Retail Redlining:
Are gasoline prices higher in poor and minority neighborhoods?

by
Caitlin Knowles Myers
Grace Close, Laurice Fox, John William Meyer, and Madeline Niemi

August, 2009

MIDDLEBURY COLLEGE ECONOMICS DISCUSSION PAPER NO. 09-06

DEPARTMENT OF ECONOMICS
MIDDLEBURY COLLEGE
MIDDLEBURY, VERMONT 05753

http://www.middlebury.edu/~econ

Retail Redlining: Are gasoline prices higher in poor and minority neighborhoods?

Caitlin Knowles Myers
Grace Close, Laurice Fox, John William Meyer, and Madeline Niemi*

August 18, 2009

Abstract

Higher retail prices are frequently cited as a cost of living in poor, minority neighborhoods. However, the empirical evidence, which primarily comes from the grocery gap literature on food prices, has been mixed. This study uses new data on retail gasoline prices in three major U.S. cities to provide evidence on the relationship between neighborhood characteristics and consumer prices. We find that gasoline prices do not vary greatly with neighborhood racial composition, but that prices are higher in poor neighborhoods. For a 10 percentage point increase in the percent of families with incomes below the poverty line relative to families with incomes between 1 and 2 times the poverty line, retail gasoline prices are estimated to increase by an average of 0.70 percent. This differential is reduced to 0.22 percent once we add controls for costs, competition, and demand. Finally, we provide evidence that the remaining, small, price differential for poor neighborhoods is likely the result of traditional price discrimination in response to less competition and/or more inelastic demand in these locations.

JEL Classification: J15, J16
Keywords: consumer prices, consumer market discrimination, race discrimination, price discrimination, redlining

*Caitlin Knowles Myers is Assistant Professor, Department of Economics, Middlebury College, Middlebury, VT 05753 and research fellow, IZA. The remaining authors were students in an undergraduate seminar who were instrumental in the planning, implementation, and analysis associated with this project. We wish to thank Jack Cuneo for his assistance in using ArcGIS to geocode gas stations and provide several geographic variables, and Carrie MacFarlane and Brenda Ellis for their assistance with ArcGIS and Geolytics software. We also wish to thank the remaining students from an undergraduate seminar who assisted with the station surveys: Harrison Brown, Michael Campbell, Matthew Engel, Ryan Fink, Annabelle Fowler, Daniel Haluska, Christopher Hench, Winslow Hicks, Blake Johnson, JiaHao Li, Quincy Liao, Shenique Moxey, Cameron Poole, Mona Quarless, Leah Shackleton, and Mary Walsh.

Anyone who has ever struggled with poverty knows how extremely expensive it is to be poor...Go shopping one day in Harlem– for anything– and compare Harlem prices and quality with those downtown.
James Baldwin, *Nobody Knows My Name*, 1961

It's not that these businesses are saying 'You, black people, you get out of my [establishment].' They are saying 'Come on in, but we're going to rip you off.'
Allison Bethel, Florida Assistant Attorney General, in U.S. News and World Report, 2000

1 Introduction

The economics literature on discrimination in consumer markets is dominated by studies of differences in negotiated prices in two markets: housing (e.g., Yinger, 1986, 1995; Ondrich et al., 2003; Myers, 2004) and automobiles (e.g., Ayres and Siegelman, 1995; Goldberg, 1996). A few additional studies examine price differentials in smaller markets in which prices are also negotiated such as trading cards (List, 2004) and car repairs (Gneezy and List, 2004). Less evidence is available from the numerous consumer markets in which prices are publicly posted and fixed. In this situation, individually targeted racial price discrimination is unlikely because, as Siegelman (1998) points out, it would require the flagrant and illegal display of different prices for whites and minorities. However, firms may still adopt practices that increase the probability that minorities or other targeted groups will pay higher prices. We use data on gasoline prices and station characteristics from three metropolitan areas to test for one such practice, commonly referred to as "retail redlining."

Following D'Rozario and Williams (2005), we define "retail redlining" as a practice among retailers that results in lower quality goods and services and/or higher prices in areas with large minority or poor populations. Claims of retail redlining arise regularly in both academic sources and the popular press, often involving catch phrases such as "the poor pay more," "the high price of poverty," or "the poorer you are the more things cost" (e.g., Sturdivant, 1969; Downing, 2007; Brown, 2009). Accusations of retail redlining also arise in courtrooms, and politics. GM, Wal-Mart, Burger King, Domino's Pizza, and KB Toys have been sued for discriminatory practices in minority neighborhoods (Jelisavcic, 1996; Smith, 1996; Fuller, 1998; Kaplan, 2000); in 1992 the mayor of Los Angeles touted the need for more equal access to supermarkets following the Los Angeles riots; and, in 2009, Illinois Senator Roland Burris introduced a request to the annual federal appropriations bill for a campaign to fight retail redlining on Chicago's south side (Shaffer, 2002; Burris, 2009).

The bulk of the empirical evidence on retail redlining comes from the large "grocery gap" literature, which explores variations across neighborhoods in the accessibility, quality, and price of food sold at grocery stores. Much of this evidence suggests that grocery prices are higher in inner-city neighborhoods and that this is largely explained by the lack of large chain stores in these areas (Hall, 1983; Kaufman et al., 1997; Chung and Myers, 1999; Shaffer, 2002). By contrast, (Hayes, 2000), using a large nationally representative sample of price data from the sampling frame used to construct the Consumer Price Index, finds that prices are lower in poor neighborhoods but that the discount is not constant across races. Poor whites and Hispanics receive discounts, but poor blacks pay similar prices as affluent whites. Turning to the market for prepared food, Graddy (1997) finds that fast food meal prices increase by about 5 percent for a 50 percentage point increase in the percent black in a zip code.

While food, which makes up a large portion of consumer budgets, is an important candidate for study of inter-neighborhood price variations, accusations of retail redlining extend beyond this single market. We provide evidence from a hitherto unexamined market: retail gasoline. There are several reasons to consider retail gasoline beyond the benefits of deviating from the extensive literature on food prices. First, like groceries, gasoline makes up a relatively large portion of the average consumer budget: 4.8 percent as compared to 7.0

percent for food purchased for home consumption (U.S. Department of Labor, Bureau of Labor Statistics, 2008). Moreover, gasoline represents an important commodity for the poor as well as for the more well-to-do. Private vehicles are the dominant mode of travel even among households with annual income below $20,000; three-quarters of these households own at least one vehicle, three quarters of their travel is done in private vehicles, and gasoline makes up 5.1 percent of their consumption expenditures (Pucher and Renne, 2003; U.S. Department of Labor, Bureau of Labor Statistics, 2008). A second reason for considering the market for gasoline is that the grocery gap literature is complicated by the heterogeneity of stores, products, and quality. Gasoline stations are considerably more homogenous in terms of size and, after controlling for branding, quality. This allows us to more precisely identify price differentials for an identical good. Finally, anecdotal evidence and accusations in the popular press suggest that gasoline prices vary between stations and neighborhoods (e.g., Douglas and Cohn, 2005; Rose, 2007), and any such variations have the potential to be correlated with race and income characteristics.

We combine three sources of survey data to produce a panel of daily price observations over the course of a year for nearly all of the gas stations in the Atlanta, Detroit, and Philadelphia metropolitan areas. We examine the relationship between prices and neighborhood racial and income characteristics with additional controls for costs and demand. The results indicate that prices do not vary greatly with neighborhood racial composition, but that prices are slightly higher in poorer neighborhoods.

