Ladies First?
A Field Study of Discrimination in Coffee Shops

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Abstract

Despite anecdotal and survey evidence suggesting the presence of discrimination against customers in stores, restaurants, and other small-transaction consumer markets, few studies exist that identify or quantify the nature of any unequal treatment. We provide evidence from a field study of wait times in Boston-area coffee shops that suggests that female customers wait an average of 20 seconds longer for their orders than do male customers even when controlling for gender differences in orders. We find that this differential in wait times is inverse to the proportion of employees who are female and directly related to how busy the coffee shop is at the time of the order. This supports the conclusion that the observed differential is driven at least in part by employee animus and/or statistical discrimination rather than unobserved heterogeneity in the purchasing behavior of female customers.

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1 Introduction

Fifty years after Gary Becker's seminal work on discrimination (Becker, 1957) and forty years after the passage of the Civil Rights Act, economists have produced a large body of literature identifying, measuring, and explaining discrimination in labor markets. Yet over the course of all this time we have devoted comparatively little attention to discrimination in consumer markets (see Yinger, 1998; Siegelman, 1998; Ayres, 2001). What we do know about consumer market discrimination is largely dominated by studies of housing discrimination which have typically used either audit studies (e.g., Yinger, 1986; Turner and Mickelsons, 1992; Yinger, 1995; Ondrich et al., 2003) or hedonic regression models (e.g., Chambers, 1992; Kiel and Zabel, 1996; Myers, 2004) to find evidence of discriminatory treatment of racial minorities. A second and considerably smaller literature exists on racial and gender price differentials in the market for new vehicles (Ayres, 1991, 1995; Ayres and Siegelman, 1995; Goldberg, 1996).

Housing and vehicle markets are natural candidates for analysis of discrimination in consumer markets both because the individual transactions account for a large portion of consumer spending and because there is ample opportunity for racial and gender price differentials to arise given that prices are typically negotiated between buyer and seller. However, as Ayres (1991) points out, even if prices are not negotiated in other retail market settings, there is still the possibility that prejudiced sellers who gain utility from imposing higher costs on minorities may generate disparities in the quality of the goods and services that these groups purchase. Moreover, while the discrete transactions in consumer markets outside of housing and vehicles may be comparatively small, they aggregated to make up 80 percent of personal consumption expenditures in 2005 (Bureau of Economic Analysis, 2006).

The lack of attention to discrimination in small-ticket consumer markets is in part due to the relative difficulty of obtaining data on these transactions. What information we do have tends to be based either on individual anecdotes or lawsuits (see, e.g., Siegelman, 1998) or on survey evidence. In a 2004 Gallup survey, 20.9 percent of black respondents reported that they were "treated unfairly" at their place of work within the previous 30 days. The percentages reporting unfair treatment in consumer markets were even larger, with 26.3 percent reporting unfair treatment in a retail store and 25.6 percent reporting such treatment in a restaurant, bar, or theater (Gallup Organization, 2004). Antecol and Cobb-Clark (2006) report that 22.1 percent of blacks reported discrimination in local businesses in the 1996 Armed Forces Equal Opportunity survey. They go on to use the random assignment of Army personnel to military bases to show that white and Asian respondents are more likely to report consumer market discrimination as the composition of their community shifts away from their own group.

While such survey results suggest that discrimination may be widespread in consumer markets, few studies have more exactly identified the types of disparate treatments or quantified their effects. Graddy (1997) uses price data for fast food chains in New Jersey and Pennsylvania to show that prices rise with the black composition of the surrounding neighborhood, controlling for other possible correlates such as income and crime. Gneezy and List (2004) find that the disabled receive higher automobile repair quotes than the non-disabled. They also find that the disabled receive differential treatment in the market for baseball cards, although the nature of the differential depends on the experience of the dealer. List (2004) finds that minorities are more likely to receive inferior offers both when selling and buying baseball trading cards.

This paper contributes to the currently small body of empirical studies of consumer market discrimination by providing evidence from a field study of

Boston-area coffee shops. Enumerators observed employee and customer characteristics, order types, and wait times. We find that female customers wait an average of 20 seconds longer for their coffee order than do males even when controlling for gender differences in orders. An examination of the wait time differential by employee composition and order type further suggests that the observed differential is driven by employee preferences and/or by statistical discrimination rather than unobserved heterogeneity in the purchasing behavior of female customers.

