\rho \neq 0$, in what follows we shall refer to the results of the LNH model, noting that we are not faced with the identification concerns associated with the ET2T model when using a model in which we constrain $Cov(u, v) = 0$. Most importantly, it should be emphasized that estimates of the LNH model are very similar to estimates of the ET2T model in all specifications to follow, and estimates obtained from the amount equation when all variables are included are very similar to the estimates associated with the same variables in an amount equation that is specified in a more parsimonious manner according to the predictions of discount size in our theoretical model.

We now proceed by interpreting our empirical results in the context of the theoretical framework in Section 2 by examining Table 6.

4.3.1 Prices and margins

Both the list price and the posted price may serve as proxies for margins. First, for items that are not on sale, if it is the case that marginal costs and absolute price-cost margins are positively correlated in the cross-section of product markets that we observe, then price levels may provide an indication regarding margin size. Informally speaking, while it is certainly plausible that margins decrease as cost

[31]Applying a χ^2 test with a number of restrictions equal to the number of variables in the Tobit model, the LR statistic is 2(LL of Tobit - LL of TNH)=2(-1649+1523)=252, which has a p-value of essentially zero. Therefore the TNH model is a superior fit than the Type I Tobit model.

increases for a particular good, it would be unreasonable to expect this to hold true given the type of large, diverse cross-section of products that we observe, as this would imply that 1,000 EUR items typically have smaller absolute margins than 30 EUR items (whose margins may be no greater than 30 EUR). Second, for items that are on sale, the amount of a sale may also be informative about the margin. In principle, the relationship between sale amount and propensity to bargain may be positive or negative, but we do expect a negative relationship. This is because most plausible explanations for sales in our dataset are price reductions due to (i) demand shocks, (ii) price randomization or (iii) inter-temporal price discrimination.

Our results indicate that discounts are more likely to be granted for higher priced products. In Table 6 we divide prices into quartiles; this allows for a certain degree of flexibility in estimating the relationship between price and bargaining propensity. As discussed above, if absolute margins do in fact increase with costs in the cross-section of product markets that we observe, this empirical finding would be consistent with the existence of such a relationship. Furthermore, the results from the amount equation indicate that the size of discounts granted are roughly proportional to a given product's list price. When using $ln(listprice)$ instead of list price quartiles in an alternative specification in Table 7, the elasticity of discount size with respect to list price is estimated to be nearly unitary. In other words, the percentage discount given by a firm is predicted to be nearly constant at all price levels in the data. This finding in the amount equation is consistent with the participation equation result that discount probability increases with price, noting that only an increasing relationship between costs and absolute margins would allow for the percentage discount to remain constant as price increases.

We categorize sale items according to the absolute size of the sale. That is, we distinguish between 85 observations for which the sale size is up to 45 EUR (to which we refer as *small sale size* items) from 84 observations for which the sale size is greater than 45 EUR (to which we refer as *large sale size* items). We find that both categories of sale items are significantly less likely to earn a discount than non-sale items by a substantial difference. Such a finding would be consistent with the hypothesis that for products with the same list price, absolute margins are lower for sale products. However, we do not find a significant difference in probability of earning a discount between the two categories of sale items.

Given the period for which we collected data, one question that arises is whether sales immediately after Christmas reflect firms' desire to clear inventory. If one assumes that sales that occur two to three weeks prior to Christmas do not reflect a desire to clear inventory, we may get a sense of whether sales during the period after Christmas are inventory-related by examining whether firms were more likely to bargain on sale items after Christmas. Figure 5C shows that the predicted probability of receiving a discount after Christmas is not higher than before Christmas for non-sale items or sale items. It is more likely the case that inventory-related clearance sales begin in earnest as end-of-the-season sales later in January, continuing into February.

Unfortunately, we only observed 26 sale items for which a discount was granted, and therefore our ability to draw conclusions regarding the relationship between sale size and discount size is limited. Items that we categorize as sold at a small sale size are granted discounts that are smaller in magnitude (with weak statistical significance) than items that are not on sale, which is consistent with our finding from the participation equation. However, we do not find a statistically significant difference in discount amounts given to large sale size items relative to non-sale items. One possible explanation for this finding is that these large sale size items comprise a small subset of items on inventory-related sales, however this is not entirely clear.

4.3.2 Firm characteristics

As noted earlier, we observe various firm-side characteristics in our data. We first briefly discuss these variables below, and then present our results related to these variables.

Firm scale. For our purposes, we define a firm's scale according to the number of stores owned by the same firm. We presume that small-scale firms will feature salespeople that are better motivated, more easily monitored, more skilled at evaluating a consumer's valuation for a good, and whom have stronger incentives to maximize firm profits than salespeople at large-scale firms. In particular, it is likely that an owner who serves as a salesperson at her own store with only one location will be more highly capable and motivated to evaluate a consumer's true valuation for a good than the average salesperson at a multinational chain.

Multinational firms. We also observe whether the firm is multinational in scope, as defined in Section 4.1. We expect that a multinational firm's decisions regarding the composition of its salesforce will be similar to large-scale firms even in cases when these two firm classifications do not overlap with one another.

A store's physical size. An additional firm-side characteristic that we observe is the physical size of the store (as measured in seconds required to walk once through the entire store). It may be reasonable to suppose that physically small stores are more likely to feature salespeople that are more adept or interested in properly evaluating a consumer's valuation for a good.

Number of employees and customer traffic. Several days prior to the bargaining interactions, RAs visited all of the stores in our study and observed the number of employees at each store and the number of customers who entered these stores during a three minute period. The advantage of recording these observations separately from the bargaining observations lied in the fact that a given bargaining observation was not burdened by an excessive amount of data collection, and therefore an RA was allowed to focus on selecting a product of interest, asking for a discount from a salesperson, and recording information related to interaction. The downside of this approach is that the data that we collected relating to the number of employees at a store and customer traffic may have been different during the week prior to the bargaining interactions.

The reasoning behind observing the number of employees is that in most environments in which some customer service is provided, it is likely that the number of employees is endogenously chosen according to the number of customers in the store; for example, stores featuring only one or two employees typically serve relatively few customers at a given point in time.[32] Such decisions are often related to a firm's scale.

Salesperson gender and age. Our data indicate that RAs encountered young salespeople and saleswomen more frequently at large-scale firms. Anecdotally, firm owners and managers are more likely to be older males. Using this reasoning, salesmen and older salespeople will have a greater interest in accurately assessing a customer's valuation than saleswomen and younger salespeople. Furthermore, there may exist sociological reasons for the age and gender of a salesperson to influence the likelihood of granting a discount to a customer.

Results: Firm characteristics. Our results indicate that discounts are significantly less likely to be granted at large-scale firms overall, and as seen in Tables 6 and 8, this finding holds whether we categorize large-scale firms as those with more than five stores, those which are multinational firms, or those with more than 15 stores.

It is natural to draw a connection between firm-scale and the parameter λ in our theoretical model because salespeople encountered at small-scale firms are more

[32]We should note that computing employee-customer ratios using our measure of customers observed is slightly problematic given the potential variation in customers observed in the IG stage relative to the bargaining stage. This is particularly true for observations in which there are several employees and a small number of customers observed. An additional possibility would be to construct a variable that indicates the difference between the number of employees and number of customers observed; however such a variable suffers from the drawback that a given difference at a store with a small number of employees and customers would be treated in the same manner as the same difference at a store with a larger number of employees and customers.

likely to own or manage the store. These individuals are more likely to be adept or interested in assessing a consumer's true valuation of the good. Therefore, we would indeed expect that a discount is more likely to be granted at small-scale stores, consistent with our theory.

Furthermore, our theory predicts that the firm's benefit from bargaining will be proportional to the price of the good, and increasingly so the more effectively the salesperson can assess the consumer's true valuation. Intuitively, when a salesperson evaluates a consumer's valuation well, the resulting extra profit will be larger in magnitude for higher-priced (higher-margin) goods because for such goods reducing the price for hagglers is more likely to be profitable after the bargaining cost is paid. Therefore, we interact our price variable with our indicator for firm scale. We find that as the price increases, the difference in probabilities of obtaining a discount between small-scale stores and large-scale stores widens. Note that for the highest price quartile, these differences are statistically significant in most specifications. This may be observed in Figures 5, 6, and 7.

