Price Discrimination and Customer Behaviour: Empirical Evidence from Marseille*

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Abstract

There exist an extensive theoretical and empirical literature on price discrimination, a large part of which is devoted to explaining who will be discriminated against and by how much. There is, however rather little data available on how buyers bargain in markets where no prices are posted and the effect this has on the prices paid. In addition there is not much evidence as to how sellers learn to discriminate against buyers in repeated situations. Our contribution is to analyse econometrically the empirical data from a stall on a specific wholesale market where no prices are posted and price discrimination is widespread. Since we have data on bargaining and on the loyalty of customers, two features which are often mentioned as being causes of discrimination, we are able to explain most of the deviations from average price by the characteristics and behaviour of the buyers. Our data allows us to establish that a customer of the stall is more likely to pay a price higher than other customers for the same good if—ceteris paribus—the customer is unknown to the sales assistants, buys only a small quantity, or buys goods sold on commission. If the customer is known to the assistants, then loyalty and bargaining make it more likely that the customer gets a better than average price.

Keywords: Face-to-face bargaining, customer loyalty

1 Introduction

Price discrimination occurs in many contexts and has been the subject of a large literature. Whilst the very basic definition, that units of the same good are sold at different prices, corresponds to a pervasive everyday reality, there are so many variants that there are no simple general results. The very existence of price discrimination depends on several factors. Imperfect competition among sellers and differentiated customers. Unfortunately, in quite general contexts one can show theoretically that, depending on the shape of cost and demand curves, discrimination can go in any direction (see e.g. Hens et al. (1999)). In other words one can always find the appropriate parameters for a model such that a change in one of the parameters can lead to an increase or a decrease in the price paid by, or charged to a specific type of customer. One has therefore to focus on very specific characteristics of buyers and of their behaviour to be able to to ascertain the influence of these on the prices that they pay. We are fortunate to have data on both the loyalty of clients and on the nature of their bargaining behaviour on the market we study, and we use this empirical evidence to determine the impact on the prices paid. In particular, we try statistically to disentangle the impact of the characteristics on which we focus.

Our data come from a wholesale market for fruit and vegetables. Markets for perishable goods—such as wholesale markets for fish, meat, flowers, or fruits and vegetables—have long fascinated economists and early authorities such as John Stuart Mill, Pareto and Marshall used them as examples. These markets are attractive for the sort of analysis that we wish to undertake, for at least three reasons: First, they avoid all the problems due to the possibility of holding inventories and the consequent intertemporal dependence in prices and sales. Second, due to the perishability of the goods, buyers and sellers need to conclude their negotiations quickly since the produce has to be resold essentially on the same day and has very limited storage life. Third, buyers and sellers meet repeatedly so we can study the effect of the frequency of encounters and the loyalty of customers on the prices that they pay. There are, of course, markets for many perishable goods which do not exhibit all these features such as the resale market for baseball tickets (Sweeting, 2008), but the data from these would not permit us to identify discrimination other than by the time of purchase.

Recently, there has been a resurgence of interest in the sort of market that we analyse here (see, e.g., Bestor (1998); Graddy (2006); Kirman and Vignes (1991); Kirman and Vriend (2001); Rivaud-Danset and Vignes (2004); Weisbuch et al. (2000)). Much of the interest in these contributions is centered on price dispersion which, in turn reflects price discrimination. Our study contributes to this literature by examining a case in which there are no posted prices and agents negotiate the terms of trade. In a sense, this provides the optimal situation for price discrimination. Specifically, we examine the bargaining process between a seller and his buyers and aim to identify certain characteristics of buyers which might have an impact on the prices that they are charged. Thus we would like to know how the intensity with which individuals bargain influences prices but we also want to know whether other characteristics have an influence. Our data from the wholesale fruit and vegetables market in Marseille permits us to observe these characteristics. For example, we know the total quantity purchased by the customer, whether or not she is loyal to the seller and the frequency of her visits. We also know certain characteristics of the goods that are provided by the seller. Not only do we have a rather detailed classification into categories of goods, but we also know whether the goods have been purchased already by the seller or whether he sells them «on consignment», meaning that the original supplier is only paid if the goods are sold otherwise he recovers them. This allows us to control for other factors which may influence the price agreed upon. Of course we cannot determine the causality of certain relations. If a certain buyer bargains a lot, is that because of his other characteristics or is it a separate phenomena? However, we do want to know how much of any price discrimination can be attributed to the level of bargaining and how much to other characteristics.

Our main findings are, that a customer is more likely to be discriminated against, if (ceteribus paribus) the customer is unknown to the seller, buys only a small quantity, and buys goods sold on commission. If the customer is known to the seller, then loyalty and bargaining makes it more likely that the customer gets a better price than other customers.

The paper is organized as follows. Section 2 discusses related literature and provides predictions, which are then confronted with the data. Section 3 contains the empirical analysis. The last section concludes.

