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INFORMATION AND PRICE DISPERSION: THEORY AND EVIDENCE*

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Limited information is the key element generating price dispersion in models of homogeneous-goods markets. We show that the global relationship between information and price dispersion is an inverse-U shape. We test this mechanism for the retail gasoline market using a new measure of information based on commuter data from Austria. Commuters sample gasoline prices on their commuting route, providing us with spatial variation in the share of informed consumers. Our empirical estimates are in line with the theoretical predictions. We also quantify how information affects average prices paid and the distribution of surplus in the gasoline market.

1. INTRODUCTION

Price competition in homogeneous-goods markets rarely results in market outcomes in line with the "law of one price." On the contrary, price dispersion is ubiquitous in such markets, and it cannot be fully explained by differences in location, cost, or services.

In his seminal paper, Stigler (1961) offered the first search-theoretic rationale for price dispersion. He argued that "price dispersion is a manifestation—and, indeed, it is the measure—of ignorance in the market" (p. 214). Following Stigler's seminal work, it has been shown that price dispersion can arise as an equilibrium phenomenon in a homogeneous-goods market with symmetric firms if consumers are not fully informed about prices—see Varian (1980) and the literature that followed (as surveyed in Baye et al., 2006).

Not only widespread adoption of the Internet, but also of earlier innovations such as automobiles, telephones, and television has made information about prices accessible to ever more consumers. Yet, price dispersion has anything but disappeared (Baye et al., 2006; Friberg, 2014) and has significant distributional consequences (Kaplan and Menzio, 2015). Price dispersion in retail gasoline has received particular attention due to the homogeneity of the product and its cost. Consumers are upset about unexpected price differences across outlets and over time, which has resulted in numerous inquiries into this sector by competition authorities (OECD,

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2013). Several countries have introduced restrictions on price setting,[2] as well as transparency regimes requiring retailers to report to an online platform.[3]

We contribute to this debate by theoretically and empirically examining the relationship between consumer information, price levels, and price dispersion. We begin by deriving the global relationship between information, prices, and price dispersion in a "clearinghouse model," as developed by Varian (1980) and further refined by Stahl (1989).[4] Consumers differ in their degree of informedness: For some, obtaining an additional price quote is costly; others are aware of all prices charged in the relevant market—they have access to the "clearinghouse." The model unambiguously implies that average prices decline as the share of informed consumers increases—our first testable prediction.

At the very extremes, the model predicts no price dispersion: If no consumer has access to the clearinghouse, all firms charge the monopoly price; conversely, if all consumers are informed, the Bertrand outcome arises and all firms price at marginal cost. If instead the fraction of informed consumers is interior, firms face a tension between charging a high price to exploit uninformed consumers and charging a low price to attract informed consumers. This tension gives rise to a mixed-strategy equilibrium, and therefore to price dispersion. This suggests that price dispersion is not a monotone function of the share of informed consumers. We prove that the Stahl (1989) model generates a *global* inverse-U–shaped relationship—our second testable prediction. Importantly, our predictions on price levels and dispersion continue to obtain in a setting where informed consumers have different (e.g., higher) demand.

We then test the model's predictions using data on the retail gasoline market in Austria. The challenge here is to find a good measure for the fraction of informed consumers. We construct such a measure using detailed data on commuting behavior from the Austrian census. The main idea is that, relative to noncommuters, commuters are likely to be better informed as they are able to sample freely all price quotes for gasoline along their commute. Using our precise commuter data, we thus compute the share of commuters passing by an individual gasoline station, and interpret this share as measuring the fraction of consumers having access to the clearinghouse in the Stahl (1989) model.

Having constructed our information measure, we combine it with quarterly data on retail gasoline prices at the station level to study the impact of consumer information on price levels and dispersion. Exploiting regional variation in commuting behavior, we find strong statistical evidence in favor of a negative relationship between consumer information and price levels, and of an inverse-U–shaped relationship between information and price dispersion. The empirical results are robust to using various alternative measures of price dispersion, taking alternative approaches to local market delineation, accounting for potential spatial correlation in the residuals of the estimating equation, taking into account different degrees of consumer informedness, and relaxing parametric restrictions.

We believe that our empirical setting is close in spirit to the seminal clearinghouse models and permits a direct test of those theories for the following reasons: (1) Firms' abilities to obfuscate consumers' search and learning efforts are limited in this market; (2) unlike other measures of information, commuting is not correlated with firms' ability to monitor each other and collude;[5] (3) gasoline is a homogeneous product and seller characteristics can be adequately controlled for; (4) we observe substantial variation in our measure of the share of informed consumers, enabling us to test the global prediction derived from theory; (5) a consumer's decision to commute—and thus to become better informed—is not determined by regional differences in price dispersion, allowing a causal interpretation of our empirical results.