2 Data

Data for this project were collected as part of an undergraduate seminar on empirical studies of discrimination. Six enumerators composed of five students and an instructor visited eight coffee shops in the central Boston area over the course of two weekdays in January 2007. The coffee shops were selected after visiting a larger sample of stores in order to evaluate which offered seating arrangements that allowed for ready but inconspicuous observation of customer orders and service received. The amount of time spent at a particular location varied depending on conditions at the shop. Enumerators spent approximately an hour and a half at a location and observed an average of 21 transactions per visit. In total, there are 295 transaction observations. Enumerators recorded customer demographics (gender, age range, race, and appearance), and the length of time for each transaction. Other controls included time of day, line length, type of payment, and the order placed by the customer.

At each site visit, the enumerator was instructed to order a beverage or snack and then take a seat with his or her laptop or notebook to observe transactions. Because there are typically many people sitting with a drink and working on a laptop or reading in a coffee shop, the enumerators' activities were intended to be subtle and inconspicuous. Indeed, for all but one site visit enumerators felt that they were not noticed.[1] In order to randomize the sample of observed customers, enumerators were instructed to follow a single customer from the time she walked in the door until the time she received her order and, once the observation was completed, to select the next customer who walked in the door. The enumerator noted the customer's gender, estimated age range (less than 25, 26 to 40, or over 40), and categorized his or her race as white, black, or other (Asian or indeterminate non-white). Enumerator observations of customer characteristics are obviously subjective and subject to error in the sense that, for example, the observer may perceive someone to belong to a racial category with which that person would not self-identify. However, it could also be argued that in the case of discrimination in consumer markets self-reported race is of less interest than is the race that observers perceive. In any event, because enumerators were instructed to assume that an individual was white unless they felt that there was strong visual evidence to the contrary, mis-categorization of this type is more likely to result in erroneous categorization as white, which would create a bias towards zero in any estimated effects for minorities.

In order to control for possible effects of appearance (and possible correlations between appearance and other demographic characteristics of interest), enumerators ranked each customer's appearance on a scale of 1 to 10. This ranking was based less on physical beauty in the sense of Hamermesh and Biddle (1994) and more on the quality and style of clothing and hair. Enumerators were instructed to consider business casual as a 5, or as average for downtown Boston during a workday. Because the raters could (and did) have different distributions of their assigned appearance rankings, each customer's ranking is standardized by enumerator.

[1] In one case a store manager happened to be sitting near an enumerator and asked what he was doing. The enumerator responded honestly and then left the store.

The gender, age, race, and appearance information was typically recorded within seconds of a customer's entrance into a store. The enumerator then also noted how many people were in line ahead of the observed customer in order to provide a measure of how busy the store employees were at the time they were preparing the order.[2] When the customer reached the counter, the enumerator listened for the order and recorded it as accurately as possible. In some cases the order could be heard directly, in many others the employee at the cash register shouted it back to a preparer or the order was announced when it was ready for pick-up.[3] Orders were recorded for 277 out of 295 total observations; in the remaining cases the order could not be overhead and is missing. In the cases of orders that were recordable, there was variability in how many details of the order could be overhead. Some orders were recorded exactly as issued, but others could only be classified as, for instance, a cappuccino, and the enumerator could not otherwise discern the size of the cappuccino or other special instructions. In other cases the enumerator could observe that the order required preparation, but not exactly what type of drink it was. For the purpose of analysis, orders were categorized and coded as a binary variable $fancy\_order$. "Fancy orders" include any item requiring preparation while non-fancy orders include a plain coffee or hot tea, which could be dispensed immediately. At times customers placed more than one order or groups of customers ordered together. In these cases enumerators were instructed to abandon the observation and

[2]We could have also recorded how many people were behind the customer when she actually placed the order. However, this would have been more difficult to accomplish while simultaneously recording the drink order and starting the stopwatch. Moreover, since orders arrive sequentially, the number of orders that had been placed ahead of the customer's seemed a better measure than the number behind her.