2 Related literature and empirical predictions

Price discrimination occurs when identical units of a homogeneous good are sold at different prices by the same seller. A more specific and widely used definition is that it takes place when the seller of a homogeneous good charges different buyers different unit prices and these differences cannot be attributed to variations in costs[1]. Economists generally follow the taxonomy of Pigou (1938), who described three different forms of price discrimination: First-degree price discrimination—sometimes known as perfect price discrimination—means that different quantities of the good are sold at different unit prices and these unit

[1] In what follows, price refers to the amount of money paid for a given quantity of the good and unit price refers to the average price, i.e., the price divided by the quantity.

prices may, in addition, vary from buyer to buyer. In effect, the seller uses a non-linear price schedule to skim all consumer surplus from the buyer. This not only requires that the seller knows the demand function of each type of buyer and can observe the type of a buyer, but also that he can prevent arbitrage between different types of buyers. Second-degree price discrimination means that different quantities of the good are sold for different unit prices, but every customer who buys the same quantity pays the same unit price. Thus, the unit price depends on the amount of the good purchased, but not on the identity of the purchaser. This requires that the seller knows buyer types' demand functions, but that he cannot distinguish which buyer is of which type. Effectively, the seller offers (*price*, *quantity*) combinations, and buyers select the combination most suitable for them.[2] Third-degree price discrimination means that different groups of buyers pay different unit prices, but every unit of the good sold to a buyer in a group sells for the same unit price.[3] Effectively, the seller does not discriminate perfectly between different individual buyers, because the observable characteristics only allow coarse market segmentation into still heterogeneous buyer groups, for example, if the willingness to pay of different

[2]Common examples of this sort of price discrimination are volume discounts or bulk offers ('Buy one, get one free').

[3]This is the most common form of price discrimination, and examples include discounts available for senior citizens and students. To be eligible for such discounts, the customer has to reveal himself with, e.g., a student id.

individuals is unknown. Again, as in the first-degree case, third-degree price discrimination requires that the seller can prevent arbitrage between buyers of the different groups.

There is by now an extensive literature on price discrimination both from the theoretical and the empirical points of view[4]. Typically the literature has focussed attention on discrimination as an explanation for price dispersion. Borenstein (1991) and Shepard (1991), for example, identify the presence of price discrimination from possible cost-based explanations for the price dispersion which they observed. Borenstein and Rose (1994) find a high degree of price dispersion due to price discrimination on the market for airline tickets despite the presence of many actors in this area. A few more recent studies employ structural methods to investigate a variety of issues in relation to price discrimination. For example, Ivaldi and Martimort (1994) examine the idea that sellers may use non-linear pricing to discriminate, and Bousquet and Ivaldi (1997) derive the optimal tariff schedule for telephone calls to exploit customer differences. Cohen (2008) looks at a different form of discrimination through differential pricing for different types of packs of paper towels and McManus (2007) examines a similar problem. This is of interest for us because the clients in our situation can choose the quantities they want but only in discrete

[4] A standard reference is Phlips (1983) and for a recent survey see Armstrong (2006).

form. Miravete (2002) looks at discriminating in the telephone market through different call plans, Garry-Bobo and Larribeau (2004) look at discrimination between types of buyers on the French mortgage market and Verboven (1996) examines discrimination on the international car market. Very few of these studies, however, have the data necessary to examine the precise empirical evidence for price discrimination through the lens of an analysis of the different types of buyer and their characteristics. Before proceeding to our empirical analysis it is important to note that, while certain buyers' characteristics may be used by sellers to discriminate between these buyers, the direction of the discrimination may depend on the parameters of these characteristics, whether they be frequencies of visits, loyalty or type of demand. As we have mentioned, in Hens et al. (1999) it was shown that, depending on the nature of demand and cost curves, discrimination could act in any direction theoretically. We have thus to depend on our empirical evidence to detect the direction of the discrimination.

The most interesting part of the literature on prices discrimination from our point of view focuses on the idea that as a seller learns more about his customers he can use this information to discriminate between the latter. For example in the price discrimination literature, a group of customers or a particular market is said to be "strong" ("weak") if a firm wishes to raise (lower) its price there compared to the situation where it must charge a uniform price across all buyers or all markets. Thus, once a seller identifies a client as being of one of these types he would like to charge the appropriate price. In the sort of market that we analyse, in which trading is completely decentralised and the prices of deals are not public, this is possible. “Strong” and “weak” are, of course, attributes in theoretical models into which buyers are simply classified. This binary classification is obviously a radical simplification of the problem, since in the case of perfect optimisation not only the sign but also the degree of the discrimination would be determined. However, it is interesting to understand what might be the basis, in reality, even for such a simple qualification. Is it true that certain characteristics of the client on the market we examine will lead to his being put into the “weak” or “strong” category.

Another important feature of the market emphasised by Armstrong (2006) is whether the information about clients is shared by other sellers. We cannot tell this from our data, but as Armstrong indicates, if all sellers identify certain buyers as “strong” then it is possible that we find an equilibrium in which all the strong buyers pay higher prices regardless of the seller with whom they trade.

The closest literature to the analysis proposed here concerns discrimination on the car market. In that case although prices are posted they are rarely the prices at which transactions are made, and moreover customers are unaware of prices paid by other customers. However, this situation is different from the one that we study since even when interactions between buyers and sellers are repeated this is only at long intervals. Nevertheless, it has been argued that the characteristics of customers play an important part in discrimination. Ayres and Siegelman (1995) show that blacks and women pay more for cars than do their male white counterparts. However, they point out that they cannot identify a single cause for discrimination. Zetttelmeyer et al (2006) pursue this and ask the obvious question, why is that, on certain markets, prices are negotiated on a pairwise basis. They argue that two things are at work. Bargaining can help to determine a customer's reservation price, and the state of inventories can influence the price proposed. In our case this amounts to saying that how much the seller has in hand at a particular moment of the day will affect his propositions. Furthermore if , as we have mentioned, some goods are sold on consignment, the seller can return them to the supplier, the inventory problem is less important. Thus one would expect there to be a difference between the prices paid for the goods owned by the seller and those he sells on consignment where he does not bear the risk if they are not sold. As we have said our main findings involve all of these considerations.