[2] This includes Australia (Byrne and de Roos, 2017), Austria (Obradovits, 2014), and Canada (Carranza et al., 2015).

[3] This includes Australia (Byrne and de Roos, 2017), Chile (Luco, 2019), Germany (Dewenter et al., 2017), and Italy (Rossi and Chintagunta, 2018).

[4] Varian's (1980) model corresponds to a special case of Stahl's (1989) model without search.

[5] For instance, Albæk et al. (1997) and Luco (2019) show that prices actually increased after the introduction of a transparency regime.

Our article is related to several strands of literature. We contribute to the literature on clearinghouse models, initiated by Varian (1980) and Stahl (1989), by studying the relationship between consumer information and the equilibrium price distribution in such models.[6] The literature has observed that price dispersion is not a monotone function of the fraction of informed consumers (see Baye et al., 2006, Conclusion 3) and conjectured, based on numerical simulations, that the Stahl (1989) model gives rise to an inverse-U–shaped relationship between these two variables (see Chandra and Tappata, 2008). We contribute an analytical proof for this conjecture, extending an earlier result by Tappata (2009) derived in the Varian (1980) model without search. We also prove the result for measures of price dispersion that go beyond the value of information (VOI) measure used by Tappata (2009).

A strand of literature has relied on Internet usage or adoption to measure the fraction of consumers having access to the clearinghouse. Analyzing price dispersion in the market for life insurance, Brown and Goolsbee (2002) use variation in the share of consumers searching on the Internet as their measure of consumer information. They find that the early increase in Internet usage has resulted in an increase in price dispersion at very low levels and in a decrease later on. Focusing on the Internet book market, Tang et al. (2010) observe that an increase in shopbot use is correlated with a decrease in price dispersion over time. Sengupta and Wiggins (2014) find no significant relationship between price dispersion and the share of Internet usage for airline fares.

Earlier literature has, however, identified a number of issues that can arise when using Internet usage or access as a proxy for consumer information. First, Baye and Morgan (2001) stress that consumers' decisions to use price comparison websites are endogenous. As consumers' expected gains from obtaining information from such platforms increase with price dispersion, a correlation between the share of Internet users and price dispersion cannot be given a causal interpretation.[7] Second, Ellison and Ellison (2005, 2009) question the extent to which the Internet has made consumers better informed. They provide evidence that firms in online markets often engage in bait-and-switch and obfuscation strategies that frustrate consumer search. Our article sidesteps these difficulties by focusing on an offline market and constructing a novel measure of consumer information based on commuting patterns.

Our empirical approach differs from that in Sorensen (2000) and Chandra and Tappata (2011), who compare price dispersion for different products and argue that search intensity differs across those different products. Sorensen (2000) finds that prescription drugs that must be purchased more frequently exhibit lower price–cost margins and less price dispersion. He interprets purchase frequency as measuring the benefit of becoming informed—this interpretation is valid provided prices stay constant over several purchases.[8] Chandra and Tappata (2011) argue that people owning expensive cars tend to purchase higher-octane fuel, implying that the opportunity cost of search is higher in markets for higher-octane grade. They find that the impact of octane grade on price dispersion is consistent with a model of endogenous access to the clearinghouse. By contrast, we focus on a single product, diesel, construct explicitly a measure of consumer information, and relate it to price dispersion.

The remainder of the article is organized as follows: Section 2 presents the clearinghouse model and derives testable prediction on the relationship between consumer information and

[6] In the Stahl (1989) model, the equilibrium price distribution is common knowledge, and the nonshoppers observe a first price quote for free before engaging in sequential search with costless recall. Extensions include models where the first price quote is costly (Janssen et al., 2005), recall is costly (Janssen and Parakhonyak, 2014), nonshoppers do not know the firms' underlying production costs (Janssen et al., 2011), nonshoppers only know the support of the price distribution (Parakhonyak, 2014), and search costs are heterogeneous (Stahl, 1996; Chen and Zhang, 2011).

[7] Indeed, Byrne and de Roos (2017) provide empirical evidence that consumers are more likely to use a gasoline price comparison website when prices are more dispersed. Such websites did not exist during our sample period (1999–2005).

