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Lowering Consumer Search Costs Can Lead To Higher Prices

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Abstract

We demonstrate that lower consumer search costs can lead to higher prices charged by firms. We estimate the distribution of consumer search costs for 366 isolated retail gasoline markets, and find that reducing the mean and standard deviation by 20% and 48%, respectively, leads to price increases in 32% of markets and an average price increase of 5.2 cents per gallon across all markets. Thus, price transparency regulation that results in higher prices may not stem from collusion, but from an equilibrium with less consumer search.

1 Introduction

Many government regulations intend to increases consumer welfare by decreasing the cost of search. For instance, to promote price transparency and competition, regulators have created online retail gasoline price aggregators,[1] or mandated how stations display prices for different payment methods (i.e., cash and credit card). While these regulations decrease consumer search costs, they also make the cost of search more homogeneous across consumers.

This paper analyzes how policy affecting the distribution of consumer search costs impact pricing and search behavior. We find decreasing both the mean and standard deviation of search costs can have the unintended consequence of raising prices and decreasing consumer welfare. In the context of gasoline markets, requiring firms to post prices to a website will decrease the search cost for consumers at the high end of the distribution, but leave unchanged the search cost of consumers at the low end who already perform comparison shopping. Similarly, requiring credit card prices to be publicly displayed reduces the search cost for consumers that prefer this payment instrument, but leaves unchanged the cost to cash buyers. Therefore, both regulations compress the search cost distribution by decreasing the mean and variance. We demonstrate through simulation and an empirical application that these policies can either increase or decrease the expected price paid by consumers, depending upon the relative decrease of the mean and variance, and demographic variables that determine the search cost distribution within a market. Previous research uses tacit collusion to explain price increases following the introduction of price aggregation technology (Borenstein (1998), Luco (2017)) – we show that price increases could result from competitive firms pricing to consumers with less heterogeneous search costs.

To perform the analysis, we employ a variant of the Burdett and Judd (1983) search cost model extended to allow for vertical product differentiation by Wildenbeest (2011). We first demonstrate how changing (i) the mean (ii) standard deviation and (iii) both simultaneously affect the distribution of equilibrium prices and consumer search behavior. Using a panel data set of retail gasoline prices, we estimate the distribution of consumer search costs separately for 366 markets. With these estimates, we perform a counterfactual experiment that reduces both the mean and variance of search costs by 20% and 48%, respectively, in each market, and find that prices increase in 32% of markets. Prices increase by $\$0.052$ per gallon, on average across all markets.

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[1]In 2008, South Korea required retail gas stations to report prices to a public website, Opinet. In 2011, the Austrian government enacted similar legislation.

2 Modeling Consumer Search

We analyze the fixed-sample search model developed by Burdett and Judd (1983) and extended by Wildenbeest (2011) to incorporate vertical production differentiation. For ease of exposition, we present the homogeneous product version of the model. The simulations and empirical model account for vertical product differentiation and differences in marginal cost.[2]

Consider N firms selling a homogeneous product to a continuum of consumers with inelastic demand for one unit. Each consumer has a cost of search $c \geq 0$, distributed i.i.d according to the CDF, F_c. Firms do not observe a consumer's search cost, but know F_c. Firms simultaneously choose price, which generates the equilibrium price CDF, $F_p(p)$; $\underline{p}$ and $\bar{p}$ are its lower and upper bound, respectively. Firms have constant and identical marginal costs, r. In equilibrium, firms either play a symmetric mixed strategy that generates price dispersion, or all set the monopoly price, $\bar{p}$.[3]

Consumers know $F_p(p)$, but engage in fixed-sample search to learn individual prices. Each consumer receives one free quote, chooses the number of additional prices to search at a per-quote cost, c, learns all prices in the sample, and finally purchases one unit from the lowest-priced firm in the sample. Consumers minimize total expected expenditure by choosing the number of firms to search, $l-1$, where,

$$l = \arg\min_{l \geq 1} \{c \cdot (l-1) + \int_{\underline{p}}^{\bar{p}} l \cdot p(1-F_p(p))^{l-1} f(p)dp\}.$$

The first term, $c(l-1)$, is the total cost of search and the second is the expected price paid. Searching $i+1$ firms yields expected marginal savings of $\Delta_i \equiv Ep_{1:i} - Ep_{1:i+1}$, where $p_{1:i}$ is the minimum price when i draws are taken from F_p. Accordingly, a consumer with search cost c samples i stores when $\Delta_{i-1} > c > \Delta_i$. The proportion of consumers with i price quotes, q_i, is therefore $q_1 \equiv 1 - F_c(\Delta_1)$ and $q_i \equiv F_c(\Delta_{i-1}) - F_c(\Delta_i)$ for $i \geq 2$.