Given our theoretical prediction regarding the interaction between λ and the product's absolute margin, we would be faced with an identification issue if margins tended to be larger for firms with a higher value of λ. However, it is not unreasonable to presume that margins of large-scale, multinational firms (those with a presumably low value of λ) are typically at least as large as those of smaller-scale firms.[33] Intuitively, one would expect large-scale firms to have higher margins because their buying power should allow them to purchase their inventory at a lower marginal cost than their competitors, and these cost savings are not necessarily passed on to consumers. If this is the case, then our estimate of the difference of the effect of λ across small-scale stores and large-scale stores would be conservatively low.

If one were to make a case for small scale firms differing from large scale firms in terms of their product line, then one may also attribute the lower probability of obtaining a discount to this difference. In particular, one could build a theoretical argument that firms with multiple vertically differentiated products would be able to cater to various consumer types to such a degree that their incentives to use bargaining to differentiate between consumers would be lower than for firms with a limited product line. However, it is not clear that small scale firms in our study have less deep product lines, and in fact one could also make a case for the opposite given that smaller firms tend to specialize. For this reason, it is useful that we have data regarding the physical size of a store, which may be an indicator of the depth of a store's product line. When controlling for the physical size of a store, our results are qualitatively similar.

An additional prediction from our theory is a second-order effect relating to the

[33]For example, see Kwoka (1979), Nooteboom (1982), and De Loecker and Warzynski (2012).

interaction between λ and the size of a sale. That is, while any sale (for which absolute price-cost margins decrease) reduces the propensity to bargain, an increase in the amount of a sale reduces the propensity to bargain of small-scale firms (for whom λ is presumably closer to one) by a larger amount than for large-scale firms. Therefore we would expect that small-scale firms' decreases in propensity to bargain will be more substantial than large-scale firms' decreases in propensity to bargain as the size of a sale increases. This may be observed in Figure 5B, in which the slope of the line representing large firms that stretches from 0 to 1 on the x-axis is larger than the slope of the line representing small firms over the same horizontal domain, and this is also true when comparing the two slopes from 1 to 2. We can also reject at the .01 level a joint hypothesis test that these differences of the slopes are both equal to zero.

We find that stores in which one employee is observed are predicted to grant discounts with a higher probability than stores that employ four or more employees. One possible interpretation of this finding is that large-scale firms, which typically employ a large number of employees at a given store, (knowingly) hire employees with an inferior ability or interest in accurately assessing a consumer's valuation, and therefore such employees are more often forbidden from granting discounts. Furthermore, the probability that our RAs interacted with someone with managerial or ownership duties is higher at stores with only one employee. Given that stores with many employees typically deal with a proportionally larger number of customers than stores with only one employee, this finding is also consistent with the prediction that employees at busier stores will be less likely to incur the opportunity cost associated with bargaining (a cost corresponding to b in our theoretical model).

We also find that positive discounts are significantly smaller in size at stores at which no customers were observed.[34] One explanation for this finding is that the presence of other customers disciplines the salesperson from offering large discounts at the risk of setting a precedent for other customers in the store.

We find no significant effect of firm scale on discount size. Recall that our theory predicts that λ will not influence the size of a discount for consumers who are located at the median valuation of hagglers below the posted price. Therefore, this finding would be consistent with our theory if our RAs indeed were perceived near the median valuation of consumers who ask for a discount. Unfortunately, only 47 of the 303 discounts that are offered in our data occur at what we characterize

[34] In an alternate specification we do not report in which the number of customers is analyzed as one variable, we find that an increase of one customer observed decreases the probability of receiving a discount by approximately 2%. However, one drawback with specifying the number of customers in this manner is that no special distinction is made between empty stores and stores with customers, a distinction which is likely to be important in reality given the type of store that one often observes to be empty.

as large-scale stores, and we do not observe large variation in the prices of these products (only 16 of these 47 observations lie below the median list price). This is not surprising given that our theory predicts that fewer large-scale firms will be selected into the set of observations for which we observe a positive discount due to the increasing relationship between a firm's ability to assess consumer's valuations and its propensity to bargain.

4.3.3 Other controls

We also include controls which relate to our theoretical model but for which predictions are less clear. In our analysis we classify observations into one of five categories: clothing, shoes/leather goods, jewelry, household, and other (summary statistics are provided in Table 3). We further divide each product category into two subcategories: low-priced stores within a category and high-priced stores within a category. We classify the price level of a store within a category according to the second highest price observed at that store. One advantage of including variables that classify products into categories is that such variables may capture crude differences in competition, which are otherwise very difficult to measure given the heterogeneity of products in the dataset. Competition reduces margins in most theoretical models of firm behavior, and therefore to the extent that two products share the same price but a product for which more competition exists has a higher marginal cost, product category indicator variables will seek to control for differences in margins across industries.[35] What is important to remember is that we are somewhat less interested in the coefficient estimates of the product indicator variables per se than we are in controlling for factors that may result in mismeasurement of the price variable coefficient estimates.

We predict a nearly 70% probability of earning a discount on what we classify as expensive jewelry. No other product category exceeds a predicted probability of 45%. In addition, jewelry is the only product category for which RAs are predicted to earn a discount with a significantly higher probability for more expensive stores within-category. One potential explanation for RAs receiving discounts with a higher probability for products at more expensive jewelry stores relative to inexpensive ones is that the perceived percentile at which the RA is located within the distribution of haggler valuations (denoted by r in our model) may be lower at higher-priced jewelry stores. It also may be that margins are higher in the jewelry industry than in others that we examine, and that this effect is more pronounced at the more expensive jewelry stores that we observe.

Finally, although we sought to minimize the extent to which RAs gave hetero-

[35]Increased competition would imply a lower p and in turn a smaller absolute margin in our theoretical monopoly model.

geneous impressions to the salesperson, it may be that the salesperson's judgment of an RA's willingness to pay varied across RAs. Therefore we also account for RA identity in our analysis. Examining the fixed effects for our 12 RAs, we find that of the 66 comparisons across all possible RA pairings, only 5 of the 66 fixed-effect pairs were significantly different than one another. In the amount equation, 10 of the 66 fixed-effect pairs were significantly different than one another. In other words, RAs appear to have been perceived quite homogeneously by the salespeople who were approached for this study.

In a study such as this, not only are RAs assigned to collect observations in the field, the outcome of their observations is partially dependent upon their own behavior. Therefore the "human element" is a non-trivial issue in our study. In Appendix B we examine the behavior of the RAs.

4.3.4 Conditional discounts

It is important to note that not all discounts were offered unconditionally. That is, of the 303 observations in which a discount was granted, in 70 of these cases the discount was contingent on payment in cash. The average cash discount was approximately 8% whereas the average non-cash discount was approximately 10%, and distinguishing between cash and non-cash discounts does not alter our empirical results in a substantial manner.[36] Furthermore, 22 of the 303 cases in which a discount was granted required the customer to be registered in some manner as a regular customer, in many cases via a membership or loyalty card. This typically would have required the RA to provide brief personal information in exchange for a discount. In these cases, this possibility was raised by the salesperson only after a discount was requested by the RA.[37] Removing these 22 observations does not qualitatively alter our results.

[36]Removing cash discounts from our analysis changes our results very little, particularly with regards to our variables related to product price, sale status, and firm scale. Referring to cash discounts as non-discounts also does not substantially alter our results. In both cases, significance is lost with respect to the effect of the number of employees on the likelihood of earning a discount (but signs remain the same). When running a multinomial logit regression in which there are three categories (no discount, non-cash discount, and cash discount), we do not detect substantial differences in the interpretation of discounts according to whether they are cash-dependent. That is, as the price of the product increases, it becomes more likely that both non-cash discounts and cash discounts are granted. Both non-cash discounts and cash discounts are less likely to be granted at large-scale stores, and both non-cash discounts and cash discounts are less likely to be granted for sale items.

[37]The average membership discount was approximately 7% whereas the average non-membership discount was approximately 10%.