[8] Daily data in Loy et al. (2018) on a subsample of 282 gasoline stations in Austria between January 2003 and December 2004 show that the median gasoline station changes prices at least twice a week, and that 90% of stations change prices at least once a week. Prices are thus very unlikely to be the same between two purchases. Differences in demand will affect the probability of purchase instead of search costs per purchase. Our theoretical predictions are robust to different purchase frequency (see Remark 2 in Section 2).

prices. Section 3 describes the industry, the retail price data, and our construction of a measure of informed consumers based on commuting patterns. Section 4 presents the empirical results. Section 5 provides quantitative implications and concludes.

2. INFORMATION AND PRICE DISPERSION IN CLEARINGHOUSE MODELS

In this section, we use a unit-demand version of the Stahl (1989) search model, which subsumes the Varian (1980) model of sales as a special case, to obtain predictions on the relationship between consumer information and firms' pricing behavior. Our main testable predictions are derived in Subsection 2.1. Further results on heterogeneous consumer demand, the role of market structure, and alternative measures of price dispersion are stated in Subsection 2.2.

2.1. *Main Testable Predictions.* There is a finite number of symmetric firms, $N > 1$, selling a homogeneous product. They face constant marginal cost c and compete in prices. There is a unit mass of consumers with unit demand for the product and willingness to pay v. A share $\mu \in (0, 1)$ of consumers, referred to as "informed" consumers or "shoppers," observes all prices through the clearinghouse and buys at the lowest price provided it does not exceed their willingness to pay. The remaining fraction of consumers $(1 - \mu)$, referred to as "non-shoppers," engages in sequential search with costless recall: The first price sample is free; thereafter, each sample costs $s > 0$.

2.1.1. *Equilibrium price distribution.* It is well known that the unique symmetric equilibrium is in mixed strategies. The equilibrium price distribution $F(\cdot)$ ensures that each firm is indifferent between setting any price p in the support $[\underline{p}, \overline{p}]$ and setting $\bar{p}$:

$$(1) \qquad (p - c)\left(\mu(1 - F(p))^{N-1} + (1 - \mu)\frac{1}{N}\right) = (\overline{p} - c)(1 - \mu)\frac{1}{N}.$$

The first term in large brackets on the left-hand side corresponds to the expected quantity sold to shoppers (which the firm serves with probability $(1 - F(p))^{N-1}$). The second term corresponds to the quantity sold to the the firm's $(1 - \mu)/N$ nonshoppers. Manipulating condition (1) yields:

$$(2) \qquad F(p) = 1 - \left(\frac{1 - \mu}{\mu}\frac{1}{N}\frac{\overline{p} - p}{p - c}\right)^{\frac{1}{N-1}}$$

for all $p \in [\underline{p}, \overline{p}]$. Solving for $F(\underline{p}) = 0$ gives the lower bound of the support:

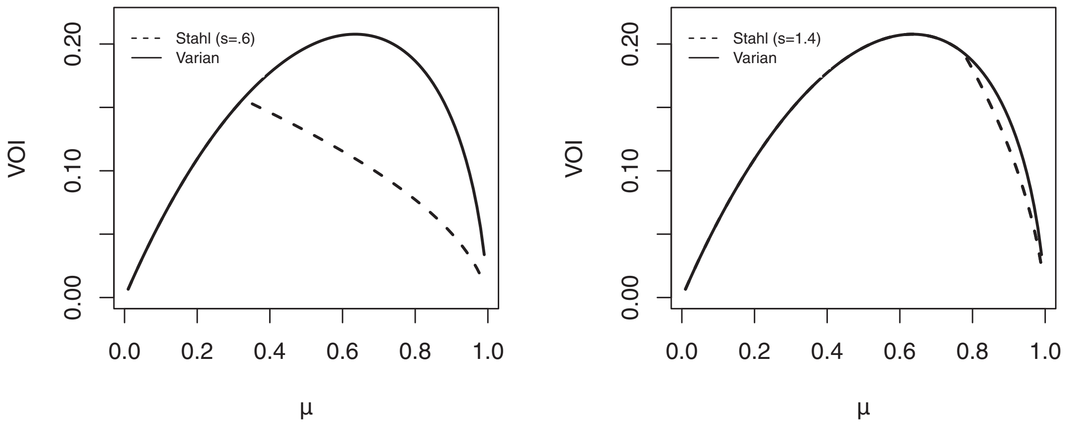
$$\underline{p} = c + \frac{\bar{p} - c}{1 + \frac{\mu}{1-\mu}N}.$$