Firms maximize profits by choosing a symmetric, mixed-strategy, $F_p(p)$, for all $p \in [\underline{p}, \bar{p}]$. Total profit is therefore $\Pi(p) = (p-r)[\sum_{i=1}^{N} q_i \cdot \frac{i}{N}(1-F_p(p))^{i-1}]$. Mixed strategies imply an equilibrium condition that each firm is indifferent between charging the monopoly price $\bar{p}$ and any other price $p \in [\underline{p}, \bar{p}]$,

$$\frac{(\bar{p}-r)\tilde{q}_1}{N} = (p-r)[\sum_{i=1}^{N} \tilde{q}_i \cdot \frac{i}{N}(1-F_p(p))^{i-1}]. \tag{1}$$

Firms therefore face a trade-off between setting a high price and selling to less informed customers or setting a low price and also capturing more informed customers. Implicitly solving equation (1) for price yields the inverse pricing function,

$$p(z) = \frac{\tilde{q}_1(\bar{p}-r)}{\sum_{i=1}^{N} iq_i(1-z)^{i-1}} + r, \tag{2}$$

where $z = F_p(p)$.

3 Estimating the Model

The data and estimation routine are identical to those in Nishida and Remer (2017), which extends Wildenbeest (2011) to allow for marginal cost changes over time. We provide a high-level summary of the estimation, and refer interested readers to those articles for further details. We estimate the model using 30 days (February 27th to March 28th, 2007) of daily, gas station-level data for stations located in California, Florida, New Jersey, and Texas. We estimate search cost distributions using data from 366 "isolated" markets: a set of stations all within 1.5 miles of each other, and all stations outside of the market are more than 1.5 miles from every station within the market. To control for marginal cost changes, we use the NYMEX spot price of reformulated gasoline delivered to NY Harbor, Gulf Coast, and Los Angeles for gas stations located in those

[2]See Nishida and Remer (2017) for a more complete treatment of the model.

[3]See Burdett and Judd (1983) for a proof of this claim, and Nishida and Remer (2017) for evidence of mixed-strategy pricing in the data.

respective regions. To control for demographic differences across markets, we use income, education, and age data from the 2006-2010 American Community Survey.

For each observed price, we subtract a firm-specific fixed-effect to control for vertical product differentiation and subtract the daily measure of wholesale cost to control for marginal cost changes. These "cleaned" prices are then used in a nonparametric MLE routine, where the likelihood function is obtained by applying the implicit function theorem to equation (1). Separately for each market, we estimate a collection of points, $\{q_i, \Delta_i\}$, on the search cost CDF, $F(c)$. The estimated points of each market's search cost distribution are then pooled, and nonlinear least-squares (NLS) regression is used to fit a log-normal distribution. In the NLS regression, the mean and variance parameters of the log-normal distribution, μ and σ, respectively, depend upon market-level characteristics. Table 1, which is reproduced from Nishida and Remer (2017) details the regression results. The next section uses these estimates to explore changes to the search cost distribution in an "average" market, as well as changes to each individual market.

4 Policy Experiments

Policy Experiment Within an Average Market. To build intuition, we first separately isolate the effect of changing the (i) mean or (ii) standard deviation of the search cost distribution. We then analyze the impact of changing both simultaneously, as would most real-world policies. Using average market demographics, we calibrate a log-normal search cost distribution to fit the estimated parameters in Table 1. We then perturb the search cost distribution and use equation (2) to solve for the pre and post-policy price distributions.

To analyze a decrease in the mean of the search cost distribution while holding the standard deviation constant, we consider a "baseline" search cost CDF (F_c) that first-order stochastically dominates a "hypothetical" CDF, (F_c'): $F_c'(t) > F_c(t)$ for any $t > 0$. We assume the market has five firms.[4] Column 1 in Table 2 presents the results for a 20% decrease in search costs, which are qualitatively the same for more pronounced changes.

The results confirm conventional wisdom; a FOSD shift in the search-cost CDF leads to lower prices. The mean price decreases from $\$2.727$ to $\$2.716$ per gallon, and the expected price paid, on average across all consumers, decreases by $\$0.016$ from $\$2.727$. The magnitude of the effect differs across consumers with different search costs. For example, consumers in the 25th percentile experience the largest decrease in the price paid ($-\$0.038$), whereas consumers in the 50th and 75th percentile experience the smallest decrease ($-\$0.011$) among the four categories of consumers in Table 2.