One other contribution, that of Goldeberg (1996) argues that when there is little information about customers the seller prior as to the distribution of reservation prices will have a higher variance than in the case where more information is available. The initial offers to such buyers should, theoretically, be higher than to those customers who are better known, for example, those who are regular or loyal clients. Another important argument is that those with lower reservation prices will bargain more and will, in the end, pay lower prices. This provides a possible answer to the question that we mentioned earlier as to why some clients bargain more than others.

Thus, the findings of this paper which we have spelled out, seem to confirm the predictions of these contributors. A last remark is that we observe a market on which buyers and sellers meet regularly and on which some buyers become loyal to certain sellers. This would suggest that sellers would have a much tighter prior on the distribution of the reservation prices of such a buyer and this should lead in theory to proposing lower prices. Again our results confirm this prediction.

3 Empirical analysis

The data comes from a single stall on the site of the fruit and vegetable wholesale market MIN in Marseille (Marché d'Intérêt National). The MIN is jointly owned by the city of Marseille and private shareholders and leases stalls on its site to wholesalers. The MIN adminstration ensures that only eligible professional customers enter the market site and purchase goods there. Registered customers are often retailers, who sell fruits and vegetables in their own stall or on farmers' markets, but customers also include supermarkets, caterers, food producers and restaurant owners. The MIN is open six days a week and is closed on Sundays. In 2006, 50 stalls were leased to wholesalers, 905 people were working on the market, and 1733 customers were registered.[5]

The data cover all transactions that took place in the stall during the eleven opening days between October 14 and October 26 in 2006. The information on individual transactions comes mainly from the electronic billing and bookkeeping system of the stall. Further information was provided as copies of the daily print-outs of the system, often with additional hand-written information. Information on customer characteristics was obtained by interviewing the stall assistants and the owner of the stall.

A transaction is characterized by the type of good, its country of origin, agreed price per unit of the good, the total quantity bought, and the day the trans-

[5]Would-be customers have to apply to the MIN adminstration, providing evidence that they are listed in the commercial register. Further, once registered, customers have to pay a fee to use the market.

action took place.[6] A good is defined and classified according to the official Ctifl (Centre Technique Interprofessionnel des Fruits et Légumes) classification, which is very detailed, taking variety and quality of the good into account.[7] The units of quantity in which the goods are sold vary and can be the number of packs, kilograms, or items.

Goods are sold either by the stall on its own account or on commission, or consignment, for an external supplier. In more than half of the transactions, the goods are sold by the stall on its own account. Because the goods are perishable, any such good not sold at the end of the day may be worthless, incurring a loss for the stall. For the remaining transactions, the stall earns the difference between the unit price agreed with the customer and the supply unit price arranged with the external supplier. Because the stall does not own the goods, it is not exposed to a loss if some of these goods are unsold at the end of the day.[8]

[6]Transactions that took place on the two Saturdays during the sample period were recorded jointly with transactions taking place on the respective following Monday. Saturday and Monday transactions cannot be identified separately in the data set, leaving us in effect with nine trading days.

[7]For example, different varieties of apples such as Golden Delicious or Granny Smith count as separate goods. The items of a good, such as individual Golden Delicious apples, are nearly identical and very homogeneous.

[8]This is a convenient simplification. Failure to sell goods on commission may lead to

The 2454 transactions can be classified into four different types. Type 1 are transactions where the customer buys the good in the stall, often after bargaining over the price and occasionally the quantity. Type 2 are transactions where the customer pre-orders the good by telephone on the previous day, but picks up the goods himself at the stall. The customer might then bargain over the pre-negotiated price of the order. Type 3 are transactions where the customer pre-orders the good via phone on the previous day and the stall delivers the goods to customer's address on the next day. The price is usually pre-arranged and billed directly to the customer, so that no face-to-face bargaining takes place. Type 4 are transactions where the good was given to the customer for free as replacement for poor quality goods bought on the previous day. There is no bargaining in this case. Our analysis focuses on the 2111 transactions of Type 1 and 2, for which face-to-face bargaining could take place.[9]

The stall's customers are of two different types. The first type visits the stall regularly and is known personally to the stall assistants. Regular customers are often registered with the stall to allow them to purchase on account and to facilitate the billing process.[10]

the loss of the supplier of the goods in the long run, so sales on commission are not totally riskless.

[9] Of all transactions, 9 are of Type 4 and 334 of Type 3.

[10] The credit aspect of markets is very important, since the degree of creditworthiness of the client may induce the seller to charge a "risk premium" and this is one source of price

Some regular customers have more than one buying agent visiting the stall on consecutive days or even the same day. Visiting the stall on a regular basis does not necessarily mean, however, that the customer is a loyal buyer in the sense that the client buys his produce there exclusively. The second type are walk-in customers, who visit the stall only occasionally. We know for regular customers if they are loyal buyers, i.e., if they not only visit the stall regularly but also regularly buy goods; if they haggle over the price regularly, occasionally, or never; and if, as already mentioned, they are reliable payers in the case that they do not pay cash. For walk-in customers, we only know that they pay in cash and do not pre-order.

The interaction between stall assistant and customer is usually very short and at any stage the customer may walk away. The bargaining process is mostly over the price and starts with the stall assistant announcing an offer price. The customer can accept or decline the offer. The declining customer might then make a counteroffer. The stall assistant will either accept directly or make a final offer, perhaps in conjunction with offering a different quantity, which the customer then either accepts or declines.[11]

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discrimination. We observed this on the Marseille fish market (see Weisbuch et al. (2000)). Other markets are organised in such a way that all debts are cleared at the end of the day as in the case of the Ancona fish market (see Gallegati et al. (2009)).