[3]During busy periods, orders were frequently prepared by an employee other than the cashier who received them. To the extent that this decreases the opportunity for discrimination against customers, significant findings are even more striking. On the other hand, orders were often recorded with the name of the customer and waiting customers were usually standing near the preparer, so we do believe that information about the customer was frequently available to both the employee who took the order and, if different, the employee who prepared it.

select the next customer to arrive. Once the order was placed and recorded, the enumerator also noted whether the customer paid with a credit card or cash.[4]

The outcome variable of interest was total wait time for the customer which was defined as the number of seconds from the time the customer ordered until he or she received that order. Most enumerators had a stopwatch program on his or her laptop that was used to record wait time in seconds. In the case of a few visits, the enumerator did not have a laptop computer and instead used a cell phone with a clock. The average wait time was 99.3 seconds. Figure 1 shows the distribution of wait times by gender and order type. As would be expected, wait times are shorter and less variable for orders that do not require extra preparation. In addition to having a higher mean wait time, the distribution of wait times for women exhibits larger variance and is more right-skewed, especially for women placing fancy orders. This could be reflective of discrimination against women. However, it could also be an indication that even within the category of "fancy orders" women were more likely to place an order that required extra preparation. This possibility is discussed further in the results section.

Table 1 summarizes key variables in the data set. The gender and race characteristics of the sample of coffee shop customers map quite closely to the 2000 census characteristics of the Boston CMSA. The U.S. Census Bureau (2000) reports that 51.6 percent of the population is female versus 49.8 percent of our sample and that 85.1 percent of the population is white versus 85.7 percent of the sample. However, coffee shop customers tend to be younger than the population as a whole. In our sample, 27.8 percent of customers were estimated to be below age 25 while 12.7 percent of the population of the metropolitan

[4]Some coffee shops also have pre-paid cards that customers might use. These could typically be identified because, unlike a debit or credit card, they only had to be swiped and handed back to the customer. Because payment type was included in order to control for factors that might increase transaction time, payments made with a pre-paid card were categorized as "cash."

area is aged 15-24. This could be due to mis-categorization on the part of the enumerators, but it may also reflect a younger demographic among coffee shop customers.

Characteristics of the coffee shop employees were also noted. Because most shops had multiple employees who rotated frequently between front counter and prep jobs, it was not possible to track which employees dealt with any given order. However, the characteristics of all employees present were noted, including gender, age range estimates, and race. There was frequently none or a single minority present, so a binary variable was created that indicates the presence of at least one minority employee. Thirty-nine percent of the transaction observations were in shops with at least one minority employee. Similarly, because of little variation in estimated age of employees, a binary variable indicates whether all employees present appeared to be under age 25. Fifty-eight percent of transaction observations were for coffee shops with all young employees. There was more variation in the gender of the employees, so this information was recorded as the proportion of employees who were female. Averaging across transaction observations, 53 percent of employees were female.

3 Analysis

Table 2 breaks down wait times by demographic group and order type and includes sample sizes for each cell in parentheses. The point estimates for all order types combined suggest that females wait longer than males, blacks wait longer than whites, younger customers wait longer than older ones, and customers with a below average appearance rating wait longer than those with an above average rating. However, customer characteristics may also be correlated with order type. For instance 75 percent of orders placed by female customers were classified as "fancy" while only 55 percent of orders placed by males were.

Looking at wait times by order type, women, blacks, and customers with a below-average appearance rating still have longer mean wait times. However, the sample sizes for blacks and others are quite small and the point estimates for differences by age and appearances are not far apart. Only differences by gender are significant, suggesting that even when differences in order are accounted for, the transaction time for women is longer.

Table 3 reports coefficient estimates for four regression models of wait time. As in the summary statistics, there are not statistically significant differentials by race, age, or appearance. However, in the first model we see that females wait an average of 31 seconds longer for their order than do males. Adding a control for order type in the second column reduces this differential to 20 seconds. Further controls for order and store characteristics are added in the third column, but the wait differential for women remains a significant 20 seconds, or 24 percent of the average wait time for men. In the fourth column we include store and enumerator fixed effects to account for possible correlation between a particular store or observer and the type of customer observed. Variables that do not vary by store and enumerator are eliminated. The remaining point estimates change little relative to previous specifications. The wait differential for women decreases, but is still significant at 15 seconds.

That women wait approximately 20 seconds longer for their order even when controlling for gender differences in order type is suggestive of discrimination. However, it is also possible that our crude measures of order type do not fully account for the possibility that women tend to place more complex orders. In this case, the positive coefficient for $female$ would be the result not of discrimination but of unobserved order complexity.[5] In order to explore this possibility