2 A model of retail redlining

As defined, retail redlining describes only the presence of inter-neighborhood price differentials, not their source. Such price differentials may represent animus-based discrimination or price discrimination in response to variation in the elasticity of demand. However, inter-neighborhood price differentials also may arise in perfectly competitive markets due to differences in costs between neighborhoods. In fact, firms accused of retail redlining on the basis of race often respond by claiming that, to the extent that price differentials exist, they are the result of cost-related factors such as crime (D'Rozario and Williams, 2005).

To account for these possibilities, we adopt the flexible model used by Graddy (1997) and based on the "new empirical industrial organization" as described by Bresnahan (1989). Price setting conduct of firm i in market area j at time t follows the general relation

$$P_{jt} + \frac{\partial P(Q_{jt})}{\partial Q_{jt}} Q_{ijt} \theta_{ijt} = MC_{ijt} \tag{1}$$

where P_{jt} is the price in market area j at time t, $\partial P(Q_{jt})/\partial Q_{jt}$ is the derivative of the inverse demand function, Q_{ijt} is quantity sold by firm i, and MC is marginal cost for firm i. θ_{ijt} indexes firm competitiveness, with increasing values reflecting increasing distance from perfect competition. For instance, if $\theta_{ijt} = 0$, a firm follows the perfectly competitive strategy of equating price to marginal cost. If $\theta_{ijt} = 1$, a firm follows the monopoly strategy of equating monopoly marginal revenue to marginal cost (for a full discussion, see Bresnahan, 1989).

Assuming constant elasticity of demand, ϵ, Q_{ijt} can be substituted out and Equation 1 can be expressed as $P_{jt} = MC_{ijt}/[1 + (1/\epsilon)\theta_{ijt}]$. Taking logs,

$$log(P_{jt}) = log(MC_{ijt}) - log(1 + (1/\epsilon)\theta_{ijt}). \tag{2}$$

Our last step is to introduce the possibility of animus-based discrimination by incorporating a discrimination coefficient à la Becker (1957). Let $b_j \in [0, 1]$ be the proportion of residents of neighborhood j who are black and let $d \in [0, 1]$

represent the discrimination coefficient for firms. Firms act as if the price they receive in neighborhood j at time t is $P_{jt}(1 - db_j)$ so that in the presence of discriminatory firms ($d > 0$), firms act as if marginal revenue is decreasing in the black population of a neighborhood. Equation 2 now can be written as

$$log(P_{jt}) = log(MC_{ijt}) - log(1 + (1/\epsilon)\theta_{ijt}) - log(1 - db_j). \qquad (3)$$

If we assume that neighborhoods represent individual market areas, prices could be higher in neighborhood j for four reasons: (1) higher marginal costs, (2) less competition, (3) less elastic demand in the presence of imperfect competition, which allows for classic price discrimination, or (4) a greater presence of some attribute (e.g., race) on which all firms engage in animus-based discrimination. Our empirical strategy is to first determine whether there is evidence of price variation between neighborhoods with different racial and income compositions. To the extent that any such differentials remain after controlling for costs and competitiveness, we discuss and explore whether they represent animus-based discrimination.

3 Data

We combine three sources of data: gasoline price data from Oil Price Informational Service (OPIS), neighborhood characteristics from the 2000 Decennial Census, and individual station characteristics obtained via telephone survey.

Gasoline price data were purchased from OPIS, which monitors retail gasoline prices across the United States and Canada by observing "fleet card" transactions: special credit card transactions for groups of vehicles owned or leased by businesses or government agencies. The data include daily price observations for regular unleaded gasoline purchased between December 1, 2007 and November 30, 2008 at stations in three metropolitan areas: Atlanta, Detroit, and Philadelphia. A station enters the OPIS sample on any day in which a fleet card is used to purchase gasoline there. Because fleet card transactions are quite common, OPIS estimates that nearly all of the gasoline stations and convenience stores in a metropolitan area will incur at least one fleet card transaction in a year and, hence, be represented in the sample. The exceptions will primarily be stations that do not accept credit cards.

The raw gasoline price data form an unbalanced panel of 1.4 million station-price observations for 5,736 unique stations. Of these, 322 stations are observed on fewer than 20 days and have been dropped from the sample. Some of these stations appear to have entered or exited the market during the sample period, while others appear to be automobile dealerships where fleet cards are occasionally used to purchase gasoline. The data also include the name and brand of the station and the station address.

Information about the area surrounding each gasoline station was collected using ArcGIS software and census data. ArcGIS was used to identify the geographic coordinates of each station based on the street address provided by OPIS. Of the 5,414 stations observed twenty or more times by OPIS, the coordinates of 96.5 percent of the stations could be identified in this manner; the remaining 191 stations also have been dropped from the sample. ArcGIS was then used to note the number of nearby competing stations and the distance to major roads. Finally, the census tract containing each station was identified based on the station's geographic coordinates, and variables measuring census tract characteristics were collected from the 2000 U.S. Census. An additional 20 stations have been dropped from the sample because complete characteristics of the surrounding census tract were not available.

Data measuring individual station characteristics such as capacity and the presence of a car wash were collected by telephone survey of a subsample of stations. Undergraduate students contacted a random subsample of 1,745 stations by phone and asked a brief series of survey questions which are reproduced in Appendix A. Of the contacted stations, 1,131 either had an invalid phone number, declined to begin the survey, or began but did not complete the survey. Six hundred and fourteen, or 35 percent, of the surveys were completed. However, 42 of these stations were later dropped from the sample because we could not identify their geographic coordinates using ArcGIS or because they were observed fewer than 20 times during the sampled year. An additional 5 stations were dropped because the telephone surveyor mis-coded a variable.[1]

Table 1 presents descriptive statistics for stations in the final sample. After removing stations with limited price observations or incomplete geographic variables, there are 5,203 station observations (2,288 in Atlanta, 1,612 in Detroit, and 1,302 in Philadelphia). The average station is observed on 250 of the 366 possible days in the sample period (which covers a leap year). The available variables measure or proxy for the price of gasoline, neighborhood racial and income characteristics, costs, the level of competitiveness, and demand. We describe the variables in more detail below.

Price

OPIS records the price posted at the pump, which is inclusive of applicable gasoline taxes and exclusive of any discounts or rebates that may be offered to fleet card holders. In the period and metropolitan areas covered by the sample, applicable gasoline taxes include a federal excise tax and state taxes that can include excise taxes, state sales tax, and environmental surcharges. Local taxes are applied in only one of the four states in the sample, Georgia, were they range from 6 to 7 percent and are pre-paid based on the state's announced average sales price of gasoline. We calculate the price net of all taxes using

[1]Response to the telephone surveys is clearly non-random. However, as shown in Table 1, the observable characteristics of surveyed stations are quite similar to those of non-surveyed stations.

information from the American Petroleum Institute and Georgia Department of Revenue (The American Petroleum Institute, 2009; Georgia Department of Revenue, 2007a,b, 2008, 2009). Because the incidence of state and local taxes falls almost entirely on consumers (Chouinard and Perloff, 2004), we choose to use the net price as the outcome variable in our analysis with the assumption that it more accurately reflects the pricing behavior of retailers. However, not surprisingly given the limited local variation in taxes in the sample, the results are quite similar using gross price and state indicator variables. As reported in Table 1, the average price of gasoline over the course of the year in which stations were observed was \$3.34 inclusive of taxes and \$2.86 exclusive of taxes.