[11] This is the standard professional interaction on the MIN, and we corroborated this

3.1 Buyer characteristics and bargaining activity

As we have said, several factors may potentially explain the prices charged to clients and our first task is to establish the relationship between these and the extent to which bargaining occurs and how loyal the customers are. We first analyse the relationship between buyers' characteristics and the extent to which they bargain. To do so, we use *Correspondence Analysis* as developed by Benzécri et al. (1973), see also Greenacre (1984) and Lebart et al. (1984). Correspondence analysis is a descriptive and exploratory technique designed to analyze simple two-way and multi-way tables containing some measure of correspondence between categorial variables. The results provide information similar in nature to those produced by factor analysis.

[Figure 1 about here.]

Figure 1 analyses the relationship between the type of a buyer's business and bargaining activity. Three clusters appear: the north-east quadrant gathers buyers (manufacturers of food products, or caterers) that need the fruits and vegetables as inputs for their final goods. These buyers do not bargain over the price and, on average, are likely to accept the price offered to them. Both

by interviewing other stallkeepers. See also Kirman et al. (2005), who analyse detailed bargaining process information from a different stall at the MIN.

manufacturers and caterers are usually exposed to predictable final demand with some menu cost of price changes and their derived demand should also be rather fixed and predictable. Because they require a fixed amount of produce using quantity as a bargaining instrument does not make much sense and they seldom bargain. The north-west quadrant gathers buyers with general food shops and wholesalers, who bargain occasionally. The south-west quadrant gathers buyers who sell the fruit and vegetables that they buy in retail markets (either on a local farmer's market or a retail shop). These buyers have the highest elasticity of demand and bargain regularly. There is no well developed theory to explain what sort of characteristics will induce more or less bargaining but what we see clearly here is that buyers are grouped according to the nature of their business.

[Figure 2 about here.]

Figure 2 analysis the relationship between buyer's clientele and bargaining behaviour. The following clusters appear: The north-east plane indicates that buyers that buy goods for themselves have a tendency not to bargain. The north-west plane indicates that buyers with customers who purchase high quality goods with correspondingly high prices have a tendency to bargain occasionally. The south-west plane indicates that buyers whose clientele is from the price-sensitive low quality segment have a tendency to bargain regularly. For buyers with clientele from the medium quality price segment, the graph does not provide a sufficiently clear indication. It seems that they either bargain regularly or not at all. This may mean that, within this category, there are unobserved characteristics which give rise to different behaviour.

3.2 Analysis of face-to-face bargaining

We now restrict ourselves to those transactions in which the buyers were face to face with the seller. For this, we group the individual transactions on a same day and same good basis. This grouping ensures that the goods are homogeneous between the transactions, because they come out of the same daily stock. Further, the daily grouping ensures that other circumstances on the market and day, which are not observed by us, can be assumed to be constant between transactions.

Of the 815 day-good groups, 340 consist only of one transaction and are excluded from further analysis.[12] The remaining 475 day-good groups have at least two transactions and cover 161 different goods. Table 1 provides information on the transactions of the day-good groups.

[Table 1 about here.]

[12] For instance, only one customer bought red apples on the 26th.

Two-thirds of the day-good groups show price variation between transactions during the day, see Panel A. The average number of transactions per day-good group is about five, see Panel B. Groups with price variation during the day contain slightly more transactions on average because more transactions give the stall assistants more opportunities to adjust the price. Such price adjustments are not inevitable, however, as the maximum of transactions for day-groups without price variation shows. Again, the quantity variable in Panel C is measured as the turnover of the individual transaction relative to the turnover of all transactions in the day-good group.[13] There is no discernible difference between the quantities bought by regular and walk-in customers. The median quantity is 0.2, which corresponds to the share one would expect if the quantity were the same for each of the average five transactions per day. The deviations of the quantities from the median is right skewed and positive deviations are larger on average than (absolute) negative deviations. To measure negative price discrimination, we compute the average price per unit of a good for each day-good group and compare the average price with the price paid in the individual transaction. Price discrimination is revealed by the variance of the prices for the same good and we consider that a customer is discriminated against if the customer pays a price above the average. This is

[13]We measure 'quantity' as turnover share to allow comparison between goods sold in different units such as number of packs or in kilograms.

the case for 34.5% of all transactions, see Panel D. A test using the z-Statistic indicates that discrimination against walk-in customers is significantly more likely than discrimination against regular customers (using the usual significance levels). As we have mentioned, this would seem to confirm Goldeberg's prediction that clients with less well-known characteristics will tend to receive higher price propositions. The last Panel E shows the number of transactions on a day for a given good where at least two customers bought the same quantity. Given the way in which the goods are presented, the quantities are discrete and there is a substantial amount of such transactions. If the seller would conduct a second degree price discrimination strategy, where he offers customers different price quantity bundles, into which customers self-select, then we should observe identical prices for identical quantities. However, in about one-third of the relevant transactions this is not the case. It also does not matter if he customers involved are regular or walk-in.[14] Thus, as expected from the outset, second-degree price discrimination does not seem to be of great importance in those cases where the seller observes and interacts with the customers directly. Coming back to Panel D, on the other hand, third-degree price discrimination seems to play a role, because the groups of regular and walk-in customers are treated differently.

[14] Their shares (not reported) in these transactions are very similar to their overall shares.