5 Conclusion

Many retail firms are willing to supplement their posted prices with a discount. In particular, the retail firms in Vienna which we studied were prepared to grant a discount approximately 40% of the time. We find that the likelihood of receiving a discount is substantially influenced by the product's price, whether the product is on sale, and by the scale of the firm that owns the store. In addition, stores which generally feature few visible employees were more likely to grant discounts, and stores that we found to be empty of customers several days prior to initiating our study agreed in principle to grant larger discounts.

This is clearly only one step towards understanding the circumstances under which a retail firm will agree to bargain with a consumer. In order to further address this question, it would be useful to obtain more detailed information regarding products and firms, seasonal variation in sales activity, and usage of cash discounts. It would also be informative to obtain more detailed information directly from firms regarding what they would claim to be their bargaining practices.

Of course, consumer perceptions of bargaining are interesting in their own right and may be useful for purposes of further understanding firm bargaining behavior, and therefore focusing on consumers' attitudes towards bargaining across markets and countries would be worthwhile for future study.

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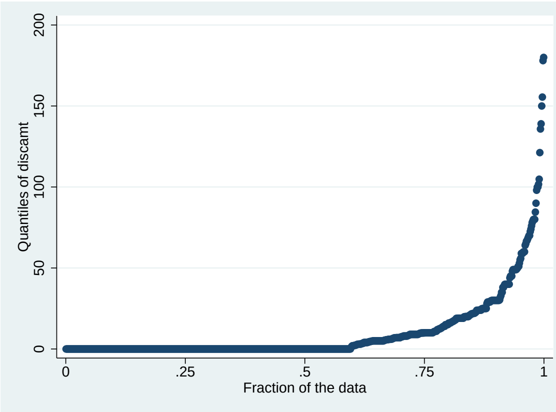
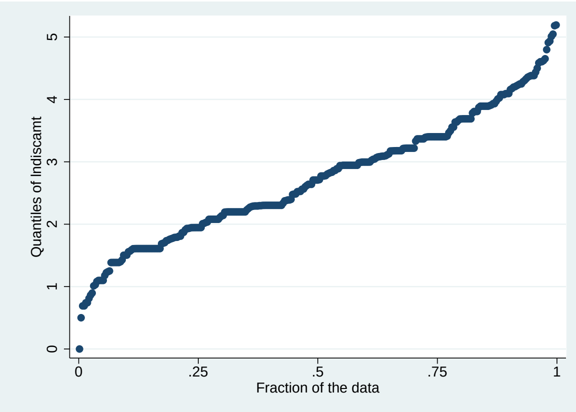
Figure 2: Quantile plots

(a) Discount amount



(b) ln(discount amount)



(c) Discount percentage

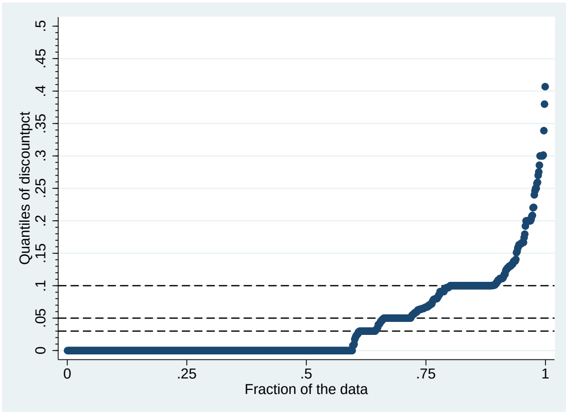
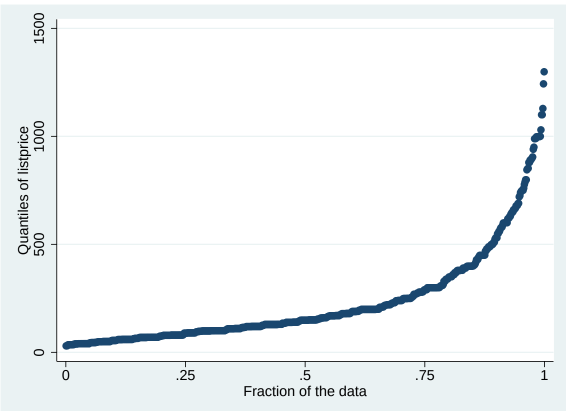


Figure 3: Quantile plots

(a) List price



(b) ln(list price)

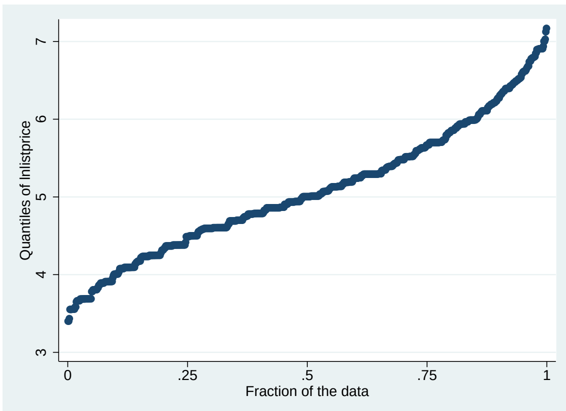
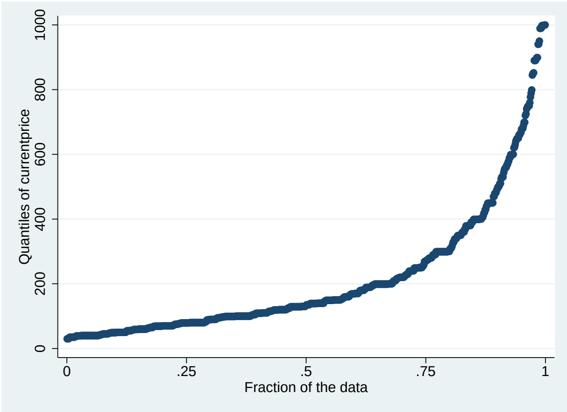


Figure 4: Quantile plots

(a) Posted price



(b) ln(posted price)

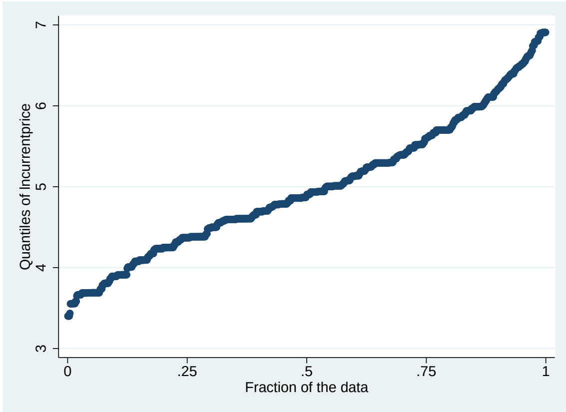
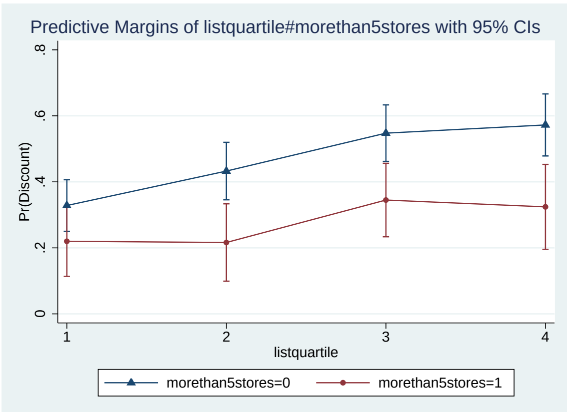
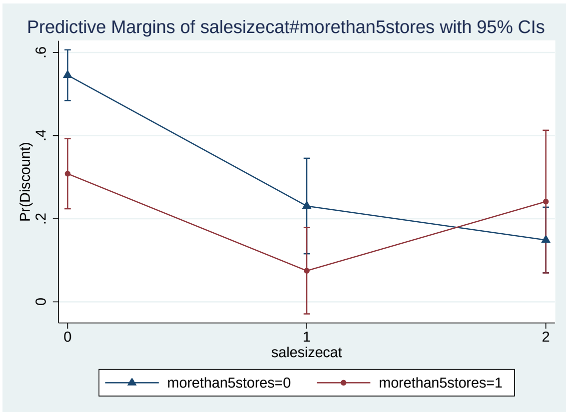