Racial and income characteristics

The racial composition of the census tract surrounding a station was obtained from the 2000 U.S. Census. Respondents classify themselves into one or more of multiple racial and ethnic categories, which we use to create four mutually exclusive and collectively exhaustive categories: white, black, Hispanic, and other. The percent white in a tract measures the percent of respondents reporting that they are non-Hispanic and white alone; similarly, the percent black in a tract measures the percent of respondents who are non-Hispanic and black alone. The percent "other" is the percent of non-Hispanic respondents reporting that they are Asian, American Indian, some other single race, or more than one race.[2] The percent Hispanic is the percent of residents belonging to any racial category who reported that they are Hispanic. Table 1 includes summary statistics for these variables; the average station in the sample is located in a neighborhood that is 69 percent white, 21 percent black, 5 percent Hispanic, and 5 percent other.

Turning to income, we use a set of three income variables from the census that measure the percent of families in a census tract with incomes placing

[2] Fewer than 2 percent of respondents in the sample indicated that they belonged to multiple racial categories.

them below the poverty line (poor), between the poverty line and two times the poverty line (lower-middle income), and above two times the poverty line (middle-upper income). Using these three categories allows for a non-linear relationship similar to that reported by Frankel and Gould (2001), who found that retails prices are increasing with both the percent of families who are poor and who are middle-upper income. As reported in the summary statistics in Table 1, the average station is located in a neighborood in which 10 percent of families are poor, 14 percent are lower-middle income, and 76 percent are middle-upper income.[3]

Costs

Three quarters of the retail price of gasoline is accounted for by the wholesale price of refined gasoline (Energy Information Administration, 2009). Time fixed effects account for temporal fluctuations in the price of crude oil, while state fixed effects account for differences in the wholesale price of gasoline arising due to regional variation in the costs of crude oil, refining, and transportation. However, the wholesale price of gasoline paid by individual stations also varies within a metropolitan area at any given time due to variation in branding and the ownership structure, which we describe.

Branded gasoline stations, which make up about 83 percent of the market, display the name of a major refiner or wholesale marketer such as Shell or Texaco and sell the wholesaler's brand of gasoline, which includes proprietary additives (Kleit, 2003). Branded gasoline stations can roughly be divided into one of three ownership structures: owned and operated by the wholesaler (19 percent of branded stations nationwide), owned by the wholesaler and leased by an independent dealer (20 percent of branded stations), and owned and operated

[3]Because so many respondents fall in the middle-upper income bracket, it would be preferable to divide it into smaller categories. However, the Census Bureau does not provide a more detailed breakdown of family income distributions above two times the poverty line.

by an independent dealer (61 percent of branded stations) (Meyer and Fischer, 2004). Stations in the first two categories typically receive gasoline directly from the wholesaler, while stations in the last category typically receive gasoline from "jobbers," independent contractors who gain the right to franchise a brand in a certain area. Unbranded stations, which make up the remaining 17 percent of the gasoline market, typically purchase gasoline from a refiner that does not have a branded presence in the retail gasoline market (Kleit, 2003).

Branded stations that are supplied directly by the wholesaler may be subject to "zone pricing," a practice in which branded wholesalers define a price zone as a contiguous set of stations within a small geographic area that face a similar market environment. A wholesaler charges all direct-supplied retailers in the price zone a common wholesale price (Meyer and Fischer, 2004). Zone-pricing clearly suggests the existence of inter-neighborhood price differentials. However, retailers who buy from unbranded wholesalers or jobbers at a uniform regional wholesale price still presumably price retail gasoline according to local market conditions. To the extent that zone pricing reflects market conditions but does not itself increase market power, one would expect inter-neighborhood variation in prices regardless of whether zone pricing is employed in a certain neighborhood.[4].

To account for differences in wholesale prices due to branded status, we include a single *branded* variable that indicates a station sells branded gasoline.[5] Accounting for price differences due to ownership structure is more difficult, and we only attempt to do so with stations that were surveyed by telephone.

[4]For more detailed theoretical and empirical evidence on ownership structure and retail prices, see Shepard (1991); Taylor (2000); Kleit (2003); Meyer and Fischer (2004)

[5]The branded variable indicates that a station displays one of the following brands: BP, Chevron, Citgo, Conoco, Exxon, Getty, Gulf, Hess, Lukoil, Marathon Ashland, Mobil, Phillips 66, Shell, Sunoco, Texaco, and Valero. The results are robust to substituting a series of indicators for each of the 19 specific retail station types that are observed most at least thirty times in the data: 7-eleven, BP, Chevron, Citgo, Clark, Exxon, Getty, Gulf, Hess, Kroger, Lukoil, Marathon, Mobil, Quik Trip, Racetrac, Sams, Shell, Speedway, Sunoco, Texas, Valero, and Wawa.

It is not feasible to collect information on ownership structure and wholesale supply via telephone because many station employees are not aware of this type of information. Instead, we asked the employee answering the phone whether the station owner regularly works behind the counter and assume that stations where this is the case are more likely to be operated by an independent dealer. We also collected information on three variables that Taylor (2000) found to be correlated with ownership structure because of their relationship to monitoring effort. These are indicators for whether the station has repair bays (as proxied by offering oil changes), full service pumps, and a convenience store (as proxied by selling milk by the gallon).[6] Stations offering repair service or full service are more likely to be owned or leased by an independent dealer, while stations with a convenience store are more likely to be owned and operated by a branded wholesaler (Taylor, 2000).

In addition to variables controlling for brand and proxying for ownership structure, we include several other controls for costs. Real estate costs are represented by the log of the median value of owner-occupied housing in the surrounding census tract. Population density, which is correlated with house values, also is included. For stations that were surveyed by telephone, we have a series of additional variables measuring station characteristics including indicators for the presence of a car wash and restaurant. A measure of the number of gasoline pumps, *capacity*, represents possible economies of scale associated with larger stations.

A final concern is that the local crime rate is correlated with gasoline price either because of the direct cost of crimes committed or because of indirect costs due to higher insurance rates or the need to pay compensating differentials to employees who feel that working at a station in a high crime area is

[6] All stations in New Jersey are full service. Stations in other states are coded as full service if they routinely pump gas for customers at any of their pumps.

risky. Because of the paucity of crime data available at a small geographic level, researchers typically control for crime at a broad geographic level such as municipality or zip code (e.g., Graddy, 1997; Hayes, 2000). We attempt to create a proxy variable measuring crime at a smaller local level by asking telephone survey respondents to rank the severity of crime in the neighborhood on a scale of one to ten and coding stations with ratings in the top third (greater than a three) as having severe local crime. Although this measure has the advantage of presumably being more local to a gas station than crime data for the entire municipality as supplied by FBI Uniform Crime Reports, it has the disadvantage of being subjective. We discuss an alternative measure in Section 6.