To examine if walk-in customers are more likely to be discriminated against per se or because of their behaviour, we fit binary probit regressions with the discrimination indicator as dependent variable.[15] The explanatory variables considered are the quantity bought in the transaction, the method of payment, and if the good bought was on commission of the external supplier or buyer (controlling for Type 2 transactions). Table 2 presents the regression results.

[Table 2 about here.]

Panel A reports the result for the regression when only the quantity and the customer type is considered; Panel B reports the result when the other variables are included. The dummy for cash payment, if included, has a coefficient with negative sign, as expected. However, the coefficient is not statistically significant. This also applies to the coefficient for the buyer commission indicator and both variables are excluded from the final regressions.[16] The significant coefficients of the estimated probit models in Table 2 show that customer behaviour plays a role for price discrimination. To evaluate the effect of the purchased quantity on the likelihood of discrimination, we plot the predicted

[15]Using a logit instead of a probit link function does not alter the qualitative results. This also applies to the other regressions presented below.

[16]Further, because the supplier commission information is missing for one day, using this variable leads to a loss of observations.

probability in Figure 3.[17]

[Figure 3 about here.]

As Figure 3 shows, quantity matters. The more the customer buys, the less likely it is that she will be discriminated against by paying a higher than average unit price.[18] The significant negative coefficients for regular customers in both regressions in Table 2 show that walk-in customers have a higher probability of being discriminated against. Whereas the probability of being discriminated for a regular customer buying the median quantity is 31.6%, it is substantially higher for a walk-in customer buying the same quantity with a probability of 41.7%. Thus, even after controlling for other observable buyer characteristics, we obtain that the group of walk-in customers is more like to be discriminated than the group of regular customers.

Panel B of Table 2 considers additionally if a good is sold on supplier's commission. As was discussed above, in this case, the risk, in the short run, of not selling the perishable good is borne by the supplier, not the stall. Because we

[17] The plots of the predicted probability as function of the quantity based on the other fitted models are very similar to Figure 3 and are not reported.

[18] This assumes that the quantity is under the full control of the customer. The Appendix presents results of an IV regression, where the actual quantity purchased is instrumented. The hypothesis that the quantity is exogenously set by the customer cannot be rejected at the usual significance levels.

do not observe information on commissioned goods for one day in our sample, the number of observations in the second regression reported is smaller than in the first. The regression results show that the probability of a buyer being discriminated against increases by about 13% if the good is sold on commission. As we have observed the reasoning here corresponds to the inventory argument proposed by Zetttelmeyer et al (2006) and can be summarised here by saying that the stall gains from high prices in case of a successful transactions, while the loss through perishing of goods from an unsuccessful transaction is limited.

Due to the frequently repeated contacts, the seller knows about several characteristics of the regular buyers, which might allow further tailoring of the prices charged. Although it seems unlikely that he can implement first-degree discrimination—especially because customers could go to other sellers on the market—he will nevertheless be led to treat each customer differently. Table 3 presents the probit regressions for regular customers, taking their characteristics and especially their bargaining behaviour into account.

[Table 3 about here.]

As might be expected, from our earlier discussion, bargaining has a significantly negative impact on the probability of being discriminated against. The probability of being discriminated against of a customer who bargains occasionally is about 13% lower than for a customer who does not bargain. Furthermore, the probability is lower by 17% if the customer haggles regularly. The coefficient for the loyalty variable indicates that loyalty pays off. Loyal customers have a 7% smaller likelihood of being discriminated against than disloyal, but regular, customers.

We further conducted some robustness checks of these results. The probit regression results are qualitatively similar if only those cases are considered where at least two different customers purchased a good on a given day. If transactions booked on Mondays are excluded, because they consist in effect of Monday and Saturday transactions, then all but the loyalty coefficient remain qualitatively the same. The loyalty coefficient is still negative, but no longer significantly different from zero at the usual significance levels. This stays unchanged if the Monday and Saturday and goods with only one customer are excluded. The general results are thus fairly robust.[19]

In summary, we find evidence of considerable direct price discrimination in our data set since different customers pay different unit prices for the same good on the same day. Furthermore the statistical analysis shows that customers' behaviour impacts on the likelihood of being discriminated. We find that it pays for customers to establish a relationship with a given stall and to stay loyal to that stall. Furthermore, the larger the quantity the customer wants

[19]The results of these regressions are not reported here.

to buy, the more can she improve the price per unit. Bargaining also leads to lower prices.

4 Conclusion

We have analysed our data set for the Marseille wholesale fruit and vegetable market in order to ascertain the extent and degree of price discrimination. We have focused on a certain number of buyers' characteristics and looked at the influence of these on price discrimination. Our econometric analysis has enabled us to explain a large part of the differences between the prices charged for the same good. While it is possible to find theoretical models consistent with some of our findings others are in contradiction with previous work. For example, the simple theoretical model developed by Weisbuch et al. (2000) suggested that loyal customers would pay more than those who shopped around. This was confirmed by the data from the Marseille wholesale fish market. Yet, in the case examined here loyal customers tend to pay lower prices. There may be several explanations for this. In the model of the Marseille fish market loyal buyers, who pay higher prices than their walk-in counterparts are still predicted to earn more profit than those who came less regularly to a seller. This was because they were more likely to find exactly the type of fish that they were looking for at their normal stall. This, in turn, was because the seller had learned to purchase what his clients want. This coevolution of behaviour led to a higher profit for both partners and the higher prices are an indication of the part of this surplus collected by the seller. On the fruit and vegetable market the supplies are perhaps more stable leading to a smaller advantage for loyal customers. The influence of variations in climate and weather yields more volatility in the supply of fish than in that of fruit and vegetables. There are, of course, many empirical examples on other markets, of lower prices for loyal customers so this issue is not resolved, neither at the theoretical nor at the empirical level.