The upper bound of the support depends on the nonshoppers' optimal search behavior, which satisfies a stationary reservation price property. The reservation price ρ is such that nonshoppers are indifferent between purchasing at ρ, and paying the search cost to receive a new price quote drawn from F:

$$v - \rho = v - s - \int_{\underline{p}}^{\rho} p dF(p) - (1 - F(\rho))\rho.$$

Janssen et al. (2005) and Janssen et al. (2011) show that $\rho = c + s/(1 - A)$, where

$$A = \int_0^1 \frac{dz}{1 + \frac{\mu}{1-\mu}Nz^{N-1}} \in (0, 1).$$



NOTES: The relationship between μ and VOI induced by the Varian (1980) model, where nonshoppers cannot search, is illustrated by the solid line in both panels. The relationship induced by the Stahl (1989) model, illustrated by the dashed line, depends on the search cost s. For low enough μ, the reservation price is not binding and the two models coincide. When s is small (left panel), the reservation price ρ starts to bind for low levels of μ, implying that $\widehat{\mu} = \overline{\mu}$. For larger search costs, ρ starts to bind for larger μ only, so that the Varian and Stahl models only differ after price dispersion peaks: $\widehat{\mu} > \overline{\mu}$. The model parameters are $N = 2$, and $v - c = 2$.

FIGURE 1

ILLUSTRATION OF PROPOSITION 1

The upper bound of the support is therefore given by $\overline{p} = \min(\rho, v)$.

Observe that the gain from search (gross of the search cost s) is at most $v - c$, since no firm ever prices above v or below c. This implies that if the search cost is too high, namely, $s \geq v - c$, then nonshoppers never find searching profitable and our model is equivalent to the Varian (1980) model. In this case, $\rho > v$ and $\overline{p} = v$ for all (μ, N).

If instead $s < v - c$, then the nonshoppers' threat of searching may constrain the firms' pricing. Specifically, as ρ is strictly decreasing in μ and has limits $+\infty$ and $c + s$ in 0 and 1, there exists a unique $\widehat{\mu} \in (0, 1)$ such that $\overline{p} = v$ if $\mu \leq \widehat{\mu}$ and $\overline{p} = \rho$ if $\mu \geq \widehat{\mu}$. Intuitively, when μ is high, firms compete fiercely to attract the shoppers, resulting in a low expected price. A nonshopper receiving a high price sample would find it worthwhile to pay the search cost s to receive a significantly lower price sample. The firm that charges the high price would then sell neither to the shoppers nor to its nonshoppers, resulting in zero profits.[9]

We have thus fully characterized the unique symmetric equilibrium: Firms draw their prices from the distribution function F defined in Equation (2), with $\overline{p} = \rho$ if $s < v - c$ and $\mu \leq \widehat{\mu}$, and $\overline{p} = v$ otherwise. Figure 1 illustrates how s and the possibility to search in the Stahl (1989) model affect the price distribution relative to the Varian (1980) model.

2.1.2. *Price level.* The expected price is given by

$$E(p) = \int_{\underline{p}}^{\min(\rho, v)} p\, dF(p) = c + (\min(\rho, v) - c)A, \tag{3}$$

where the second equality follows by using Equation (2) and the change of variables $z = 1 - F(p)$. As A and ρ are both decreasing in μ, we immediately obtain that the expected price decreases with the fraction of shoppers. We thus obtain a first testable prediction:

[9] A perhaps surprising feature of the Stahl (1989) model is that, although the nonshoppers' ability to search can constrain the firms' pricing behavior, search never occurs on the equilibrium path. Search would take place in equilibrium if the nonshoppers were (sufficiently) heterogeneous in their search costs (as in, e.g., Stahl, 1996), which we have assumed away for simplicity.

REMARK 1. The expected price $E(p)$ is declining in the proportion of informed consumers μ.

Intuitively, as the proportion of shoppers increases, firms are increasingly tempted to attract them by charging low prices, resulting in a first-order stochastic dominance shift toward lower prices (see Stahl, 1989).