Competitiveness and Demand

Our model predicts that prices will be higher in neighborhoods where stations have greater market power because of some combination of fewer competitors and/or more inelastic demand. We measure the number of competing stations within a 1 kilometer radius of each station in the sample using ArcGIS software. We proxy for the elasticity of demand using a set of variables that we expect to relate to search costs. The first two, *km to nearest interstate* and *km to nearest highway*, measure the distance from each station to the nearest limited access highway and major non-limited access highway, respectively. We assume that search costs are lower, and demand is more elastic, for vehicles traveling on major roads because they will typically encounter more gasoline stations on a trip. The remaining variables that proxy for demand are *pct commute by car*, *avg commute time*, *pct of households with* 1 *vehicle*, and *pct of households with* 2+ *vehicles*. We expect that demand is higher in areas with more vehicles both because those vehicles require gasoline and because car ownership is positively correlated with unobserved heterogeneity in income. However, we also expect that demand is more elastic in areas with more vehicles, more commuters, and longer average commutes because search costs are lower for households that drive more.

4 Empirical Model

The analysis is based on a two-way mixed error component specification:

$$log(P_{ijt}) = \alpha + N_j\beta + C_{ij}\delta + D_{ij}\gamma + \upsilon_i + \upsilon_t + \epsilon_{ijt}. \quad (4)$$

P_{ijt} is the price of regular octane gasoline observed at station i in neighborhood j on week t. N_j is a vector of racial and income characteristics of neighborhood j, C_{ij} is a vector of proxies for costs for station i in neighborhood j, and D_{ij} is a vector of proxies for the competitiveness of station i in neighborhood j. The error term includes a station-specific component, υ_i, and a time-specific component, υ_t. The final term, ϵ_{ijt}, represents a classical random disturbance. The time-specific component of the error term is treated as a fixed effect so that identification is based on the deviation of station i's prices from the mean price observed during week t. Because all of the explanatory variables are time-invariant, the station component of the error term is by necessity treated as random.[7] The (un-testable) assumption that we must make is that the unobserved station effects are not correlated with the regressors. Even if this is not the case, we still are able to address our first question– Are gasoline prices higher in poor and minority neighborhoods?– although we would be unsure whether any observed relationship is the direct effect of race and income or the result of some unobserved factor that is correlated with neighborhood and/or station characteristics.

[7] For more on two-way error component specifications, see Baltagi (2008). One might also wish to consider a three-way error component model with station random effects that are nested within neighborhood random effects. However, it is very difficult to perform the computations required to estimate such a specification because of the large size of the data set (5,203 stations in 2,117 neighborhoods observed over 52 weeks).

5 Do gasoline prices vary with neighborhood characteristics?

Table 2 reports the estimated coefficients for the two-way error component specification with week fixed effects and station random effects.[8] The estimates in Model 1 indicate the mean price differentials observed across neighborhoods with different racial and income compositions without additional control variables. In Model 2 we add the variables measuring cost, competition, and demand characteristics that we are able to observe for all stations in the sample. In Model 3 we add additional control variables for station characteristics obtained via telephone survey, which reduces the sample size accordingly.[9]

The estimated coefficients for the variables measuring neighborhood racial composition are small in magnitude and, with one exception, statistically insignificant. This suggests that there are not large price differentials associated with race. The coefficient on percent black in Model 1, for example, indicates that for a 10 percentage point increase in the percent black in a neighborhood, retail gasoline prices are about 0.02 percent higher (p-value$=0.15$). Once we control for costs, competition, and demand in Models 2 and 3 this differential is of even smaller magnitude, negative, and highly statistically insignificant. This suggests that to the extent that (small and statistically insignificant) positive price effects of minority composition were observed in Model 1, they can be accounted for by differences in costs, competition, and demand. Moreover, the single result that is statistically significant indicates that rather than paying a premium, prices are actually decreasing with the presence of *other* residents.

[8] Specification tests support the validity of this specification. Breusch Pagan tests indicate that station random effects are appropriate (p-value< 0.01 for Models 1-3). Hausman tests also indicate that week fixed effects are appropriate (p-value< 0.01 for Models 1-3). However, while the differences in coefficients between models with and without week fixed effects are statistically significant, they are not large in magnitude.

[9] The results in Model 3 may differ from Model 2 because of the change in the sample as well as because of the additional control variables. However, if we estimate Model 2 using only the stations that appear in the sample in Model 3, we get similar point estimates.

By contrast to the race results, the coefficients on the income measures are of larger magnitude as well as highly statistically significant. Like Frankel and Gould (2001), we find that prices are lowest in neighborhoods with more lower-middle income families and higher in neighborhoods both with more poor residents and with more middle-upper income residents. The estimates in Model 1 indicate that for a 10 percentage point increase in the percent of middle-upper relative to lower-middle income families, retail gasoline prices are 0.48 percent higher (p-value$<$ 0.01). And, for a 10 percentage point increase in the percent of poor relative to lower-middle income families in a neighborhood, retail gasoline prices are 0.70 percent higher (p-value$<$ 0.01). At the sample average gasoline price of $2.86 (net of taxes), a 0.70 percent increase represents a premium of about $0.02 per gallon of gas. As an alternative way to think about the magnitude of this effect, consider the spatial variation in gasoline prices across a city. We observe that the average standard deviation in gasoline prices observed in a given city on a given day in our sample is about 2.8 percent of the mean. Hence, a 0.70 percent premium paid for a 10 percentage point increase in the percent of families in a neighborhood that are poor represents about a quarter of a standard deviation increase in gasoline prices.

The relationship between income and prices diminishes in Models 2 and 3, suggesting that the premiums paid in poor and middle-upper income neighborhoods can be partially explained by costs and competition characteristics that are correlated with income. The estimated coefficient on $pct > 2$ *times poverty line* becomes much smaller as well as statistically insignificant in Models 2 and 3. The coefficient on the percent of families below the poverty line remains statistically significant in Model 2, although its magnitude is reduced by two-thirds; for a 10 percentage point increase in the percent of poor families relative to lower-middle income families, gasoline prices are estimated to be 0.22 percent higher. The corresponding point estimate is 0.37 percent higher in Model

3, although the greatly reduced sample size results in a larger standard error and a lack of statistical significance.

The remaining results in Table 2 are for the most part in keeping with our expectations and support the validity of our controls. Considering first the coefficients in Model 2, most are statistically significant, but, as with the coefficients for the race and income variables, of small magnitude. The results indicate that branded gasoline is an average of 1.4 percent more expensive than unbranded gasoline (p-value$<$ 0.01). We also find that for a 1 percent increase in the median house value, gasoline prices increase by 0.01 percent (p-value$<$ 0.01). We intend house values to proxy for real estate costs. However, if the effects of income are not fully accounted for by the poverty status variables and car ownership variables, the coefficient on house values may also represent an income effect.

As predicted, gasoline prices are lower in areas with more competition; for each additional station within a 1 km radius, the average gasoline price is 0.12 percent lower (p-value$<$ 0.01). We also expected that gasoline prices would increase with distance from both limited and non-limited access highways as search costs increased. However, we find that for each kilometer increase in distance from an interstate, prices decline by 0.02 percent (p-value$<$ 0.01), while for each kilometer increase in distance from a highway, prices increase by 0.01 percent (p-value$<$ 0.01). One explanation is that search costs are higher for consumers on limited access highways because they usually must exit the interstate to observe prices. Of the remaining variables that relate to demand, only the coefficient on the percent of residents who commute to work by car is statistically significant. For a 10 point increase in the percent of car commuters in a neighborhood, we estimate that gasoline prices are 0.51 percent lower (p-value$<$ 0.01). This is in keeping with our expectation that search costs are lower for people who regularly drive to work and, hence, stations in these areas have less power to charge higher prices.