We have deliberately focused on a rather limited set of explanations,for price dispersion and discrimination and have chosen those which seem to be important for the particular market that we studied. However, future research should try to use additional information about the economic characteristics of the customers, for instance, how price elastic is the demand that they face in their business. If the stall assistant knows that a customer can shift a high wholesale price on to his customers, then the stall assistant might be more inclined to discriminate against this particular customer. The assistant is highly unlikely to know, a priori, exactly the demand that the buyers face when they, in turn, sell. However, he may be able to develop an idea as to this elasticity by observing the customer's behaviour over time. This coupled with the information he acquires about a customer's business environment, such as the type of activity of the buyer (restaurant owner, small shopkeeper, or a supermarket etc.), the kind of clientele the customer has and the competitor should help him to refine his prior distribution over his client's reservation price and to improve his pricing policy. Here, we would agree with Ayres and Siegelman (1995) that statistical inference from observed behaviour may be very important to sellers.

Lastly, in addition to extending the analysis in this sort of direction, it would also be interesting to study other similar markets and to see whether similar conclusions hold. This would help us to build up a collection of data sets for different markets and to establish an empirical base against which to test the multitude of theoretical assumptions and predictions that one can find in the literature.

Appendix

The Appendix presents the results of a two-stage IV regression, which tests if the quantity purchased is endogenous (Wooldridge, 2002, 15.7.2). The first-stage regression explains the actual quantity bought with the exogenous customer characteristics loyalty and bargaining behaviour plus the quantity of the same variety of good bought by the same customer on the most recent previous day. We have only 666 observations available because not all customers bought the same variety of good at least twice over the sample period. Panel A of Table 4 presents the results of the first stage regression. Although the overall explanatory power is rather low with a coefficient of determination of 4%, the actual and the previous quantity have a significant positive relationship.

[Table 4 about here.]

Panel B shows the results of a probit regression where the actual quantity is replaced by the quantity predicted from the first stage regression. All estimated coefficients have the same signs as before, but the coefficient for the (predicted) quantity is not significant.[20] Panel C shows, however, that the test of exogeneity cannot be rejected at the usual levels of significance. In that

[20]Because the Newey coefficient estimators are standardized, the magnitudes of the estimates are not directly comparable to the estimates of the probit models presented above.

case, the probit regressions given in the main text are more efficient and the interpretation should be based on these.

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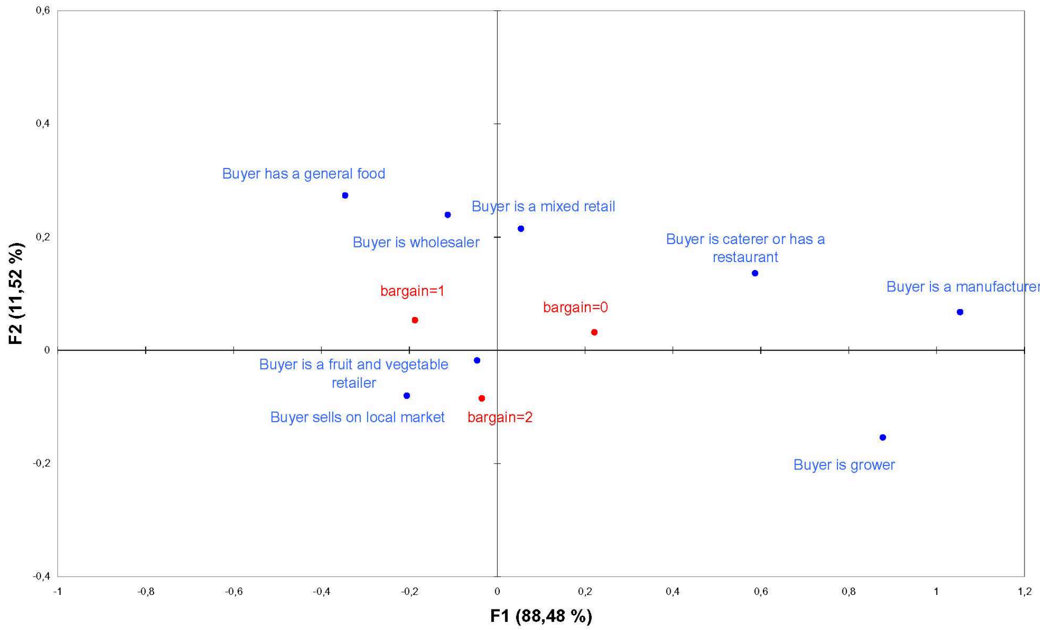

Figure 1: Correspondence analysis graph for the relationship between buyer's business and bargaining activity; bargain = 0 means no bargaining, bargain = 1 means occasional bargaining, and bargain = 2 means regular bargaining.