[5] A common solution to the problem of omitted variable bias in discrimination studies is to use an audit survey. However, while this would have allowed for drink orders to be standardized, other problems arise with this type of survey including a lack of measure of "average discrimination" and the difficulty of designing a truly blind survey (see Yinger, 1998). Moreover, our group of researchers had age and ethnic heterogeneity among the surveyors that

with the data from the field study, we ran the analysis with fancy orders further broken down into lattes, cappuccinos, or "other," which included both drinks such as a machiato as well as orders requiring preparation that could not otherwise be overheard. The coefficients of interest, particularly the estimates of gender differentials, were not substantially altered. We also informally surveyed 4 coffee shop workers from shops not included this sample. Three of the four workers reported that women were more likely than men to order fancy drinks requiring preparation, which is in keeping with our findings. These three workers also felt that when women ordered fancy drinks, they were more likely to have additional special requests than men. To further address the potential problems that this might create, we introduce interaction terms in Models 5 and 6 presented in Table 4. In both cases we find results that suggest that employee actions contribute at least in part to the gender differential in wait times.

In Model 5 customer gender is interacted with employee gender. The gender differential in wait times is estimated to decline with the presence of female employees. In a coffee shop with all male employees, a female customer waits an average of 37 seconds longer for her order than a male customer. However, in a coffee shop with all female employees a female customer's wait is estimated to be 7 seconds longer than that of a male, a differential which is not statistically significantly different from zero. Although the coefficient on the interaction term is not significant (with a p-value of 0.31), the result is suggestive that it is not order type but rather some action on the part of employees that is driving the result.[6]

Models 5 provide results that are consistent with a story of discrimination

would have made an audit study impossible.

[6]Another possibility is that unobserved heterogeneity among the shops was present and correlated with both server and customer gender. This seems unlikely, however, because the coffee shops we studied were all located in a small geographic area in downtown Boston, were quite similar to each other, and each was near a variety of other businesses.

against female customers. However, the source of such discrimination is not clear. One possibility is animus-based discrimination on the part of male coffee shop employees who wish to impose higher costs on female customers.[7] On the other hand, these longer waits presumably mean more time spent associating with the waiting women, which may offset any utility gains prejudiced employees receive from imposing greater costs on female customers. Another possibility is that rather than reflecting ill-will towards female customers, the differential is indicative of male servers garnering utility from interacting or being near female customers. In this case, the differential reflects not a desire to impose a cost on women but rather to spend time flirting, chatting with, or just being around them. However, as long as the associated increase in wait times is costly for female customers, the result reflects discrimination regardless of the intentions of the employees.

The wait gender wait differential could also from statistical discrimination in response to gender differences in the means or variance of tips. It might also reflect differences in how male and female customers respond to the quality of service either via their tipping behavior or in terms of placing demands on the employees. Women may simply be perceived as more "easy" customers. To our knowledge, among these possible explanations, the present literature has examined only gender differences in average tips. Parrett (2006) finds that women tend to give smaller tips than do men in a laboratory setting. Bodvarsson et al. (2003) find that male customers tend to tip male servers more, but the result is not significant. Conlin et al. (2003) find no differences in average tips. However, Andreoni and Vesterlund (2001) citing personal correspondence with the authors, reports that while there is no difference at the means, the estimates

[7]In the case of animus-based discrimination, one might expect to see wait time differentials by race as well as gender. The point differences in means all indicated that blacks did, in fact, wait longer for their drinks than whites, but the sample sizes were quite small and the differences were not significant.

suggest that women tip less than men for small restaurant bills, which coffee would certainly be. If women tend to tip less for their coffee or to be less responsive to the quality of service, one might expect to see that as a coffee shop becomes busier, women are treated more poorly as servers concentrate on the higher returns from male customers. The results of Model 6, in which customer gender is interacted with line length, suggest that this is, indeed, the case. While the coefficient on the interaction term is not significant (p-value of 0.13), the size of the coefficients is consistent with the gender differential increasing when the shops are busier.

4 Conclusions

Estimates using data from a field study of customer treatment in coffee shops suggest that women wait an average of 20 seconds or 24 percent longer for their orders than do men, even when controlling for differences in beverage selection. Using the Massachusetts median wage of $17.96 (Bureau of Labor Statistics, 2006) for a back-of-the-envelope calculation, this differential equates to a cost of about 10 cents or about 4 percent of the cost of a $2.50 beverage.