Among the estimated coefficients for the additional variables measuring station characteristics in Model 3, only the coefficient for *owner present* is statistically significant. Gasoline prices are about 0.30 percent higher at stations where the owner regularly works behind the counter, which are more likely to be operated by independent business people rather than by wholesalers. The point estimates for variables in common with Model 2 are quite similar, although the standard errors are larger because of the reduction in sample size. Overall, the point estimates from Model 3 suggests that station characteristics do not explain the the inter-neighborhood price differentials observed in Model 2.

Taken as a whole, the results in Table 2 indicate that gasoline prices are not higher in minority neighborhoods. Gasoline prices are slightly higher in poor neighborhoods (about 0.70 percent higher for a 10 point increase in the percent poor), and about two-thirds of this differential is explained by proxies for the cost, competition, and demand characteristics of these neighborhoods.

Estimates by metropolitan area

Table 3 presents results for Models 1 and 2 estimated separately for the three metropolitan areas in the sample. A Chow test rejects the null that the coefficients on race and income are identical for the three cities (p-value< 0.01), which indicates that the relationship between neighborhood characteristics and gasoline prices varies geographically. However, the results are, as a whole, similar to those obtained in the pooled model. We find quite small (although statistically significant) relationships between race and gasoline prices, and larger premiums associated with poverty.

For a 10 percentage point increase in the percent of families living below the poverty line relative to those living between 1 and 2 times the poverty line, gasoline prices increase by an average of 0.69 percent in Atlanta, 0.65 percent in Detroit, and 1.46 percent in Philadelphia. While this differential becomes statistically insignificant for Atlanta when additional control variables are added in Model 2, it is smaller but still statistically significant in the remaining cities. Even after accounting for cost, competition, and demand characteristics, prices are still 0.26 percent higher in Detroit and 0.75 percent higher in Philadelphia for a 10 percentage point increase in the percent of poor families in a neighborhood.

The relationship between race and income varies across the cities. In Atlanta, gasoline prices are decreasing in the black and Hispanic composition of neighborhoods, indicating that prices are actually highest in neighborhoods with more white residents. Conversely, prices are increasing in black and Hispanic composition in Detroit and Philadelphia. In Model 1, we estimate that for a 10 percentage point increase in the percent black in a neighborhood, gasoline prices increase by 0.03 percent in Detroit and by 0.14 percent in Philadelphia. The differentials remain statistically significant in Model 2. However, although the relationship between race and price is statistically significant in the individual models, all the coefficients– both negative and positive– continue to be of small magnitude both absolutely and relative to the income effects. As a whole, the evidence suggests that the the correlation between race and prices is not large.

6 Explaining the inter-neighborhood price differentials

The results in the previous section indicate that gasoline prices increase with the presence of poor residents in all three cities. The estimated premium diminishes once we control for observable costs and competitiveness, but remains positive. We consider three alternative explanations for the differentials observed both with income and with minority composition: omitted cost variables, omitted competition and demand variables, and animus-based discrimination.

Explanations based on costs

Higher prices in minority and low-income neighborhoods may reflect unobserved higher costs. A particular concern is that our measure of crime, which is available only for surveyed stations and is based on the respondent's subjective opinion, is inadequate. To the extent that crime rates are higher in poor and minority neighborhoods, and that this, in turn, raises the costs of operating gas stations there, our estimates of the coefficients on race and income may be positively biased. To investigate these possibility, we were able to obtain detailed crime information for calendar year 2007 from the City of Atlanta Police Department (City of Atlanta Police Department, 2007), and then used ArcGIS to calculate the number of total crimes (violent and property) within a 1 km radius of each station in its jurisdiction.[10] We estimated Model 2 for this small (n=116) subset of stations both with and without the additional variable measuring crime.[11] We do not report, but briefly describe the results here.[12] As expected, the point estimates indicate that higher crime is associated with higher prices; for a one standard deviation increase in the number of local crimes, we estimate that gasoline prices are 0.36 percent higher (p-value=0.15). The coefficients on variables measuring race and income, however, are similar to those reported in Table 3 and robust to the inclusion or exclusion of our measure of crime. We conclude that unobserved crime heterogeneity is unlikely to explain the observed inter-neighborhood price differentials.

Explanations based on imperfect competition

A second possibility for the residual positive price differentials is that we have

[10] Stations located near the boundary of the police district were dropped from the sample because we could not observe crimes in the full 1 km radius around their locations.

[11] Only 12 of the 116 stations were surveyed by telephone and, hence, have observations of *bad crime* from the station survey to compare the crime rate obtained from the Atlanta Police Department. Of these stations with observations of both variables, the 9 stations reporting bad crime have a higher average crime rate (560 crimes) than the 3 stations that do not report bad crime (507 crimes). The small sample size precludes testing for statistical significance.

[12] The full results are available upon request.

not fully observed lower levels of competition and/or relatively inelastic demand for gasoline in poor and minority neighborhoods. For instance, residents of poor, minority neighborhoods may be more likely to shop for goods other than gasoline at gasoline stations, and may therefore be less responsive to the price of gasoline.

If the residual income and racial price differentials are explained by imperfect competition, we expect that they will be smaller in magnitude for stations that have less market power. To investigate this possibility, we estimate Model 2 with the addition of interactions between income composition and three variables that relate to market power: *competing stations within* 1*km*, *km to nearest interestate*, and *pct commute by car*. We expect that price discrimination will be less likely when there is more competition as measured by the number of competing stations and/or when demand is relatively elastic as measured by being farther from an interstate or having more commuters in a neighborhood. Accordingly, when we observe positive price differentials in poor neighborhoods, we expect the coefficients on interactions between the poverty rate and *competing stations within* 1*km*, *km to nearest interestate*, and *pct commute by car* to be negative. We also interact these variables will all three racial and ethnic categories. As with income, we expect the relationship between racial composition and prices to be attenuated for stations with less market power.

Models 2a-2c in Table A present the estimated coefficients for interactions between race and income and three variables measuring station competitiveness.[13] As predicted, the estimated premiums paid in poor and middle-upper income neighborhoods are smaller for more competitive stations in all three models, although the differences are not always statistically significant. The positive and statistically significant premium paid in neighborhoods with more

[13]Separate estimates for the three metropolitan areas are available upon request. Overall, they are consistent with the results for the pooled model: most of the estimated differentials are attenuated for stations with less market power.

families in poverty decreases with the presence of competing stations (although the interaction term is insignificant with a p-value of 0.16), with the percent of residents who commute by car (p-value$<$0.01), and with distance from the interstate (p-value$<$0.01). For instance, in Model 2a we estimate that the average gasoline premium for a 10 percentage point increase in the poverty rate is 0.42 percent for stations with no nearby competitors (p-value$=$ 0.02), but 0.24 percent for stations with 2 competitors within a one kilometer radius (p-value$=$ 0.02). In Model 2c we estimate that the average gasoline premium for a 10 percentage point increase in the poverty rate is 0.42 percent for stations that are 1 km from an interstate (p-value$<$ 0.01) and (a statistically insignificant) 0.26 percent for stations that are 5 km from an interstate (p-value$=$ 0.90).

Similarly, we find that the positive premium paid with increasing middle-upper income families also decreases with increased competition and with increasing demand elasticity. The results for race are, again, mostly statistically insignificant. However, the point estimates do suggest that racial price differentials are attenuated in the presence of greater competition. For example, in Model 2a we estimate that the average gasoline discount for a 10 percentage point increase in the percent black is 0.03 percent for stations with no nearby competitors (p-value$=$ 0.28), but that the average discount is 0.01 percent for stations with 2 nearby competitors (p-value$=$ 0.82).