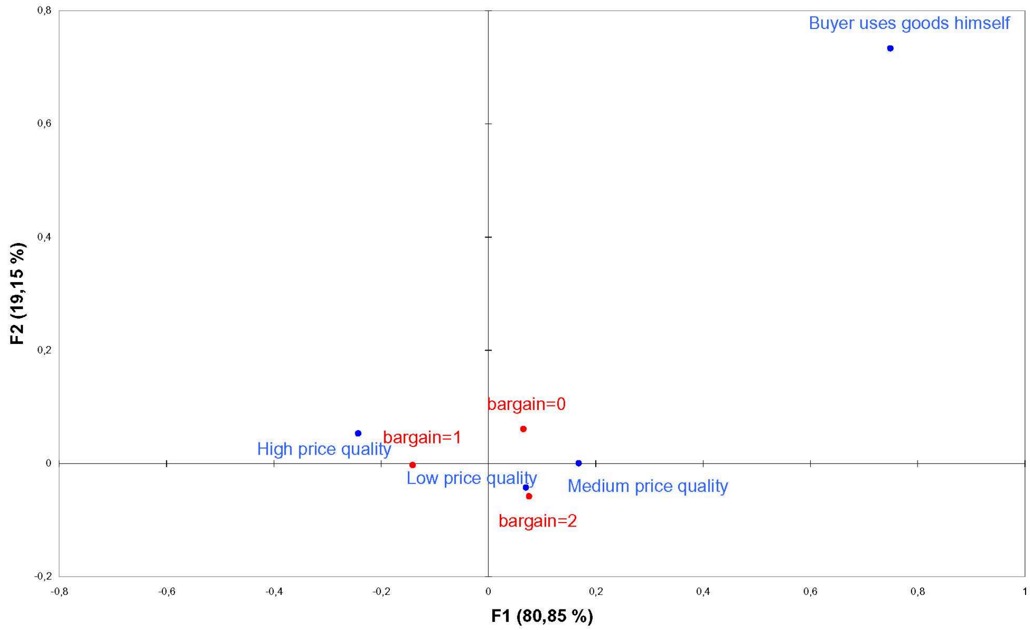

Figure 2: Correspondence analysis graph for the relationship between the type of buyer's clientele and buyer's bargaining activity; bargain = 0 means no bargaining, bargain = 1 means occasional bargaining, and bargain = 2 means regular bargaining.

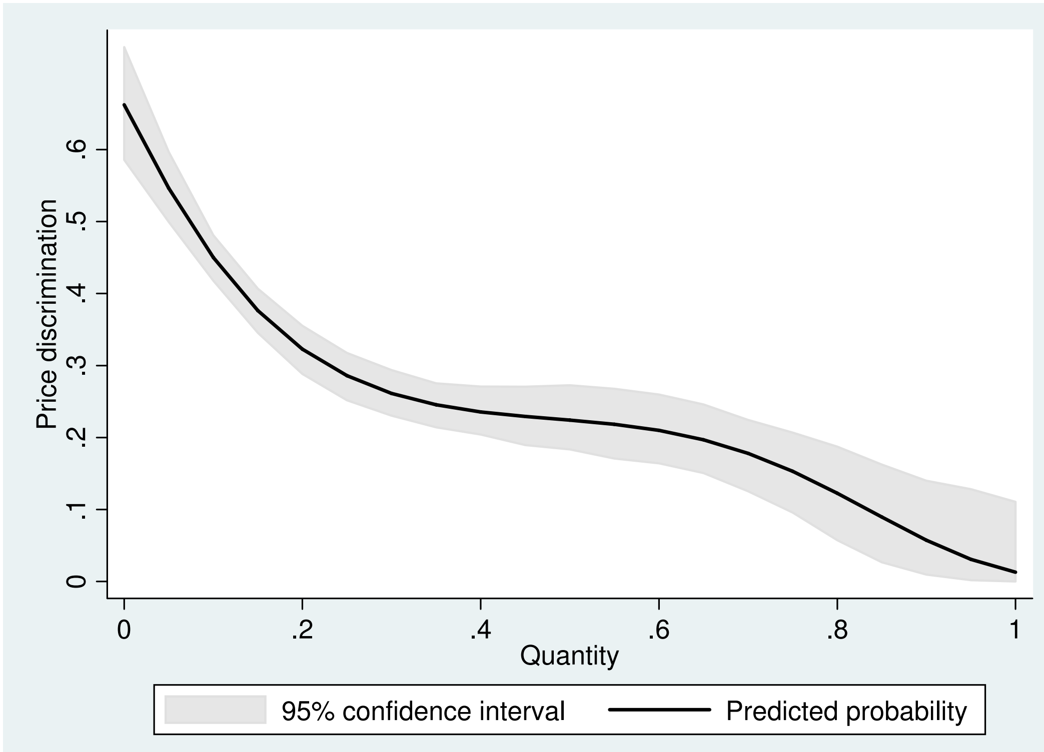

Figure 3: Predicted probability $\Phi(x\beta)$ of being price discriminated as a function of the quantity purchased. The probability is computed using the estimated coefficients given in Table 2 Panel A by varying the quantity variable. The share of regular customers is fixed at its sample mean. The 95% confidence interval for the predicted probabilities are based on 1000 bootstrap replications per grid point.

List of Tables

Table 1: Summary statistics for day-good groups and price discrimination.

Panel A: Day-good groups						
	With	Without	All			
Price variation	296	179	475			
Panel B: Transactions per day-good group						
	Mean	Median	Std. Dev.	Min	Max	Total
With price variation	5.1	5	2.5	2	12	1188
Without price variation	4.3	3	2.6	2	14	583
All	4.8	4	2.5	2	14	1771
Panel C: Quantity per transaction						
	Mean	Median	Std. Dev.	Min	Max	Total
Regular customer	27.2%	20.2%	21.4%	0.6%	93.9%	1641
Walk-in customer	22.4%	16.7%	19.8%	1.8%	85.7%	130
All	26.8%	20.0%	21.3%	0.6%	93.9%	1771
Panel D: Customer type and price discrimination						
	All transactions		With discrimination		z-Statistic	
Regular customer	92.7%		33.5%		3.05***	
Walk-in customer	7.3%		46.9%			
All	100.0%		34.5%			
Panel E: Same quantity transactions						
	With	Without	All			
Unit price variation	112	283	395			