2.1.3. *Price dispersion.* Various measures of price dispersion have been used in the literature. In this subsection, we focus on one common measure, the VOI, which corresponds to a consumer's expected benefit of becoming informed. (See subsection 3.1 in Baye et al., 2006, for a discussion of this and other measures of price dispersion.) In equilibrium, the expected payoff of a nonshopper is given by $v - E(p)$, whereas a shopper receives an expected payoff of $v - E(p_{\min})$, where $p_{\min} \equiv \min_{1 \le i \le N} p_i$ is the minimum price in the market. The VOI is therefore given by:

$$\text{VOI} = E(p - p_{\min}) = \int_{\underline{p}}^{\overline{p}} p\Big(1 - N(1 - F(p))^{N-1}\Big) dF(p). \tag{4}$$

Substituting the equilibrium price distribution (2) into Equation (4) and applying again the change of variables $z = 1 - F(p)$ yields:

$$\begin{aligned} \text{VOI} &= \int_0^1 \left(c + \frac{\overline{p} - c}{1 + \frac{\mu}{1-\mu} N z^{N-1}}\right)(1 - N z^{N-1}) dz, \\ &= (\min(\rho, v) - c)\left(A - \frac{1-\mu}{\mu}(1 - A)\right). \end{aligned}$$

An immediate observation is that the relationship between information and price dispersion is nonmonotonic. This holds as the VOI vanishes when μ tends to zero or one, whereas VOI is strictly positive for every μ in (0, 1).[10,11] The following proposition, which delivers a second testable prediction, characterizes the global relationship between information and price dispersion:

PROPOSITION 1. *There is an inverse-U–shaped relationship between price dispersion $E(p - p_{\min})$ and the proportion of informed consumers μ: There exists a $\overline{\mu} \in (0, 1)$ such that price dispersion is increasing in μ on $(0, \overline{\mu})$ and decreasing in μ on $(\overline{\mu}, 1)$.*

PROOF. Lemma 1 in Tappata (2009) implies that $A - \frac{1-\mu}{\mu}(1 - A)$ is strictly concave in μ. Combining this with the fact that VOI tends to 0 as μ tends to 0 and 1 proves the proposition for the case $s \ge v - c$. Next, assume $s < v - c$. Then, VOI is strictly concave on the interval $(0, \widehat{\mu})$, and we now claim that it is strictly decreasing on $(\widehat{\mu}, 1)$. If $\mu \ge \widehat{\mu}$, then $\overline{p} = \rho$ and VOI simplifies to $s(\frac{A}{1-A} - \frac{1-\mu}{\mu})$, which is indeed strictly decreasing in μ by Lemma A.1, stated and proven in Appendix A.1. This concludes the proof of the proposition.

[10] To see this, notice that $\lim_{\mu \to 0} A = 1$, $\lim_{\mu \to 1} A = 0$, and

$$\lim_{\mu \to 0} \frac{1-\mu}{\mu}(1 - A) = \lim_{\mu \to 0} \int_0^1 \frac{N z^{N-1}}{1 + \frac{\mu}{1-\mu} N z^{N-1}} dz = 1.$$

[11] The result that VOI vanishes when $\mu = 0$ and 1 but is strictly positive when μ is interior continues to hold in the extensions of the Stahl model mentioned in Footnote 6. Janssen et al. (2005) is a notable exception: In that paper, due to the first price sample being costly as well, it can be shown that VOI is constant and strictly positive over $(0, \widehat{\mu})$ and strictly decreasing over $(\widehat{\mu}, 1)$. Note however that in that paper, a positive mass of nonshoppers drops out of the market when μ is low—a prediction that appears unappealing in our empirical application to retail gasoline.

We now provide a brief sketch of the proof of Lemma A.1. We first argue that $s(\frac{A}{1-A} - \frac{1-\mu}{\mu})$ is strictly decreasing in μ on (0, 1) if and only if $\frac{B(x)}{1-B(x)} - \frac{1}{x}$ is strictly decreasing in x on $(0, \infty)$, where $B(x) = \int_0^1 \frac{dz}{1+xNz^{N-1}}$. In turn, this is equivalent to $B(x) > \Gamma(x)$ for all $x > 0$, where $\Gamma(x)$ is the smallest root of a quadratic polynomial. Using a third-order Taylor approximation, we show that $B(x) > \Gamma(x)$ when x is in the neighborhood of 0. Next, we show that $B(\cdot)$ is the solution of a differential equation, and that $\Gamma(\cdot)$ is a subsolution of the same differential equation. From this, we can conclude that $B(x) > \Gamma(x)$ for all $x > 0$. We refer the reader to Appendix A.1 for details. ■

To see the intuition behind this result, consider starting at $\mu = 0$, where all firms charge the monopoly price v and there is no price dispersion. As μ increases, firms have an incentive to charge lower prices to capture the shoppers. Hence, the lower bound of the distribution shifts down, the support widens, and dispersion increases. As μ increases further, more mass shifts toward the lower bound. This effect tends to offset the support-widening effect, so that eventually price dispersion falls. In the case $\mu \geq \widehat{\mu}$, the reservation price ρ is binding, and therefore, both the upper bound and the lower bound of the distribution shift down: When firms are constrained by the optimal search behavior of nonshoppers, the support widens less as μ increases. Consequently, price dispersion decreases for all $\mu \geq \widehat{\mu}$. The argument is also illustrated in Figure 1.