Figure 5: Predicted probability of a discount: Interactions

(a)



(b)



(c)

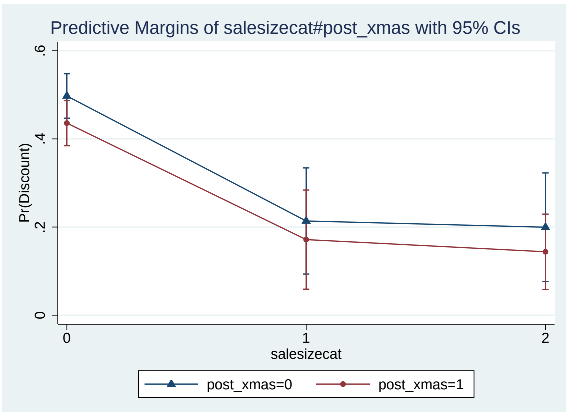


Figure 6: Predicted probability of a discount: Interactions of alternate specifications of price with firm scale

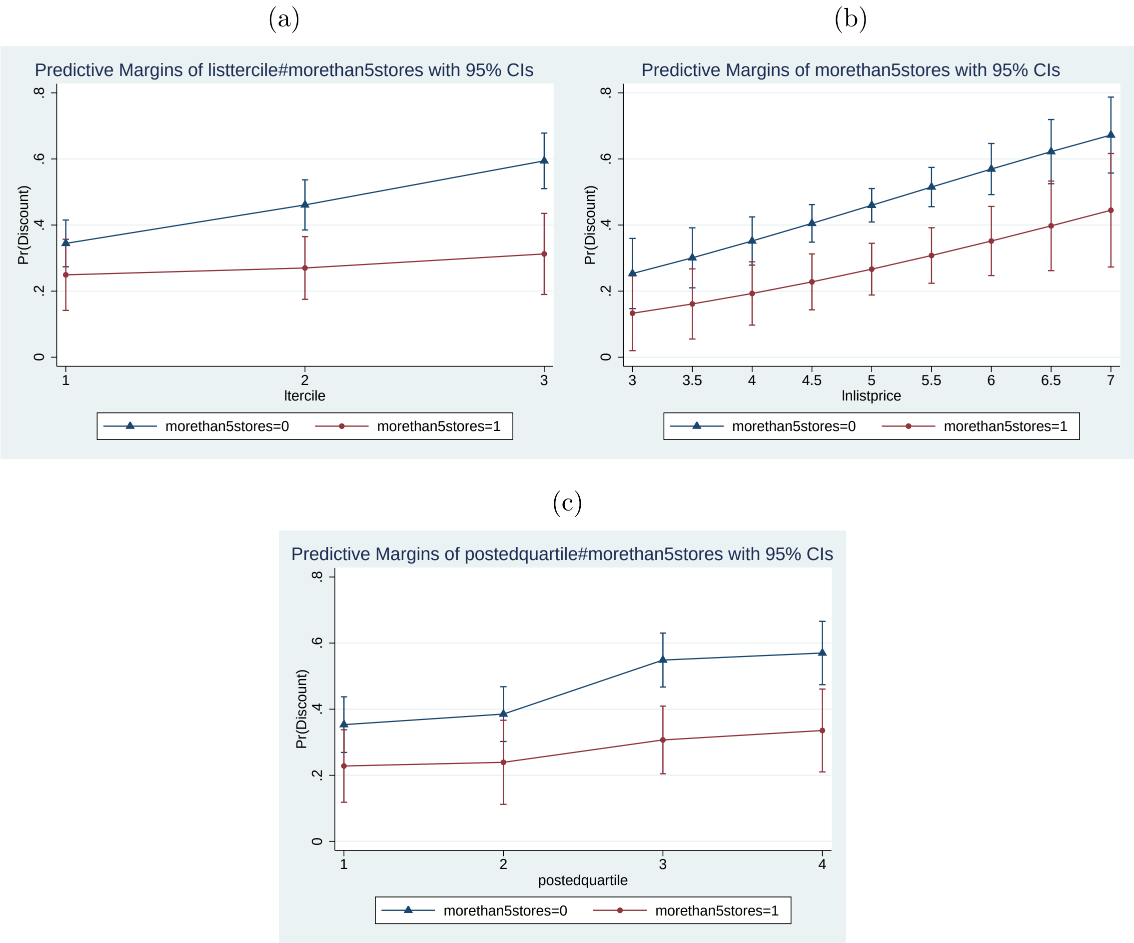
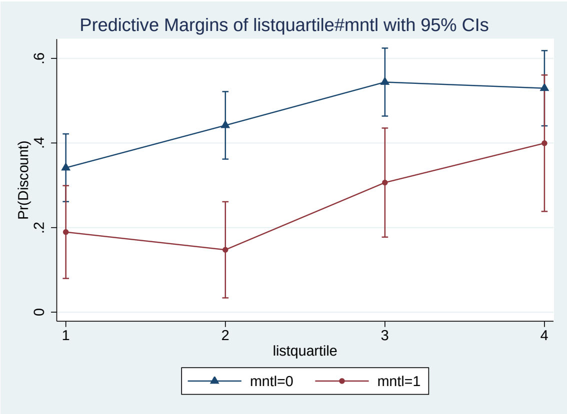
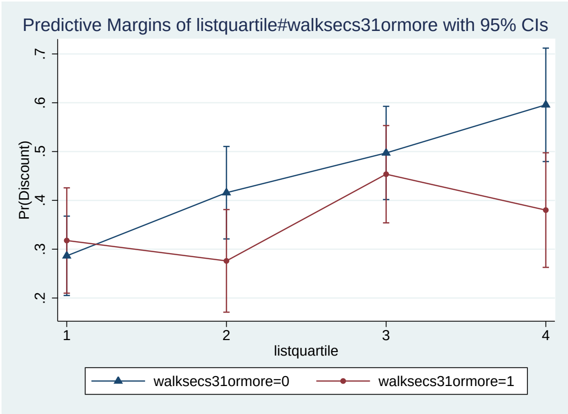


Figure 7: Predicted probability of a discount: Interactions of price with alternate specifications of firm scale

(a)



(b)



(c)

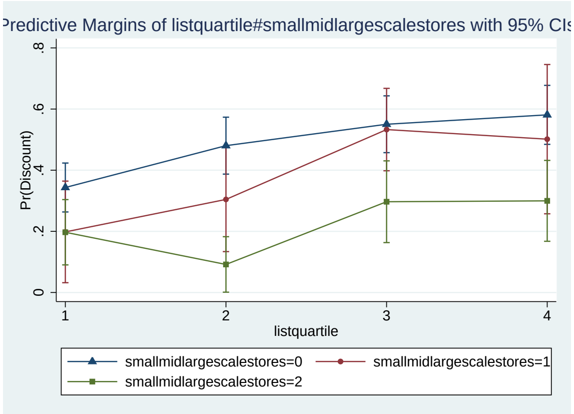
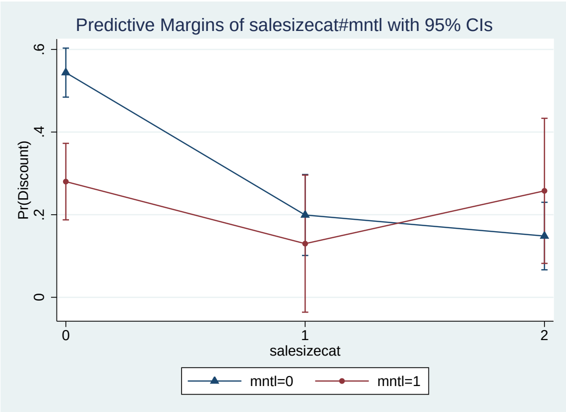
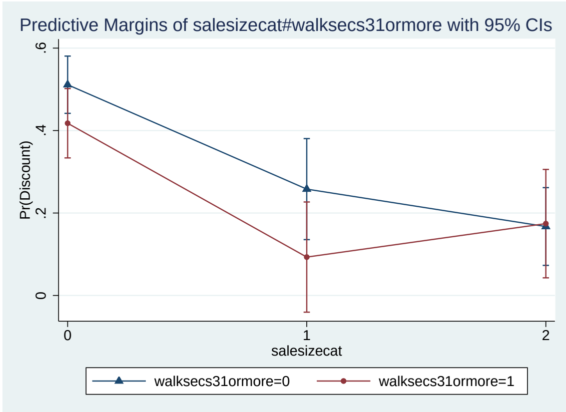