Notes: Price variation in Panels A and B indicates if the sales price per unit varies between transactions on a day. Quantity in Panel C is transaction's share relative to the turnover of all the transactions in the same day-good group. Panel D shows first the share of transactions the two customer types were involved in and then the share of transactions in which a customer paid more than the daily average price. The z-Statistic is the square root of a Wald-Statistic based on a bootstrapped covariance matrix estimator using 500 replications. The one-sided hypothesis 'Discrimination The share of walk-in customers who are discriminated against is at most as large as the proportion for regular customers' can be rejected at the 1% significance level (***). The z-Statistic is asymptotically standard normal distributed and the critical value is 2.33. Panel E focusses on day-good groups which have at least two transactions where the same quantity was bought.

Table 2: Probit models for price discrimination of regular and walk-in customers.

Panel A				
Variable		Coefficient	z-Statistic	P-Value
Quantity		-6.671	-5.04	0.000
Quantity squared		13.247	3.24	0.001
Quantity cubed		-9.220	-2.67	0.008
Regular customer		-0.270	-2.36	0.018
Constant		0.668	4.60	0.000
Observations	1771	Wald-Statistic		129.88
Pseudo R^2	0.063	P-Value(Wald-Stat.)		0.000

Panel B				
Variable		Coefficient	z-Statistic	P-Value
Quantity		-6.576	-5.10	0.000
Quantity squared		12.861	3.32	0.001
Quantity cubed		-9.121	-2.81	0.005
Regular customer		-0.276	-2.32	0.021
Commissioned good		0.282	4.02	0.000
Constant		0.522	3.35	0.001
Observations	1674	Wald-Statistic		148.05
Pseudo R^2	0.076	P-Value(Wald-Stat.)		0.000

Notes: The dependent variable is the price discrimination indicator. The indicator is 1 if the customer pays a price above the daily average in the same day-good group; and is 0 otherwise. The probability of the indicator is modeled as $\Phi(x\beta)$. Φ is the distribution function of a standard normal variable, x contains the explanatory variables, and the coefficients are estimates for β. z-Statistics are computed using bootstrapped standard errors with 500 replications. Panel B includes additionally a dummy that is 1 if the good bought in the transaction was sold on commission for an external supplier. This variable is missing for one day, which leads to fewer observations.

Table 3: Probit models for price discrimination of regular customers taking their behaviour into account.

Panel A				
Variable		Coefficient	z-Statistic	P-Value
Quantity		-5.751	-4.18	0.000
Quantity squared		10.927	2.69	0.007
Quantity cubed		-7.505	-2.24	0.025
Occasional bargaining		-0.336	-2.28	0.023
Regular bargaining		-0.498	-2.58	0.010
Loyal buyer		-0.183	-1.77	0.076
Constant		0.736	3.14	0.002
Observations	1641	Wald-Statistic		86.17
Pseudo R^2	0.067	P-Value(Wald-Stat.)		0.000
Panel B				
Variable		Coefficient	z-Statistic	P-Value
Quantity		-5.433	-3.63	0.000
Quantity squared		9.720	2.22	0.027
Quantity cubed		-6.661	-1.86	0.063
Occasional bargaining		-0.354	-2.23	0.026
Regular bargaining		-0.535	-2.62	0.009
Loyal buyer		-0.193	-1.73	0.084
Commissioned good		0.332	4.57	0.000
Constant		0.567	2.39	0.017
Observations	1548	Wald-Statistic		124.72
Pseudo R^2	0.081	P-Value(Wald-Stat.)		0.000

Notes: Dependent variable is the price discrimination indicator. The indicator is 1 if the customer pays a price above the daily average in the same day-good group; the indicator is 0 otherwise. The probability of the indicator is modeled as $\Phi(x\beta)$. Φ is the distribution function of a standard normal variable, x contains the explanatory variables, and the coefficients are estimates for β. z-Statistics are computed with bootstrapped standard errors with 500 replications and clustered with respect to the buyers. Panel B includes additionally a dummy that is 1 if the good bought in the transaction was sold on commission for an external supplier. This variable is missing for one day, which leads to less observations.

Table 4: IV Probit regression where the actual quantity is instrumented using Newey's efficient two-step estimator.

Panel A: First Stage Regression				
Variable		Coefficient	z-Statistic	P-Value
Previous quantity		0.272	4.11	0.000
Occasional bargaining		0.058	2.97	0.003
Regular bargaining		0.048	1.64	0.101
Loyal buyer		0.030	1.34	0.182
Constant		0.172	6.25	0.000
Observations	666		R^2	0.040
Panel B: Second Stage Probit Regression				
Variable		Coefficient	z-Statistic	P-Value
Quantity		-0.056	-0.03	0.974
Occasional bargaining		-0.668	-4.07	0.000
Regular bargaining		-1.118	-4.82	0.000
Loyal buyer		-0.284	-1.76	0.079
Constant		0.336	0.91	0.363
Observations	666	Wald-Statistic		38.08
		P-Value(Wald-Stat.)		0.000
Panel C: Wald Test of Exogeneity				
Test Statistic	1.30	P-Value(Wald-Stat.)		0.254

Notes: Dependent variable in the first stage regression is the quantity bought. Previous quantity is the amount of good of the same variety bought by the same customer in the most recent transaction. Second stage probit regression has the discrimination indicator as dependent variable. Quantity in the second stage regression is the predicted quantity of the first stage regression.