As a whole, these results are consistent with the explanation that the unexplained price differentials in poor and minority neighborhoods can be accounted for by unobserved lower competition and/or less elastic demand.

Explanations based on animus-based price discrimination

A final possibility is that the unexplained inter-neighborhood price differentials may reflect animus-based price discrimination on the basis of race or, in the case of the income differentials, some factor associated with income that is observable to station owners but not to us. If it is the case that the price differentials result from animus-based discrimination related to race or income, we expect that the differentials will be larger in magnitude at stations in which the owner is routinely present and, hence, interacts with customers. Model 3a in Table A reports estimated coefficients when racial and income characteristics are interacted with the *owner present* indicator. Although the reduced sample size in Model 3 again generates large standard errors and the coefficients of interest are not statistically significant, we note that the point estimates are mixed. The small and statistically insignificant discounts paid with increasing minority composition (which would have to suggest animus-based discrimination *against* whites) are more negative in the presence of owners in two of the three cases, but still very small. The statistically significant premia paid in neighborhoods with more poor or middle-upper income residents decrease in the presence of station owners, which is not consistent with animus-based discrimination.

As a whole, the estimated racial and income price differentials do not behave in a manner that is consistent with our predictions of the effects of animus-based discrimination. However, like most Becker-type models, our theoretical model allows animus-based discrimination to be maintained only if all stations have a similar discrimination coefficient. If tastes for discrimination vary in a perfectly competitive market, discriminating firms will go out of business. A second, un-modeled, possibility is that tastes for discrimination vary and that firms in less competitive markets are more likely to be able to engage in animus-based discrimination without being priced out of business. In this case, the attenuated price differentials observed at stations with more competition in Models 2a-2c would be consistent with animus-based discrimination as well as with classic price discrimination, and the two would not be separable.

7 Conclusion

We have introduced a large and unique data set to examine neighborhood variation in retail prices. Despite anecdotal evidence of higher prices in minority neighborhoods, we estimate that any premiums paid for gasoline are quite small. For instance, for a 10 percentage point increase in the black composition of a Detroit or Philadelphia neighborhood, gasoline prices are estimated to increase by about 0.05 percent, or by about 2 cents for a 15 gallon tank at the observed mean price. The corresponding premium paid in Hispanic neighborhoods is about 0.20 percent, or about 8 cents for a tank. Moreover, in Atlanta we find evidence of discounts rather than a premium paid with minority composition, although the magnitude of the discounts is similarly small.

Larger premia are observed in relation to income. On average across the three cities in the data set, a 10 percentage point increase in poor relative to lower-middle income families is associated with a 0.70 percent increase in gasoline prices. Two-thirds of this differential can be accounted for by the observable cost, competition, and demand characteristics of poor neighborhoods. The remaining differential is again smaller for stations that have observably less market power, suggesting that it may be explained by lower levels of competition and/or more inelastic demand in poor neighborhoods.

We conclude that the evidence from the market for gasoline indicates that prices are not greatly inflated in minority neighborhoods, but that there is a small poverty premium that may represent a noteworthy burden for the very poor living in very poor neighborhoods.

A Appendix: Station Telephone Survey Methodology and Script

The telephone surveys of gasoline stations were conducted by undergraduate students as part of a class research project. Students piloted an initial script on approximately 100 stations. The students then worked together during an afternoon workshop to refine the survey script based on their experience with the pilot. The refinements included shortening the introduction and several of the questions. The final version of the survey script is replicated below. Surveyors reported that only a handful of respondents asked for more detailed information on the nature of the survey.

Survey Script

First verify that you have the correct station. When the respondent answers the phone, if he or she identifies the station in some way that matches what you were expecting, simply begin the script. If the respondent does not identify the station, ask ***"Hi, is this the [brand] station on [street]?"*** *If it is, continue. If it is not, say that you have the wrong number and hang up.*

Then, ask the respondent if he or she is willing to complete the survey. You can say whatever feels comfortable, but try to keep it brief and clear. Something like:

Hi, can I ask you a few questions for a class project? It will only take a minute.

Wait for response

- *No: Thank them and hang up*
- *Ask you to call back: Record suggested time and call back as instructed*
- *Ask you for more information: Tell respondent that you are working on a research project on gasoline prices across neighborhoods. Answer all questions briefly and truthfully.*
- *Yes: Proceed with Survey*

Great! Thanks very much.

1. **Does your station have a car wash?**

2. **Does your station perform oil changes?**
3. **Do you sell milk by the gallon?**
4. **Is there a restaurant like a McDonald's that is part of your station?**
5. **Is your station open 24 hours a day?**
6. **Does your station pump the gas for customers?**

   (Question 6 excluded from surveys of New Jersey stations.)
7. **How many cars can get gasoline at your station at the same time?**
8. **On a scale of 1 to 10, how bad a problem would you say crime is in your area?**
9. **Does the owner of your station also work behind the counter?**

Thank you very much for you time.

References

Ian Ayres and Peter Siegelman. Race and gender discrimination in bargaining for a new car. *The American Economic Review*, 85(3), June 1995.

Badi Baltagi. *Econometric Analysis of Panel Data*. John Wiley and Sons, Ltd, fourth edition, 2008.

Gary S. Becker. *The Economics of Discrimination*. University of Chicago Press, 1957.

Timothy Bresnahan. Empirical studies of industries with market power. In Richard Schmalensee and Robert Willig, editors, *Handbook of Industrial Organization*, volume 2. North-Holland, 1989.

DeNeen L. Brown. Poor? pay up. *The Washington Post*, May 18, 2009.

Roland Burris. Senator Roland W. Burris: FY2010 appropriations requests, April 29, 2009. Press Release.

Hayley Chouinard and Jeffrey Perloff. Incidence of federal and state gasoline taxes. *Economics Letters*, 83(1), 2004.

Chanjin Chung and Samuel Myers. Do the poor pay more for food? an analysis of grocery store availability and food price disparities. *The Journal of Consumer Affairs*, 33(2), 1999.

City of Atlanta Police Department. 2007 crime data, downloaded February 24, 2007. URL `http://www.atlantapd.org/index.asp?nav=CrimeMapping`.

Elizabeth Douglas and Gary Cohn. Zones of contention in gasoline pricing. *The Los Angeles Times*, June 19, 2005.

David Downing. Driving shoppers to the suburbs. *St. Paul Pioneer Press*, March 13, 2007.

Denver D'Rozario and Jerome Williams. Retail redlining: Definition, theory, typology, and measurement. *Journal of Macromarketing*, 25(2), December 2005.

Energy Information Administration. A primer on gasoline prices, 2009. URL `http://www.eia.doe.gov/bookshelf/brochures/gasolinepricesprimer/`. Informational brochure published by a division of the U.S. Department of Energy.

David Frankel and Eric Gould. The retail price of inequality. *Journal of Urban Economics*, 49(2), 2001.

Chevon Fuller. Service redlining: The new Jim Crow? *Civil Rights Journal*, 3 (1), May 1998.

Georgia Department of Revenue. Motor fuel tax bulletins, 2007a.

Georgia Department of Revenue. Motor fuel tax bulletins, 2008.

Georgia Department of Revenue. Motor fuel tax bulletins, 2009.

Georgia Department of Revenue. Information bulletin #2007-12-19: House bill 219– prepaid local tax on motor fuel, December 19, 2007b.