Figure 8: Predicted probability of a discount: Interactions of sale size category with alternate specifications of firm scale

(a)



(b)



(c)

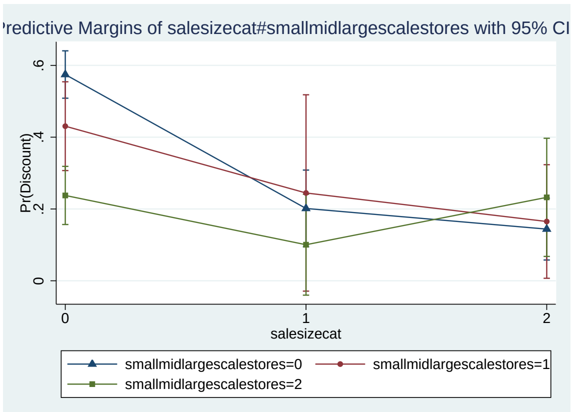


Table 1: Consumer survey results

	Firm type: Domestic		
Respondent	Asked for a discount	Consumers surveyed	Percentage
Buyer	13	104	12.5%
Non-buyer	4	138	2.9%
Total	17	242	7.0%
	Firm type: Multinational		
Respondent	Asked for a discount	Consumers surveyed	Percentage
Buyer	4	59	6.8%
Non-buyer	1	79	1.3%
Total	5	138	3.6%
	Overall		
	Asked for a discount	Consumers surveyed	Percentage
All respondents	22	380	5.8%

Table 2: Summary price, sale, and discount statistics

Variable	Mean	St. Dev.	Median	Mode	Min	Max	Obs
List price	237.133	302.48	149	199	30	5,900	751
Posted price (after any sale)	212.405	204.52	135	199	30	999.99	751
Sale amount (off of list price)	109.884	411.653	45	20	5	5,240	169
Sale percentage	0.306	0.147	0.3	0.3	0.034	0.888	169
Discount amount (off of posted price)	25.464	29.286	15	5	1	180	303
Discount percentage	0.098	0.066	0.098	0.1	0.008	0.407	303

Table 3: Summary statistics of categorical variables

Variable	Unique stores in the dataset	Observations
Number of stores in the world, per firm		
1	130	323
2	30	85
3	13	36
4	10	30
5	5	13
6	5	15
7	5	13
8	2	6
10-15	6	17
>15	74	213
Scale		
Domestic	204	532
Multinational	76	219
Geographic area		
1st district	55	157
2nd and 20th districts	57	143
18th and 19th districts	54	137
6th and 7th districts	114	314
Employees		
1	117	293
2	67	187
3	30	87
4	22	61
5	9	24
> 5	35	99
Number of customers observed		
0	138	349
1	42	120
2	26	72
3	20	56
4	4	12
5	6	17
6-10	26	73
> 10	18	52
Store category		
Clothing	96	270
Shoes	33	94
Jewelry	36	96
Household	26	66
Other	89	225
Walking seconds		
Up to 30 seconds	158	411
31-60 seconds	47	130
61-120 seconds	28	76
More than 2 minutes	47	134

Table 4: Ratio of round percentage discounts: Small-scale vs. large-scale firms

	Small-scale firm discounts			Large-scale firm discounts		
	Round percentage	In euros	Ratio	Round percentage	In euros	Ratio
Integer posted price	93	126	0.42	23	10	0.7
Non-integer posted price	25	12	0.68	12	2	0.86
Total	118	138		35	12	
Zero-ending integer posted price	81	30	0.73	42	2	0.95
Non-zero ending posted price	268	108	0.71	210	10	0.95
Total	349	138		252	12	

Table 5: Discounting behavior of multinational stores

Granted a discount at least once	Incidence	Never granted a discount	Obs
Bucherer	2 of 2 obs	Aldo (franchise store)	3
Cadenza	1 of 3 obs	Bonita	3
Colli	3 of 3 obs	Boss	3
Dorotheum	2 of 3 obs	Butlers	2
Douglas	2 of 3 obs	Camper	3
EMI Music	1 of 2 obs	Casa (franchise store)	3
Fogal	1 of 3 obs	Comma	3
Freytag&Berndt	2 of 3 obs	Cos	3
Högl	2 of 3 obs	Desigual	3
J&L Lobmeyr	2 of 2 obs	Diesel	3
Jacques Lemans (franchise store)	3 of 3 obs	Energie	3
Le Clou	1 of 3 obs	Escada	2
Levis (franchise store)	1 of 3 obs	Esprit	3
Marionnaud	1 of 3 obs	Footlocker	3
Matratzen Concord	3 of 3 obs	Fossil	3
Pandora (franchise store)	1 of 3 obs	Gabor	3
Samsonite	2 of 3 obs	Georges Rech	3
Saturn	1 of 3 obs	Geox	3
Sidestep	2 of 3 obs	Gerry Weber	3
Sport 2000 (franchise store)	3 of 3 obs	Gloriette	3
Stiefelkönig	1 of 3 obs	Grüne Erde	3
Tchibo	1 of 3 obs	G-Star (franchise store)	3
Vans	1 of 3 obs	Gucci	3
Wmf	2 of 3 obs	H&M	3
		Hallhuber	3
		Humanic	3
		Jack Wolfskin	2
		Jack Jones	2
		Joseph Ribkoff (franchise store)	3
		Kare (franchise store)	3
		Lacoste	3
		Mango	3
		Meblik Kids	2
		Moncler	3
		Mont blanc	3
		Müller	3
		Nespresso	3
		Peak Performance	3
		Pearle	2
		Puma	3
		S. Oliver	3
		Salamander	3
		Sisley (franchise store)	3
		Sports Experts	3
		Stefanel	3
		Swarovski	3
		Swatch	3
		Tom Tailor	3
		Triumph	3
		Weltbild	3
		Wolford	3
		Zara	3

Note: The designation as a franchise store was determined based on a telephone conversation with at least one salesperson at each of the above stores. As noted in Table 2, observations at multinational stores account for 219 of 751 observations overall.

Table 6: Average partial effects in the participation and amount equations

	LNH		ET2T	
	Part Eq	Amt Eq	Part Eq	Amt Eq
List price: 2nd quartile	0.071*	0.525***	0.073*	0.529***
	(0.039)	(0.101)	(0.038)	(0.102)
List price: 3rd quartile	0.182***	1.139***	0.182***	1.155***
	(0.044)	(0.117)	(0.043)	(0.121)
List price: 4th quartile	0.192***	1.86***	0.191***	1.87***
	(0.05)	(0.123)	(0.05)	(0.126)
Small sale item	-0.274***	-0.446**	-0.281***	-0.502**
	(0.05)	(0.227)	(0.047)	(0.222)
Large sale item	-0.295***	0.15	-0.296***	0.145
	(0.046)	(0.201)	(0.044)	(0.175)
More than five stores	-0.185***	-0.033	-0.18***	0.005
	(0.052)	(0.128)	(0.051)	(0.134)
Dec 27 - Jan 4	-0.059**	0.098	-0.057**	0.099
	(0.027)	(0.072)	(0.026)	(0.071)
Female salesperson	-0.066*	-0.132	-0.068*	-0.136
	(0.039)	(0.09)	(0.039)	(0.091)
One customer	-0.057	-0.27**	-0.064	-0.305**
	(0.054)	(0.126)	(0.051)	(0.125)
Two customers	-0.086	-0.276*	-0.087	-0.301*
	(0.061)	(0.15)	(0.061)	(0.151)
Three or more customers	-0.067	-0.361**	-0.066	-0.37**
	(0.071)	(0.162)	(0.07)	(0.156)
Two employees	-0.027	0.003	-0.022	0.003
	(0.051)	(0.101)	(0.05)	(0.099)
Three employees	-0.108	-0.164	-0.107	-0.193
	(0.068)	(0.155)	(0.065)	(0.155)
Four or more employees	-0.178**	0.124	-0.172**	0.109
	(0.076)	(0.185)	(0.074)	(0.185)
2nd and 20th districts	0.099	0.091	0.103	0.135
	(0.067)	(0.156)	(0.066)	(0.158)
18th and 19th districts	0.101	-0.035	0.106*	0.005
	(0.066)	(0.15)	(0.064)	(0.149)
7th district	0.022	-0.068	0.024	-0.037
	(0.055)	(0.129)	(0.053)	(0.13)
Salesperson age: 35-50	0.005	-0.069	0.005	-0.077
	(0.038)	(0.095)	(0.037)	(0.092)
Salesperson age: Over 50	-0.027	-0.012	-0.021	-0.019
	(0.05)	(0.132)	(0.049)	(0.131)