We now consider a situation in which consumers' search costs become less heterogeneous but not completely homogeneous, while holding constant the mean of the search cost distribution. More precisely, we consider a case in which F_c' second-order stochastically dominates the baseline search CDF (F_c); therefore, $\mathrm{E}[c] = \int c\, dF_c' = \int c\, dF_c$ and $\int_0^x F_c(c)dc \geq \int_0^x F_c'(c)dc$ for all x. To perform the experiment, we decrease the standard deviation parameter of the log-normal CDF, σ, for the hypothetical distribution, F_c', relative to the baseline CDF. We then update the mean parameter, μ, for the hypothetical distribution that yields the same unconditional expected search costs, $\mathrm{E}[c]$.[5]

Column 2 in Table 2 summarizes the results when the standard deviation parameter σ is decreased by 5%, which reduces the standard deviation of search cost distribution by 19.8%.[6] Prices become less dispersed and increase. As search costs become more homogeneous, firms have less incentive to sell to consumers with relatively low search costs, and therefore prices cluster at the high end of the price distribution. When the standard deviation parameter is decreased by 7% there is a striking result – all firms set the monopoly price. This is akin to Diamond (1971)'s monopoly equilibrium; however, in this case, there is still heterogeneity in consumer search costs. This occurs because when search costs become sufficiently homogeneous sales from low search cost consumers are insufficient to make the expected profit equal across all prices in the price distribution, and therefore all firms set the monopoly price.

To highlight this point, we decrease the mean search cost by 20% in addition to reducing the standard deviation. When σ decreases by 10% there is still price dispersion; however, when σ decreases by 15% no

[4]Additional parameter values are set to match averages in the data: income, year of education, age, and distance among stations.

[5]Note that we distinguish the mean parameter μ and the expected value of the log-normal distribution ("mean search cost"), which is $E[c] = e^{\mu + \frac{\sigma^2}{2}}$.

[6]The standard deviation of search cost is given by $\sqrt{\mathrm{Var}[c]} = \sqrt{[(\exp(\sigma^2) - 1)]\exp(2\mu + \sigma^2)}$.

consumers search and all firms set the monopoly price. Thus, even small changes to the cost of search can have large implications for prices and welfare.

Policy Experiment Within Each 366 Isolated Markets. We now reduce the mean search cost by 20% and standard deviation parameter by 10%, which reduces the standard deviation of search cost distribution by 48%, separately for each of the 366 isolated markets in the data. To perform the experiments, we recover the mean and variance of the search cost distribution for each market using the estimates in Table 1 and pertinent demographic variables. Then we solve for the equilibrium price distribution and consumers search behavior using the structural model. Because multiple price dispersion equilibria may exist, we try 10 unique starting values for each market.

Figure 1 depicts the mean price change in each market. The distribution is bimodal with the modes falling on opposite sides of zero. In the left mode, price dispersion exists and average prices decrease, due to lower mean search costs and increased search intensity. In the right mode, average prices increase. Prices increase in 32 % of markets, and the average price change across markets is positive and $\$0.052$ per gallon. Of the markets that experience a price increase, 51% move to the monopoly equilibrium and 49% still have price dispersion. In the latter markets, the effect of decreasing σ outweighs the impact of reducing μ. To confirm the finding, we reduce the standard deviation parameter by 15%, while maintaining a 20% reduction in mean search cost. We find more markets with price increases (41%) and an average price change across markets of $\$0.088$ per gallon.

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Figure 1

Change in Average Price by Market: 20% Decrease in Expected Value and 10% Decrease in Standard Deviation of Search Costs