Uri Gneezy and John List. Are the disabled discriminated against in product markets? Evidence from field experiments. Working paper, 2004.

Pinelopi Koujianoi Goldberg. Dealer price discrimination in new car purchases: Evidence from the consumer expenditure survey. *The Journal of Political Economy*, 104(3), June 1996.

Kathryn Graddy. Do fast-food chains price discriminate on the race and income characteristics of an area? *Journal of Business and Economic Statistics*, 15 (4), 1997.

Bruce Hall. Neighborhood differences in retail food stores: Income versus race and age of the population. *Economic Geography*, 59(3), 1983.

Lashawn Richburg Hayes. Do the poor pay more? An empirical investigation of price dispersion in food retailing. 2000.

Betsy Jelisavcic. When redlining isn't; only banks and insurers are required to do business in minority neighborhoods. *The Cleveland Plain Dealer*, November 17, 1996.

Sheila Kaplan. The new face of racism. *U.S. News and World Report*, 128(1), January 1, 2000.

Phillip Kaufman, James MacDonald, Steve Lutz, and David Smallwood. Do the poor pay more for food? Item selection and price differences affect low-income household food costs. Agricultural Economic Report 759, U.S. Department of Agriculture, 1997.

Andrew Kleit. The economics of gasoline retailing: Petroleum distribution and retailing issues in the U.S., December 2003. American Petroleum Institute.

John List. The nature and extent of discrimination in the marketplace: Evidence from the field. *Quarterly Journal of Economics*, 119(1), February 2004.

David Meyer and Jeffrey Fischer. The economics of price zones and territorial restrictions in gasoline marketing, 2004. Federal Trade Commission working paper no. 271.

Caitlin Knowles Myers. Discrimination and neighborhood effects: Understanding racial differentials in U.S. housing prices. *Journal of Urban Economics*, 56(2), September 2004.

Jan Ondrich, Stephen Ross, and John Yinger. Now you see it, now you don't: Why do real estate agents withhold available houses from black customers? *Review of Economics and Statistics*, 85(4), November 2003.

John Pucher and John Renne. Socioeconomics of urban travel: Evidence from the 2001 NHTS. *Transportation Quarterly*, 57(3), 2003.

Craig Rose. Gasoline prices all over the map. *San Diego Tribune*, August 16, 2007.

Amanda Shaffer. The persistence of l.a.'s grocery gap: The need for a new food policy and approach to market development, 2002.

Andrea Shepard. Price discrimination and retail configuration. *The Journal of Political Economy*, 99(1), 1991.

Peter Siegelman. Racial discriminationi in "everyday" commercial transactions: What do we know, what do we need to know, and how can we find out? In Michael Fix and Margery Austin Turner, editors, *A National Report Card on Discrimination in America: The Role of Testing*. The Urban Institute, 1998.

Eric Smith. Caught red-handed? Civil rights group charges Wal-Mart with retail redlining. *Black Enterprise*, 26(10), May 1996.

Frederick Sturdivant. *The Ghetto Marketplace*. The Free Press, 1969.

Beck Taylor. Retail characteristics and ownership structure. *Small Business Economics*, 14(2), 2000.

The American Petroleum Institute. State motor fuel excise and other taxes, January 12, 2009.

U.S. Department of Labor, Bureau of Labor Statistics. Consumer expenditure survey, 2007 data tables, November 26, 2008.

John Yinger. Measuring discrimination with fair housing audits: Caught in the act. *American Economic Review*, 76(5), December 1986.

John Yinger. *Closed Doors, Opportunities Lost: The continuing costs of housing discrimination*. Russell Sage Foundation, 1995.

Table 1: **Descriptive statistics for gasoline stations used in analysis**

Variable	Source	Full sample *mean*	*s.d.*	Non-surveyed stations *mean*	*s.d.*	Surveyed stations *mean*	*s.d.*
Outcome							
price	OPIS	3.34	(0.16)	3.34	(0.16)	3.36	(0.12)
price net taxes	authors	2.86	(0.15)	2.86	(0.16)	2.86	(0.12)
Location							
Michigan (d)	OPIS	0.31	(0.46)	0.30	(0.46)	0.36	(0.48)
New Jersey (d)	OPIS	0.07	(0.26)	0.07	(0.26)	0.05	(0.22)
Pennsylvania (d)	OPIS	0.18	(0.38)	0.18	(0.38)	0.22	(0.41)
Georgia (d)	OPIS	0.44	(0.50)	0.45	(0.50)	0.38	(0.49)
central city (d)	OPIS	0.17	(0.37)	0.17	(0.38)	0.13	(0.34)
competing stations within 1 km	ArcGIS	2.13	(1.37)	2.14	(1.37)	2.09	(1.39)
km to nearest interstate	ArcGIS	4.29	(4.92)	4.28	(4.84)	4.38	(5.51)
km to nearest highway	ArcGIS	5.13	(10.16)	4.95	(9.74)	6.55	(13.01)
Census tract characteristics							
pct white	Census	68.95	(30.18)	68.52	(30.37)	72.49	(28.35)
pct black	Census	21.39	(28.90)	21.79	(29.15)	18.16	(26.53)
pct other	Census	4.52	(4.17)	4.52	(4.18)	4.54	(4.13)
pct Hispanic	Census	5.13	(8.31)	5.17	(8.38)	4.81	(7.72)
pct below poverty line	Census	9.90	(9.30)	10.00	(9.45)	9.01	(7.96)
pct 1 to 2 times poverty line	Census	14.09	(7.55)	14.15	(7.54)	13.63	(7.57)
pct $>$ 2 times poverty line	Census	76.01	(15.55)	75.85	(15.67)	77.36	(14.48)
people/km2	Census	1301	(1620)	1317	(1649)	1176	(1348)
pct commute by car	Census	90.35	(9.38)	90.25	(9.55)	91.17	(7.81)
avg commute time (minutes)	Census	30.57	(5.08)	30.64	(5.08)	29.99	(5.00)
pct of households with 1 vehicle	Census	33.82	(10.98)	33.81	(10.98)	33.92	(16.84)
pct of households with 2+ vehicles	Census	57.02	(17.82)	56.97	(17.94)	57.41	(16.84)
median house value	Census	127,787	(65,197)	127,159	(65,159)	132,925	(65,338)
Station characteristics							
number of days in sample		250.17	(107.19)	248.54	(107.65)	263.49	(102.55)
branded gasoline (d)	OPIS	0.79	(0.40)	0.79	(0.41)	0.81	(0.39)
car wash (d)	survey					0.12	(0.33)
oil change (d)	survey					0.19	(0.39)
milk (d)	survey					0.75	(0.43)
restaurant (d)	survey					0.15	(0.36)
24 hours (d)	survey					0.45	(0.50)
full service (d)	survey					0.23	(0.42)
capacity	survey					9.20	(3.99)
bad crime (d)	survey					0.45	(0.50)
owner present (d)	survey					0.56	(0.50)
n		5203		4636		567	

*Descriptive statistics for for all stations in analysis sample and by survey status. *Price* is the average price observed over the year for a station. Dummy variables are noted by a (d).