2.2. *Further Results.*

2.2.1. *Heterogeneous demand.* In our empirical application to retail gasoline, where shoppers are proxied by commuters, shoppers' and nonshoppers' demand may well differ systematically. The following remark shows that our testable predictions (Remark 1 and Proposition 1) continue to obtain if shoppers have higher (or lower) demand than nonshoppers:

REMARK 2. Consider the following modification of the Stahl (1989) model: A shopper is willing to pay v with probability $\phi \in (0, 1]$, and 0 with complementary probability $1 - \phi$; a nonshopper is willing to pay v (respectively, 0) with probability $\psi \in (0, 1]$ (respectively, $1 - \psi$). There is still a decreasing relationship between the expected price and the share of shoppers, and an inverse-U–shaped relationship between price dispersion and the share of shoppers.

PROOF. Indifference condition (1) becomes:

$$(p - c)\left(\mu\phi(1 - F(p))^{N-1} + (1 - \mu)\psi\frac{1}{N}\right) = (\bar{p} - c)(1 - \mu)\psi\frac{1}{N}. \tag{5}$$

Define $\nu(\mu) \equiv \frac{\mu\phi}{\mu\phi+(1-\mu)\psi}$ and note that $\nu' > 0$. Condition (5) is then equivalent to

$$(p - c)\left(\nu(1 - F(p))^{N-1} + (1 - \nu)\frac{1}{N}\right) = (\bar{p} - c)(1 - \nu)\frac{1}{N},$$

which is equivalent to condition (1) if we replace μ by ν. The equilibrium mixed strategy in the heterogeneous-demand model with proportion of shoppers μ is therefore the same as the equilibrium mixed strategy in the Stahl model with proportion of shoppers $\nu(\mu)$.

Let VOI(μ) be the VOI in the Stahl model. The VOI in the heterogeneous-demand model is $\widetilde{\text{VOI}}(\mu) = \text{VOI}(\nu(\mu))$. As $\nu(\cdot)$ is strictly increasing and VOI($\cdot$) is strictly quasi-concave by Proposition 1, $\widetilde{\text{VOI}}$ is strictly quasi-concave. Moreover, as $\nu(0) = 0$ and $\nu(1) = 1$, $\widetilde{\text{VOI}}(0) = \widetilde{\text{VOI}}(1) = 0$, and so $\widetilde{\text{VOI}}$ is inverse-U shaped. By the same argument, the expected price in the heterogeneous-demand model decreases with μ. ■

2.2.2. *Alternative measures of price dispersion.* We now show that our prediction of an inverse-U–shaped relationship between information and price dispersion continues to obtain with other commonly used measures of dispersion. We focus on two alternative measures: the standard deviation of prices and the expected sample range (defined as $E(p_{\max} - p_{\min})$, where $p_{\max} = \max_{1 \leq i \leq N} p_i$).

PROPOSITION 2. *There is an inverse-U–shaped relationship between the standard deviation of prices and the proportion of informed consumers.*

PROOF. As in the proof of Proposition 1, we prove the result by exploiting the properties of super- and subsolutions of a certain differential equation. See Appendix S1.1.2 (available online) for details. ■

REMARK 3. There is an inverse-U shaped relationship between the expected sample range and the proportion of informed consumers.

PROOF. See Appendix S1.2.2 for analytical proofs for low N. Simulations suggest that the result also holds for higher N. ■

2.2.3. *The role of the number of firms.* The Varian and Stahl models have the surprising feature that the equilibrium expected price, $E(p)$, *increases* with the number of firms (Morgan et al., 2006; Janssen et al., 2011).[12] We do not think this prediction should be taken literally for the following reasons. First, using a version of the Varian model with a richer information structure, Lach and Moraga-González (2017) show theoretically and empirically that the impact of N on $E(p)$ depends on the entire distribution of consumer information and how that distribution changes with N. Under the natural assumption that an increase in N lowers the share of consumers who observe one price only and increases the average number of prices observed in the market, they find that an increase in N tends to *lower* $E(p)$. Second, in our empirical application, it seems likely that an increase in N, which, everything else equal, reduces the average driving distance between two gas stations in the market, will also lower the search cost s, resulting in lower prices.