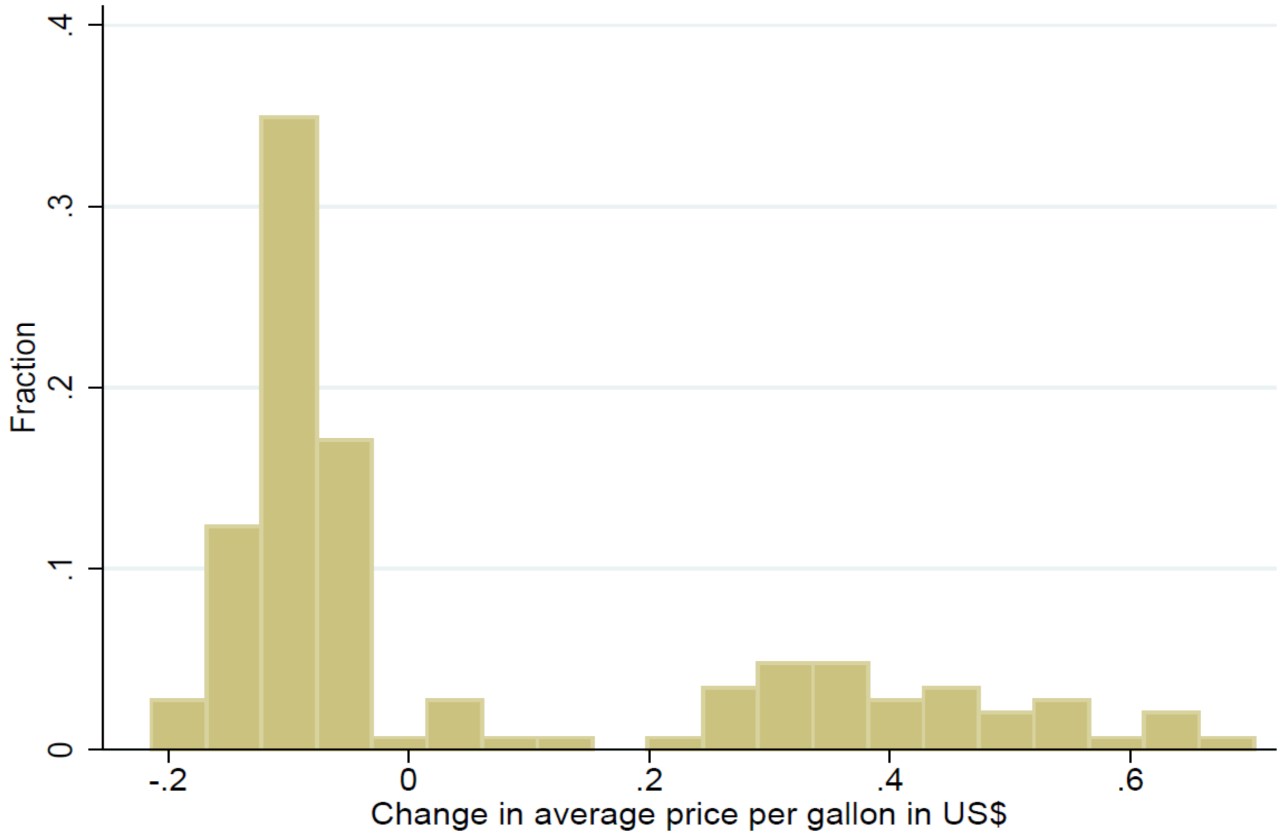

Table 1

Nonlinear Least Square Estimation of Search-Cost Cumulative Distribution

Distributional assumption	Lognormal
Mean of distribution	
Constant	-6.926***
	(1.980)
Mean income	0.716***
	(0.175)
Mean years of education	-0.361
	(0.962)
Mean age	-0.572
	(0.510)
Mean distance among stations	-0.594***
	(0.214)
Standard deviation of distribution	
Constant	-0.014
	(2.590)
Standard deviation of income	0.502***
	(0.123)
Standard deviation of years of education	-0.284
	(0.326)
Standard deviation of age	-1.392**
	(0.571)
Mean squared error	17.33
Number of observations	726

Note: Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The regressors are in logs.

Table 2

The Effect of a Change in Search Costs on Equilibrium Price Distribution

	Baseline	(1)	(2)
		20% Mean Decrease	5% Decrease in SD parameter
Expected price (Ep)	2.727	2.716	2.746
Expected price paid	2.718	2.702	2.743
people with 10%ile search costs	2.682	2.657	2.732
people with 25%ile search costs	2.727	2.689	2.746
people with 50%ile search costs	2.727	2.716	2.746
people with 75%ile search costs	2.727	2.716	2.746
Expected search cost	1.005	0.804	1.005
Expected paid search cost	0.004	0.003	0.002
people with 10%ile search costs	0.022	0.023	0.010
people with 25%ile search costs	0.000	0.021	0.000
people with 50%ile search costs	0.000	0.000	0.000
people with 75%ile search costs	0.000	0.000	0.000
Proportion of people with i price quotes (qi)			
q1	0.767	0.708	0.864
q2	0.071	0.085	0.490
q3	0.045	0.055	0.028
q4	0.030	0.037	0.017
q5	0.087	0.114	0.042

Notes: The number of simulated price observations is 100. SD parameter referes to the standard deviation parameter of the log-normal distribution.