Continued on next page

Table 6 : Continued from previous page

	LNH		ET2T	
	Part Eq	Amt Eq	Part Eq	Amt Eq
Expensive clothing	-0.126**	0.072	-0.126**	0.055
	(0.062)	(0.162)	(0.06)	(0.159)
Inexpensive shoes	-0.118	-0.004	-0.11	0.008
	(0.09)	(0.267)	(0.089)	(0.26)
Expensive shoes	-0.08	-0.21	-0.063	-0.178
	(0.087)	(0.281)	(0.091)	(0.285)
Inexpensive jewelry	-0.025	0.31*	-0.024	0.303*
	(0.071)	(0.181)	(0.07)	(0.178)
Expensive jewelry	0.283***	0.188	0.268***	0.257
	(0.093)	(0.187)	(0.094)	(0.191)
Inexpensive household	-0.007	0.286	-0.01	0.247
	(0.112)	(0.217)	(0.11)	(0.198)
Expensive household	-0.09	0.379	-0.075	0.366
	(0.094)	(0.245)	(0.093)	(0.244)
Inexpensive "other"	-0.105	-0.105	-0.105*	-0.115
	(0.064)	(0.165)	(0.063)	(0.168)
Expensive "other"	-0.014	-0.156	-0.016	-0.149
	(0.063)	(0.181)	(0.062)	(0.181)
Log likelihood	-1473.399		-1472.042	
ρ	Zero-constrained		-0.664**	
			(0.207)	

Note: Default categories are 1st quartile, non-sale items, firms with up to five stores, Dec 9 - Dec 14, male salesperson, no customers observed, one employee observed, 1st district, salesperson age < 35, and inexpensive clothing. Results related to interactions in the participation equation and RA fixed effects in both equations are not shown for space reasons. Interaction effects are reported in Figure 5. Standard errors are clustered at the store level.

Table 7: Average partial effects in the participation and amount equations (LNH model): Alternative price variables

	Part Eq	Amt Eq	Part Eq	Amt Eq	Part Eq	Amt Eq
List price: 2nd tercile	0.085**	0.684***				
	(0.035)	(0.102)				
List price: 3rd tercile	0.183***	1.603***				
	(0.045)	(0.111)				
ln (list price)			0.093***	0.91***		
			(0.022)	(0.054)		
Posted price: 2nd quartile					0.025	0.491***
					(0.04)	(0.120)
Posted price: 3rd quartile					0.152***	1.05***
					(0.045)	(0.124)
Posted price: 4th quartile					0.174***	1.821***
					(0.053)	(0.137)
Small sale item	-0.267***	-0.469*	-0.273***	-0.532**	-0.258***	-0.288
	(0.049)	(0.263)	(0.049)	(0.237)	(0.05)	(0.255)
Large sale item	-0.285***	0.021	-0.304***	-0.028	-0.256***	0.348*
	(0.047)	(0.219)	(0.045)	(0.181)	(0.049)	(0.192)
More than five stores	-0.181***	0.056	-0.184***	-0.079	-0.182***	-0.019
	(0.052)	(0.136)	(0.051)	(0.133)	(0.052)	(0.138)
Dec 27 - Jan 4	-0.063**	0.026	-0.058**	0.085	-0.057**	0.081
	(0.027)	(0.080)	(0.027)	(0.070)	(0.027)	(0.079)
Female salesperson	-0.066*	-0.094	-0.062	-0.108	-0.064	-0.106
	(0.039)	(0.096)	(0.039)	(0.093)	(0.039)	(0.098)
One customer	-0.049	-0.158	-0.054	-0.217*	-0.059	-0.278**
	(0.054)	(0.139)	(0.053)	(0.125)	(0.053)	(0.133)
Two customers	-0.092	-0.322**	-0.054	-0.338**	-0.091	-0.304*
	(0.061)	(0.162)	(0.053)	(0.156)	(0.061)	(0.166)
Three or more customers	-0.066	-0.362**	-0.062	-0.362**	-0.071	-0.428**
	(0.07)	(0.177)	(0.071)	(0.172)	(0.07)	(0.170)
Two employees	-0.026	-0.011	-0.024	0.008	-0.027	0.042
	(0.052)	(0.108)	(0.052)	(0.105)	(0.052)	(0.112)
Three employees	-0.109	-0.136	-0.106	-0.17	-0.111	-0.171
	(0.069)	(0.166)	(0.068)	(0.152)	(0.068)	(0.169)
Four or more employees	-0.176	0.184	-0.18**	0.101	-0.178**	0.132
	(0.075)	(0.201)	(0.076)	(0.194)	(0.075)	(0.190)
Observations	751	303	751	303	751	303
Log likelihood	-1486.753		-1460.289		-1478.4	

Note: Default categories are 1st tercile (list), 1st quartile (posted), non-sale items, firms with up to five stores, Dec 9 - Dec 14, male salesperson, no customers observed, and one employee observed. Interactions, area, age, product type, and RA effects are not shown. Standard errors are clustered at the store level.

Table 8: Average partial effects in the participation and amount equations (LNH model): Alternative firm-scale variables

	Part Eq	Amt Eq	Part Eq	Amt Eq	Part Eq	Amt Eq
List price: 2nd quartile	0.063 (0.039)	0.525*** (0.109)	0.062 (0.039)	0.517*** (0.108)	0.075** (0.037)	0.528*** (0.108)
List price: 3rd quartile	0.174*** (0.045)	1.135*** (0.126)	0.18*** (0.044)	1.134*** (0.125)	0.188*** (0.044)	1.147*** (0.125)
List price: 4th quartile	0.188*** (0.053)	1.858*** (0.132)	0.202*** (0.052)	1.847*** (0.131)	0.203*** (0.05)	1.863*** (0.131)
Small sale item	-0.287*** (0.048)	-0.451* (0.241)	-0.266*** (0.049)	-0.456* (0.248)	-0.282*** (0.048)	-0.447* (0.242)
Large sale item	-0.296*** (0.046)	0.132 (0.205)	-0.299*** (0.046)	0.139 (0.216)	-0.302*** (0.043)	0.152 (0.216)
Multinational firm	-0.196*** (0.055)	0.053 (0.165)				
Walking seconds > 30			-0.083 (0.055)	-0.105 (0.117)		
Between 4-15 stores					-0.105* (0.062)	-0.083 (0.133)
More than 15 stores					-0.26*** (0.05)	-0.02 (0.174)
Dec 27 - Jan 4	-0.065** (0.027)	0.101 (0.076)	-0.054** (0.027)	0.094 (0.075)	-0.058** (0.027)	0.096 (0.077)
Female salesperson	-0.098** (0.038)	-0.133 (0.098)	-0.09** (0.039)	-0.143 (0.098)	-0.055 (0.038)	-0.13 (0.097)
One customer	-0.101** (0.05)	-0.269* (0.138)	-0.078 (0.055)	-0.254* (0.138)	-0.056 (0.051)	-0.265* (0.137)
Two customers	-0.091 (0.05)	-0.271* (0.160)	-0.055 (0.055)	-0.236 (0.169)	-0.089 (0.057)	-0.281* (0.161)
Three or more customers	-0.038 (0.057)	-0.367** (0.175)	-0.08 (0.068)	-0.339* (0.176)	-0.052 (0.066)	-0.371** (0.178)
Two employees	-0.037 (0.05)	-0.002 (0.108)	-0.024 (0.052)	0.01 (0.107)	-0.038 (0.048)	0.001 (0.107)
Three employees	-0.106 (0.067)	-0.17 (0.171)	-0.106 (0.074)	-0.132 (0.172)	-0.104 (0.069)	-0.166 (0.167)
Four or more employees	-0.199*** (0.072)	0.109 (0.195)	-0.193** (0.079)	0.166 (0.2)	-0.167** (0.073)	0.135 (0.195)
Observations	751	303	751	303	751	303
Log likelihood	-1471.108		-1481.014		-1463.161	

Note: Default categories are 1st quartile, non-sale items, walking seconds ≤ 30, firms with ≤ 3 stores, Dec 9 - Dec 14, male salesperson, no customers observed, and one employee observed. Interactions, area, age, product type, and RA effects are not shown. Standard errors are clustered at the store level.