Table 2: **Gasoline price as a function of neighborhood and station characteristics**

	Model 1		Model 2		Model 3	
dep. var: ln(price net taxes)	*coef*	*se*	*coef*	*se*	*coef*	*se*
Race and income composition						
pct black	0.00002	0.00001	$-2.0\text{x}10^{-6}$	0.00002	-0.00001	0.00005
pct Hispanic	-0.00002	0.00004	-0.00004	0.00004	-0.00004	0.00013
pct other	0.00007	0.00007	-0.00015**	0.00007	-0.00018	0.00022
pct below poverty line	0.00070***	0.00009	0.00022**	0.00010	0.00037	0.00033
pct > 2 times poverty line	0.00048***	0.00006	0.00002	0.00007	0.00020	0.00021
Add'l neighborhood characteristics						
central city (d)			-0.00490***	0.00108	-0.00660*	0.00340
density (1,000 ppl/km^2)			-0.00056**	0.00027	-0.00010	0.00088
pct commute by car			-0.00051***	0.00006	-0.00050**	0.00020
avg commute time (minutes)			-0.00009	0.00007	-0.00030	0.00023
pct of households with 1 vehicle			0.00008	0.00008	0.00012	0.00021
pct of households with 2+ vehicles			0.00002	0.00007	0.00003	0.00020
ln(median house value)			0.01105***	0.00104	0.00884***	0.00314
Station characteristics						
branded gasoline (d)			0.01410***	0.00069	0.01568***	0.00220
competing stations within 1 km			-0.00117***	0.00021	-0.00210***	0.00062
km to nearest interstate			-0.00021***	0.00006	-0.00024	0.00017
km to nearest highway			0.00009***	0.00003	0.00014*	0.00007
car wash (d)					0.00006	0.00254
oil change (d)					0.00328	0.00259
milk (d)					0.00017	0.00240
restaurant (d)					-0.00308	0.00231
24 hours (d)					0.00127	0.00197
full service (d)					0.00257	0.00224
capacity					-0.00015	0.00022
badcrime					0.00075	0.00169
owner present (d)					0.00295*	0.00169
state indicators	yes		yes		yes	
n	5,203		5,203		567	
nT	1,301,636		1,301,636		149,399	

*Two-way error component model with date fixed effects and station random effects. Dependent variable is the natural logarithm of the per-gallon price of regular, unleaded gasoline net of taxes.

**p<0.10 **p<0.05 ***p<0.01*

Table 3: **Gasoline price as a function of neighborhood characteristics, by metropolitan area**

	Model 1		Model 2	
dep. var: ln(price net taxes)	*coef*	*se*	*coef*	*se*
Atlanta				
pct black	-3.1x10^{-6}	0.00002	-0.00004*	0.00002
pct Hispanic	-0.00002	0.00006	-0.00018***	0.00007
pct other	0.00011	0.00012	0.00001	0.00012
pct below poverty line	0.00069***	0.00014	0.00010	0.00016
pct > 2 times poverty line	0.00023***	0.00008	-0.00015	0.00011
Detroit				
pct black	0.00003*	0.00002	0.00005**	0.00002
pct Hispanic	0.00008	0.00006	0.00018***	0.00006
pct other	0.00039***	0.00010	0.00020*	0.00010
pct below poverty line	0.00065***	0.00012	0.00026**	0.00013
pct > 2 times poverty line	0.00062***	0.00008	0.00012	0.00009
Philadelphia				
pct black	0.00014***	0.00004	0.00007*	0.00004
pct Hispanic	-0.00005	0.00011	0.00022**	0.00011
pct other	-0.00008	0.00016	-0.00050***	0.00015
pct below poverty line	0.00146***	0.00024	0.00075***	0.00025
pct > 2 times poverty line	0.00113***	0.00014	0.00064***	0.00016
additional controls	no		yes	

*Two-way error component model with date fixed effects and station random effects. Dependent variable is the natural logarithm of the per-gallon price of regular, unleaded gasoline net of taxes. Additional controls in Model 2 are the same as reported previously: central city, density, percent commute by car, mean commute time, vehicle ownership, median house value, branded gasoline, nearby competing stations, and distance to major roads. State indicators are not included for the Atlanta and Detroit metropolitan areas, which are each contained in one state, but a New Jersey indicator is included in both models for Philadelphia.

**p<0.10 **p<0.05 ***p<0.01*

Table 4. **Gasoline prices as a function of neighborhood and station characteristics, with interaction terms**

	Model 2a		Model 2b		Model 2c		Model 3a	
dep. var: ln(price net taxes)	*coef*	*se*	*coef*	*se*	*coef*	*se*	*coef*	*se*
pct black	-0.00003	0.00003	0.00002	0.00013	-0.00001	0.00002	-0.00000	0.00007
pct Hispanic	-0.00016*	0.00008	-0.00055*	0.00029	0.00004	0.00005	-0.00009	0.00020
pct other	-0.00028**	0.00013	-0.00119**	0.00055	0.00004	0.00010	-0.00016	0.00034
pct below poverty line	0.00042**	0.00018	0.00171***	0.00047	0.00046***	0.00012	0.00044	0.00049
pct > 2 times poverty line	0.00012	0.00012	0.00114***	0.00040	0.00015**	0.00008	0.00020	0.00029
pct commute by car	-0.00051***	0.00006	0.00056	0.00041	-0.00051***	0.00006	-0.00050**	0.00021
competing stations within 1 km	0.00179	0.00374	-0.00119***	0.00021	-0.00115***	0.00021	-0.00208***	0.00062
km to nearest interstate	-0.00022***	0.00006	-0.00020***	0.00006	0.00414***	0.00111	-0.00024	0.00017
owner present (d)							0.00487	0.03120
pct black∗competing stations	0.00001	0.00001						
pct Hispanic∗competing stations	0.00005*	0.00003						
pct other∗competing stations	0.00006	0.00004						
pct below poverty line∗competing stations	-0.00009	0.00006						
pct> 2 times poverty line∗competing stations	-0.00004	0.00004						
pct black∗pct commute by car			-0.00000	0.00000				
pct Hispanic∗pct commute by car			0.00001*	0.00000				
pct other∗pct commute by car			0.00001*	0.00001				
pct below poverty line∗pct commute by car			-0.00002***	0.00001				
pct> 2 times poverty line∗pct commute by car			-0.00001***	0.00000				
pct black∗km to interstate					0.00001*	0.00000		
pct Hispanic∗km to interstate					-0.00003***	0.00001		
pct other∗km to interstate					-0.00009***	0.00002		
pct below poverty line∗km to interstate					-0.00004***	0.00001		
pct> 2 times poverty line∗km to interstate					-0.00004***	0.00001		
pct black∗owner present							-0.00001	0.00008
pct Hispanic∗owner present							0.00009	0.00025
pct other∗owner present							-0.00004	0.00043
pct below poverty line∗owner present							-0.00012	0.00060
pct> 2 times poverty line∗owner present							-0.00001	0.00034
additional controls			yes				yes	
state indicators			yes				yes	
n			5,203				567	
nT			1,301,636				149,399	

*Two-way error component model with date fixed effects and station random effects. Dependent variable is the natural logarithm of the per-gallon price of regular, unleaded gasoline net of taxes. Additional controls in Model 2 are the same as reported previously: central city, density, percent commute by car, mean commute time, vehicle ownership, median house value, branded gasoline, nearby competing stations, and distance to major roads. Additional controls in Model 3 include all station characteristics obtained via telephone survey: car wash, oil change, milk, restaurant, 24 hours, full service, capacity, and bad crime.

*$p<0.10$ **$p<0.05$ ***$p<0.01$*