Because the controls for beverage selection are necessarily crude, it is possible that the observed differences in wait times are partially due to unobserved heterogeneity in the types of drinks ordered by men and women. However, when customer gender is interacted with employee gender the results suggest that the wait differential declines greatly with an increase in the female composition among employees. In addition, when customer gender is interacted with line length we see that the gender wait differential increases when the shops are busy. While the small sample sizes unsurprisingly yield insignificant results for these models with interaction terms, the sign of the coefficients is somewhat reassuring that something beyond heterogeneity in orders is generating the difference in wait times. The results suggest that some form of discrimination against customers contributes to gender differences in wait times and that this discrimination is greater when male employees are present and when the shops are busy. It may be the case that this reflects a combination of animus-based and statistical discrimination. Or, there may be an interaction between the gender of the customer and the gender of the server that generates an impetus for male servers to statistically discriminate against female customers.

The gender differential in wait times estimated in this study is large in relative terms, but small in monetary ones. However, this is among the first studies of discrimination in consumer markets. If such differentials are present in the markets for other small-ticket items, the cumulative effect could be quite burdensome.

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Table 1: **Summary Statistics**

	mean	s.d.
Customer Characteristics		
female	0.498	0.029
white	0.857	0.020
black	0.051	0.013
other	0.092	0.017
appearance (1-10)	5.485	1.124
age < 25	0.278	0.026
age $26 - 40$	0.444	0.029
age > 40	0.278	0.026
Transaction Characteristics		
line length	1.215	1.347
morning (7 a.m.–12 p.m.)	0.441	0.029
midday (12 p.m.–3 p.m.)	0.136	0.020
late-day (3 p.m.–7 p.m.)	0.424	0.029
fancy order	0.650	0.029
paid with credit card	0.189	0.024
wait (seconds)	99.272	59.133
Employee Characteristics		
minority present	0.393	0.028
all <age 25	0.576	0.029
proportion female	0.525	0.254
n	295	