Similarly, Morgan et al. (2006) and Janssen et al. (2011) show that $E(p_{\min})$ is nonincreasing in N, implying that VOI increases with N. Due to the concerns raised above, this prediction should also be taken with a grain of salt.[13]

3. INDUSTRY BACKGROUND AND DATA

3.1. *Commuters as Informed Consumers.* The main idea behind our measure of information is that commuters can freely sample prices along their daily commuting path. The idea that commuters have lower search costs for gasoline dates back at least to Marvel (1976), who argues that "[T]he low search costs [of commuters] arise simply because stations can be canvassed along the route taken to work with only slight additional effort and delay" (p. 1043 f.). A survey among German car drivers shows that commuters purchase from a larger number of gasoline stations, indicating that commuters indeed sample more prices than noncommuters.[14] (Recall

[12] Another question that arises is that of the interaction between μ and N. Simulations suggest that the cross-partial derivative $\partial^2 E(p)/\partial\mu\partial N$ is negative when μ is large and N is small, and positive otherwise. We refer the reader to Appendix S1.3 for details and further comparative statics.

[13] In Appendix S1.2.3, we show analytically that the expected sample range increases with N. Numerical simulations suggest that the standard deviation of prices is inverse-U shaped in N (see Appendix S1.1.3).

[14] The survey, which was conducted among 1,005 individuals by the German automobile club ADAC between December 2011 and January 2012, finds that nearly half of all noncommuters (46%) always fuel at the same station, although this is the case for only 29% of all commuters. A descriptive analysis is provided in Dewenter et al. (2012). We thank Ralf Dewenter for providing us with those numbers.

from Remark 2 that our predictions continue to obtain if commuters have a higher demand for fuel.)

We therefore rely on the share of long-distance commuters as a measure of the proportion of shoppers in the market. We implement this idea by sorting the potential consumers of a given station into two groups based on the length and regularity of their commute. Long-distance commuters are defined as individuals who commute to work by car on a daily basis and go beyond the boundaries of their own municipality. Our estimate of the share of informed consumers at a given gasoline station depends on the relative size of this group compared to the total size of the station's market.

3.1.1. *Commuter flows.* According to the 2001 census, 2,051,000 people in Austria go to work by car on a daily basis. For 1,396,426 of these people, the commute involves regular travel beyond the boundaries of their home municipality. We refer to these consumers as informed consumers. The Austrian Statistical Office provides detailed information on the number of individuals commuting from an origin municipality o to a different destination municipality d for each of the 2,381 administrative units in Austria. All commuters are assigned to an origin–destination pair of municipalities based on their home and workplace addresses.[15] As municipalities are generally very small regional units, we are able to create a detailed description of the commuting patterns in Austria. The average (median) municipality is 13.8 (9.4) square-miles large, and has 3,373 (1,575) inhabitants, 1.19 (1) gasoline stations, and commuter flows to 51 (32) other municipalities.

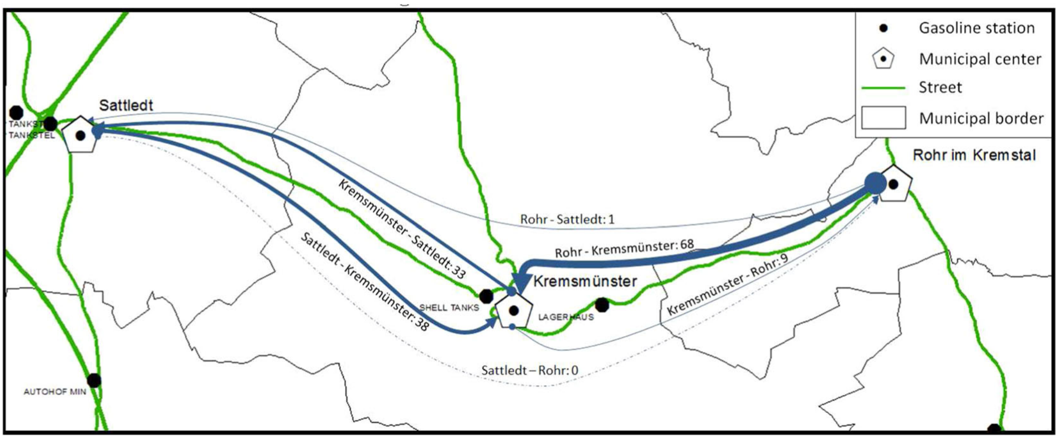
In order to assign commuter flows to gasoline stations, we merge the municipality-level data on the spatial distribution of commuters with data on the location of each station within the road network using a GIS software (WiGeoNetwork Analyst, ArcGIS). This allows us to determine the number of individuals who reside in the municipality where a station i is located and commute to a different municipality. We denote this number by C_i^{out}, the number of individuals commuting *out* of station i's municipality. Commuters who work in station i's municipality but live in a different municipality also belong to the station's informed potential consumers. We denote the corresponding number by C_i^{in}, the number of consumers commuting *in*to station i's municipality.