Table 9: Average price percentile and percentage of sale items chosen by RA identity

RA ID	Pctile of assigned range (avg)	St. Dev.	Sale items observed (pct)	St. Dev.
1	0.365	0.271	0.149	0.359
2	0.425	0.342	0.133	0.343
3	0.513	0.341	0.279	0.452
4	0.372	0.355	0.323	0.471
5	0.525	0.304	0.182	0.389
6	0.376	0.308	0.305	0.464
7	0.515	0.32	0.233	0.427
8	0.425	0.339	0.185	0.392
9	0.512	0.312	0.231	0.425
10	0.509	0.305	0.292	0.458
11	0.441	0.312	0.172	0.38
12	0.469	0.343	0.213	0.413

Note: RAs #1-#6 are females and RAs #7-#12 are males.

Table 10: Discounts granted to RAs that followed a particular RA at the same store (three observations per store required)

	First follower		Second follower		Both followers	
Leader ID	Discounts	Observations	Discounts	Observations	Discounts	Observations
1	4	10	4	10	8	20
2	8	18	6	18	14	36
3	9	16	5	16	14	32
4	12	23	6	23	18	46
5	5	19	6	19	11	38
6	7	15	5	15	12	30
7	6	19	5	19	11	38
8	7	16	6	16	13	32
9	13	25	9	25	22	50
10	8	19	5	19	13	38
11	7	16	6	16	13	32
12	5	15	3	15	8	30

Note: RAs #1-#6 are females and RAs #7-#12 are males.

Table 11: Discounts granted to RAs that followed a particular RA at the same store within the same week

	Leader & follower visit pre-xmas		Leader & follower visit post-xmas	
Leader ID	Follower Discounts	Follower Obs.	Follower Discounts	Follower Obs.
1	2	6	7	20
2	5	8	7	10
3	7	10	1	11
4	5	10	1	9
5	4	11	3	9
6	4	8	4	10
7	7	13	1	8
8	5	10	2	5
9	9	16	2	7
10	2	10	0	7
11	4	10	2	5
12	3	9	1	7

Note: RAs #1-#6 are females and RAs #7-#12 are males.

Appendix A: Instructions for the RAs

Dear All,

Please read this text very carefully and follow it precisely. Have a copy with you to consult safely tucked away in your pocket. It's crucial for our study that all issues mentioned below are taken into account. One of us will call you on Monday morning to review this with you and make sure everything is clear.

Please take a look at your assignment carefully. If you do not wish or are able to visit some stores for reasons such as you are uncomfortable visiting the store, you have some conflict of interest, etc., please let us know immediately so that you are reassigned to other stores.

The first bargaining period will occur between December 9 – December 14 and the second bargaining period will occur between December 27 – January 4. In the attached spreadsheet you will find your bargaining assignments. This includes a store name, address, type of the store, interval of prices (more about this below), and restriction on when to visit the store (some stores will have no restrictions). Each of you will receive about 35-40 to be visited between Dec 9 and Dec 14, and approximately the same quantity between December 27 and January 4. So overall you will visit 70-80 stores. You were randomly assigned to different periods, so it may happen that in a 3-day window you need to do up to 16 shops. Please plan ahead and if you anticipate problems, let us know immediately.

Furthermore, a given store may have a date restriction for a given period. For example, if Store A is assigned to you in the period Dec 9 – Dec 14, you may be required to perform this observation at some time between Dec 9 – Dec 11, or alternatively between Dec 12 – Dec 14. If it is assigned to you in the second period, you may be required to visit between Dec 27 – Dec 31, or alternatively between Jan 2 – Jan 4. This information will be provided to you in your assignment spreadsheet.

You should dress in a similar way for every observation. You should dress nicely, but not overly so (no ties, no suits, no evening dresses etc.). No sneakers. Do not carry a backpack. If you wear jeans, wear a nice pair. For men, shirt should be tucked in, you should be shaved, closely trimmed, or have a properly trimmed beard. For women, everyday makeup is OK.

For each store you will receive a price interval in which to find a product. For example, you will need to find something between 45 and 120 euros in shop X. As we discussed, you need to find something in which you could show genuine and credible interest. If no such product can be found in the interval, find a product closest to the interval for which you can credibly bargain.

Make sure that the product you choose has a price tag on it, or its price is identifiable in some other way; do not ask a salesperson for a price. If you have difficulty finding a posted price in the interval you were given because most prices are not posted, drop the store and note this in the comments section for that store. Please do not avoid or favour products on sale, just find a product for which you could show genuine and credible interest.

Once you have expressed interested in a particular product in a very brief conversation with a salesperson, ask a salesperson something along the following lines: "Can we do something about the price", "Can I get a discount", "Can I get this cheaper", or "Can we talk about the price" (**everything should be done in German, unless the salesperson switches to another language that he/she prefers**). **Do not suggest a price you would like to pay**, even if asked for it (e.g. "how much would you want to pay?") Avoid this question politely by telling them something like "I don't know, please tell me what you could offer me"). Similarly, **do not suggest a percentage discount** (e.g., do not suggest "can I get 10% off?").

When showing interest for a product, or bargaining for it, **do not mention you are a student, unless directly asked, and do not give any other occupational details**. **Do not say you have little money or you are poor**, but you may say that an item is a bit too expensive for you if this comes naturally in the conversation. **Do not say that you've seen this or a similar item elsewhere (e.g. Amazon) cheaper.**

If the salesperson agrees and offers a discount, find a polite way to say that you will not buy now and leave. **If the salesperson denies your initial request for a discount, try to ask for a discount again** in a way that is appropriate for the situation. **If the salesperson denies your second request, leave.**

Do not ask for a manager at any time, but if you ask for a discount and the salesperson responds by offering to speak to a manager on his/her own initiative, remain to interact with the manager (as long as the manager arrives within 5 minutes, otherwise you should leave politely).

Once you are done, record the following (and put into the appropriate column of the provided excel file when convenient) next to the store observation details that we provide for you:

1. **Gender of the final person with whom you interacted (if no manager was involved, this is simply the gender of the salesperson from whom you asked for a discount)**
2. **Approximate age of this person in one of the following ranges (below 35, 35 to 50, or above 50)**
3. **Name of the good (e.g. leather bag)**
4. **Current price of the good (the one you would have to pay without bargaining)**
5. **List price of the good. List price may be the same as current price. The list price is higher if the good is currently discounted on the price tag. (e.g. if the price tag says 100 euro and is crossed out, and then says 80 euro below, list price is 100 euro, current price is 80 euro).**
6. **If you are granted a discount, record either the final price offered, or if the discount is given in percentages, the discount percentage. These are two separate fields; please fill out only one of them (e.g. if a product costs 100 euro, and the salesperson offered to sell it for 90, you record 90 in the "final price". For the same product, if the salesperson tells you instead that you can get 10% off, then leave "final price" blank, and put 10% in "% discount")**
7. **Was discount offered on the condition that cash was paid?**
8. **Time and date at which you exit the store**
9. **Anything strange/interesting that happens should be recorded in the comments section (also, if a manager/owner/superior was mentioned, put this in the comments section).**

Please make sure that your observations are somewhat spread out over three different time periods: weekdays before 2 pm, weekdays after 2 pm, and Saturdays (time of the day on Saturday is not important). Do not bargain after 5:30 pm on any day.