Figure 1: **Wait Times by Gender and Order Type**

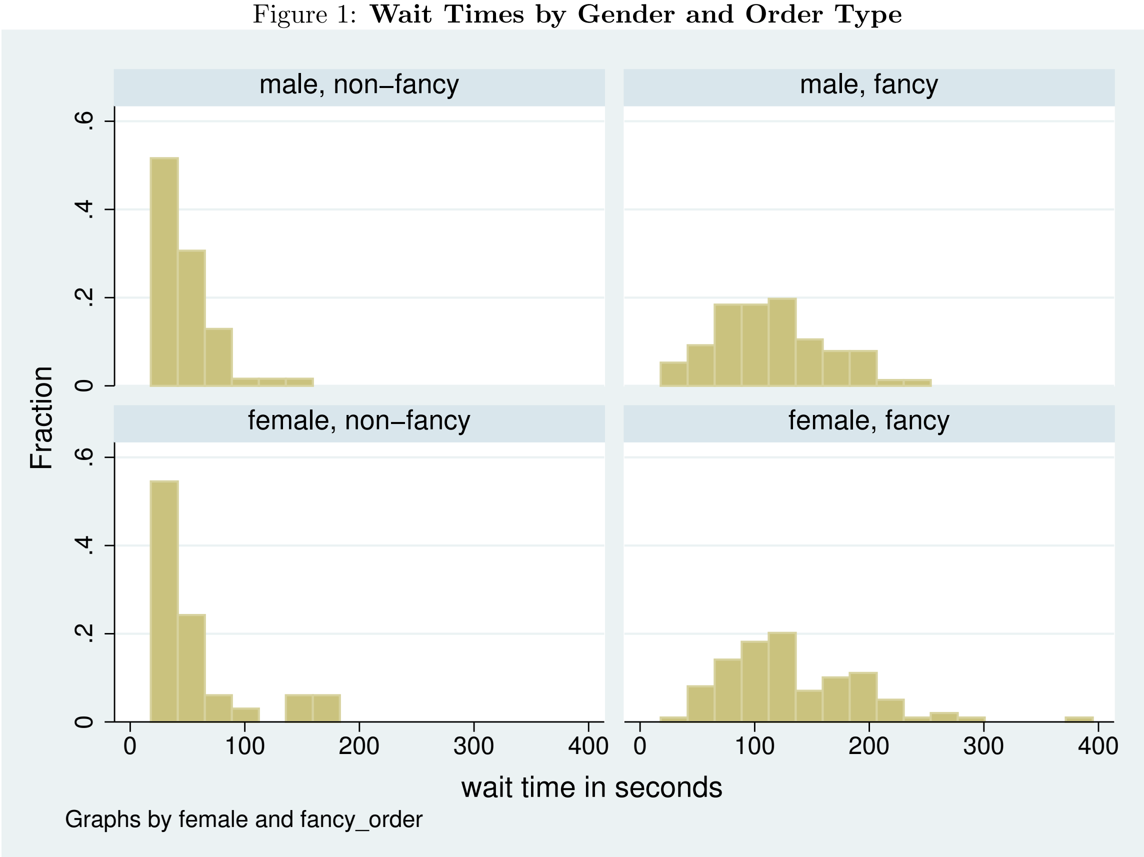

Table 2: **Average Customer Wait by Group and Order Type**

	All Orders	Fancy Orders	Non-fancy Orders
Gender			
male	85.207	114.092	47.500
	(145)	(76)	(62)
female	113.738	133.970	56.364
	(141)	(99)	(33)
Race			
white	98.626	125.674	49.730
	(243)	(147)	(83)
black	115.286	138.375	73.400
	(14)	(8)	(5)
other	94.111	111.579	50.333
	(27)	(19)	(6)
Age			
age < 25	103.475	124.648	51.400
	(80)	(54)	(20)
age $26 - 40$	100.408	121.638	52.111
	(125)	(80)	(36)
age > 40	93.370	133.463	48.744
	(81)	(41)	(39)
Appearance			
below average	99.673	127.925	53.643
	(156)	(93)	(56)
above average	98.792	122.402	46.179
	(130)	(82)	(39)

**Sample sizes for each cell appear in parentheses. Sample Sizes for fancy and plain orders do not necessarily add up to those for all orders because of missing order type observations.*

Table 3: **Regression Results**

dep. variable: wait time in seconds

	Model 1		Model 2		Model 3		Model 4	
	coef.	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*	*coef.*	*s.e.*
constant	**79.66**	8.39	**35.69**	7.48	**20.37**	13.54	.	.
Customer Characteristics								
female	**30.71**	7.95	**20.29**	6.49	**20.31**	6.52	**14.92**	6.46
black	14.71	14.08	16.64	13.20	2.74	12.55	8.05	11.68
other	-5.98	10.20	-8.67	9.44	-6.07	10.51	-7.03	9.53
standardized appearance	-0.27	3.51	-3.50	2.99	-1.28	2.95	-1.95	2.99
age 25–40	6.70	8.34	5.37	6.97	4.99	6.88	1.17	6.95
age >40	3.59	10.52	12.46	8.69	14.73	9.28	11.33	9.19
Transaction Characteristics								
fancy order	.	.	**72.46**	5.45	**67.63**	5.47	**69.91**	5.50
paid credit	.	.	.	.	10.98	10.11	15.84	9.97
line length	.	.	.	.	**12.85**	2.45	**13.00**	2.65
midday	.	.	.	.	**32.39**	14.38	.	.
late-day	.	.	.	.	7.71	6.26	.	.
Employee Characteristics								
minority present	.	.	.	.	-3.13	7.02	.	.
all <age 25	.	.	.	.	**15.70**	7.19	.	.
proportion female	.	.	.	.	-21.89	17.11	.	.
Store and enumerator fixed effects included	no		no		no		yes	
n	284		268		255		255	
R^2	0.07		0.40		0.48		0.52	

**Standard errors are robust. Coefficients in bold are significant at a 5 percent level.*

Table 4: **Specifications with Interactions**

dep. variable: wait time in seconds

	Model 5		Model 6	
	coef.	*s.e.*	*coef.*	*s.e.*
constant	11.92	14.42	26.87	12.31
Customer Characteristics				
female	**36.92**	16.98	11.18	7.20
black	2.89	12.51	2.67	12.62
other	-5.93	10.50	-6.00	10.55
standardized appearance	-1.31	2.97	-1.05	2.94
age 25–40	4.87	6.90	3.75	6.66
age >40	14.83	9.32	14.61	9.13
Transaction Characteristics				
fancy	**67.38**	5.43	**67.99**	5.58
paid credit	10.94	10.14	10.45	9.95
line length	**13.03**	2.44	**8.80**	2.78
midday	**33.96**	14.20	**31.03**	14.40
late-day	6.93	6.39	6.58	6.37
Employee Characteristics				
minority present	-4.25	7.23	-3.28	7.06
all <age	**15.20**	7.43	**14.56**	7.13
proportion female	-5.48	23.77	-21.39	17.38
Interactions				
customer female*proportion employees female	-29.46	28.95	.	.
customer female*line length	.	.	7.04	4.62
n	255		255	
R^2	0.48		0.49	

Standard errors are robust. Coefficients in bold are significant at a 5 percent level.