Good luck!

Appendix B: Research Assistant Behavior

RA performance over time

Hot hand

We perform several tests in order to examine the extent to which discount outcomes for a particular RA vary over time. First, for each individual RA, we run a simple vector autoregression (VAR) in which the dummy variable indicating whether a discount was granted is the dependent variable. On the right hand side we analyze five lags of the dependent variable as well as all of the explanatory variables in Table 6 (but without any interactions). In addition to the fact that all lags of the dependent variable are found to be insignificant for the majority of RAs, lag-order selection statistics using the Akaike Information Criterion (AIC) support the inclusion of no lags for 9 of the 12 RAs, one lag for 2 of the 12 RAs, and two lags for 1 of the 12 RAs. When rerunning the VAR for these three RAs, only the second lag for one of the RAs is significant (and negatively so). Therefore we have strong evidence that previously observed discount outcomes do not affect an RA's subsequent discount outcomes.

Next, we run a Prais-Winsten regression using the same variables (again without lags of the dependent variable and without interactions) in order to check for the presence of unobserved serial correlation; in one instance we combine all observations and include fixed effects for each RA and we also run 12 separate regressions for each RA. In no cases do we find evidence of any type of serial correlation.

Learning and fatigue

In order to address the question of whether there is a deterministic trend with regards to the rate with which RAs obtain a discount, we run a simple linear probability model with the same regressors as in the previous specification and also include a variable that tests for the existence of a deterministic trend, the order in which the RA visited the store. We run this regression separately for each of the 12 RAs. The trend variable is negative and significant for two of the RAs at the .05 level (magnitudes of -.014 and -.021), one of the RAs at the .1 level (magnitude of .013), and insignificant for the remainder of the RAs. A positive and significant estimate might have suggested evidence of learning. We cannot rule out the possibility that a negative coefficient might suggest that a particular RA exerted less effort in obtaining a discount over time.

Effect of first RA visit on subsequent visits to the same store

It is also worthwhile to check whether a particular RA, by visiting a store first, somehow contaminated the observations that followed at the same store. This might occur if, for example, an RA inadvertently angered a salesperson during his or her interaction by asking for a discount (for one of a variety of possible reasons). This could result in a very small number of discounts granted at stores at which that particular RA visits prior to other RAs. Although our sample size is relatively small for any given "leading" RA, restricting our analysis to stores which appear three times in our dataset in Table 10 we do not find evidence that a particular RA visiting a store first led to a substantially lower incidence of discounts afterward at the same store.

In Table 11 we restrict follower RAs to those that observed a store within the same week as the leading RA. When analyzing the data in this fashion we are dealing with a particularly small sample size, but we report these summary statistics nevertheless. In Columns 2 and 3 we report the outcomes related to observations at the same store between Dec 9 - Dec 14 and in Columns 4 and 5 we report the outcomes related to observations at the same store between Dec 27 - Jan 4. RAs who follow RA #10 do record a particularly low number of discounts in both periods (2 of 10 observations and 0 of 7 observations, respectively), however this does not appear to occur for any of the other RAs.

RA product choices

It is also important to check whether RAs sought to choose products that they thought would generate a discount. The RAs were given the freedom to choose any product within a particular price range. This means that there were two variables which the RA could in effect influence in their search for a product - the product's price and whether the product was a sale item. Our concern would be if there was a large degree of heterogeneity in the percentile of the price range chosen across RAs; this might imply that individual RA effects could contaminate the price coefficients, and vice-versa. Likewise, if individual RAs chose a significantly different percentage of sale items relative to other RAs, the same concern would apply. While the nature of the product chosen is also up to the discretion to the RA, the degree of heterogeneity of products in our data set is far too large to investigate systematic biases in this direction. In fact, any combination of variables which we do not interact but for which RAs favored (e.g. high prices in the second period) might lead to spurious estimates.

In Table 9 we display summary statistics of the average price percentile at which each RA chose a product within the assigned price range. While RAs #1, #4, and #6 chose relatively low prices within the assigned range on average, none of the remaining RAs' price percentiles chosen are significantly different from one another. Here we use the term "percentile" loosely as we do not know the distribution of prices at a given store within a particular price range; however we surmise that in any given price range that there will be typically be a larger number of products at the lower end of the range than at the higher end.

In Table 9 we also display summary statistics of the average number of instances in which an RA chose a product that was on sale. Eight of these 66 pairs' price percentile choices are statistically significantly different from one another, and seven of these eight pairs include either RA #1 or RA #2, who observed sale items the least frequently.

Of secondary concern is whether RAs favored products which they (correctly or incorrectly) thought would generate a discount via price preferences or sale/non-sale preferences. While this would not influence our coefficient estimates due to the fact that we control for these variables, this would influence the overall incidence of discounts. This is not the primary interest of our study, however we did seek to construct a representative sample of stores and products of a certain nature that retail consumers face in the West; therefore we are interested in how representative our prediction of bargaining is evaluated at the average values of the variables.

Pairwise behavior of RAs / honesty

Although we attempted to conceal the identities of the RAs from one another during the project, it is possible that some of our RAs knew the identities of other RAs working on the project during the data collection period. If this were the case, one concern that might arise is that an RA who was assigned the same store as another RA would use data collected by that RA in order to fabricate what he or she considered to be realistic results from that store without actually carrying out the observation assignments. This would only be a concern in the second period because first period data were submitted prior to the beginning of the second period; during the first period the median number of stores for which a given RA pair was mutually assigned was only one, the mode was zero, and the maximum number of mutual store assignments was seven.

Over all observations, a given RA pair was allocated a median of 10 mutually assigned stores, with a maximum of 17 mutually assigned stores. For each of the 66 RA pairs, we calculated the percentage of observations for which they both recorded a discount for the same store, the percentage of observations for which they both recorded not receiving a discount for the same store, and the percentage of observations for which one RA received a discount and the other RA did not receive a discount. On average, both RAs received a discount approximately 26 percent of the time whereas neither RA received a discount approximately 46 percent of the time. There were no RA pairs which always recorded a discount at mutually visited stores and one out of 66 RA pairs always recorded not receiving a discount at mutually visited stores (8 stores, or 16 total observations). Therefore we feel comfortable claiming that there does not appear to be evidence that RAs fabricated observations based on data collected by a fellow RAs.

It should be noted that a priori it is not entirely obvious that cheating is more likely to manifest itself as the same observation at the same store. For example, if RAs were concerned that the co-authors would analyze the data for cheating, they might try to avoid recording the exact same outcome for all mutually visited stores.111

Missed observations and errors

We now address the observation assignments that were not performed and the errors in the observations that the RAs recorded. Our analysis uses 751 out of 861 total observation assignments. Of the 110 observations that we do not analyze, 86 observations were never performed. Of these 86 observations, in approximately 75 percent of these cases the RA visited the store when it was closed. In certain cases this was avoidable, as a visit to the store's website or a phone call would have indicated the shop's hours. This was usually the case when the RA visited on a Saturday when the shop was closed. In other cases, the shop closed during the week following Christmas, and advance information in this regard was not always obtainable. In yet other cases, stores were closed during times for which it should have been open according to its own publicized business hours. In some cases reasons were given on the storefront (e.g. illness), but in most cases no explanation was given. Nearly all of the remaining 25 percent of observations were not performed either because the RA could not find a product with a posted price for which he or she could credibly bargain or because the RA did not properly locate the store for one reason or another. Furthermore, there were five observations that were mistakenly unassigned. One characteristic of nearly all of these 86 observations is that they pertain to small-scale stores.

The 24 observations which were recorded but which were not analyzed contained errors, ambiguities, inconsistencies, or applied to stores which in retrospect should not have been included in the sample due to the nature of the product sold. For example, one store's focus is bathroom and pool installation (three observations), and another store is a non-profit organization that sells used clothes (three observations). Eight observations utilized products outside of the posted price range of 30 - 1,000 EUR, four observations were recorded on products for which there was no posted price, and eight observations were recorded with ambiguities or inconsistencies (e.g., a discount was granted but the size of the discount was not stated explicitly or recorded).