For a complete measure of informed consumers, we also need to take into account commuters passing by a station directly, despite neither working nor living in the municipality where it is located. We refer to these consumers as transit (tr) commuters. We assume that transit consumers are familiar with the prices of gasoline stations located directly on their commuting path, but not with the entire gasoline market in the municipality.

In order to obtain a measure C_i^{tr} of transit consumers, we use ArcGIS's shortest path algorithm. The algorithm computes the optimal route from origin municipality o to destination d by minimizing the time required to complete the trip. As the location of each consumer is only known at the municipality level, we approximate the location of the residence and workplace of commuters with the address of the administrative center of the municipalities (usually the town hall) when calculating distances. Given the small size of the municipalities, we can determine quite accurately which road transit commuters take. Our prediction will be less accurate in densely populated municipalities as high population densities usually go hand in hand with more complex infrastructure. We therefore drop gasoline stations located in Vienna from the sample in our main specification.

3.1.2. *Assigning commuter flows to gasoline stations.* We use the shortest path algorithm to determine whether a commuter flow passes through a station i. We do so by comparing the length of the optimal route from the origin to the destination municipality ($dist_{od}$) with the length of the optimal route that passes through the station (see Figure 2). If the difference in

[15] The data were prepared by the Austrian Federal Ministry for Transport, Innovation and Technology for the project "Verkehrsprognose Österreich 2025+." We thank the Ministry for sharing the data with us.



NOTES: We illustrate the commuter flow assignment using two stations in the municipality of Kremsmünster. Commuter flows from and to Kremsmünster are automatically assigned to the two stations located there (33 + 38 + 68 + 9 commuters are added to the share of informed consumers). The assignment of the one commuter from Rohr to Sattledt to one of the stations (e.g., Lagerhaus) is based on the distance of the time-minimizing path from Rohr to Sattledt (12.9 km). This distance is compared to the distance from Rohr to the station (5.2 km) and the distance from the station to Sattledt (7.8 km). If the commuter passes the Lagerhaus station in transit, he will have to travel 5.2 + 7.8 = 13 km, which is 100 m more than he would travel otherwise. As 100 m is within our critical distance, we count the commuter as one of the informed consumers in the Lagerhaus station's market.

FIGURE 2

COMMUTER FLOWS [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

distance between those two routes is less than a critical value ($\overline{dist}$), then the commuter flow may pass by the station and, as such, plays a role in the local market.[16] Specifically, we assign the commuter flow from municipality o to municipality d to station i whenever

$$dist_{oi} + dist_{id} - dist_{od} < \overline{dist}, \tag{6}$$

where $dist_{oi}$ ($dist_{id}$) is the distance of the optimal route between o and i (i and d). For our main specification, we use a small critical distance ($\overline{dist} = 250$ m) to ensure that the price of the station can be sampled without turning off the road (i.e., the station is visible without deviating from the commuting route).

If the distance between the origin and the destination municipality is large, there may be multiple routes whose length is similar to that of the optimal one. In this case, not all stations satisfying Equation (6) are necessarily on the same route. In order to account for this, we weight transit commuters for a particular station by the fraction of possible routes passing by this particular gasoline station, which boils down to assuming that consumers randomize uniformly over those routes. The details of the weighting scheme are given in Appendix A.2. The results from our algorithm show that consumers pass by a substantial number of gasoline stations: The average (median) commuter passes by 20 (11) gasoline stations, and 90% of commuters pass by at least two gasoline stations.

Using the methodology outlined above, we construct the following measure for the total number of informed consumers in the market of station i (I_i):

$$I_i = C_i^{out} + C_i^{in} + C_i^{tr}.$$

[16] We allow for this slack variable in distance as the translation of the address data to coordinates and the mapping of these coordinates might not be precise. Moreover, stations located on an intersection might be mapped on either the main or the intersecting road. Note that a critical value of $\overline{dist} = 250$ m means that a station is on the commuting path if it is located less than 125 m off the optimal route.

TABLE 1
DESCRIPTIVE STATISTICS ON THE SHARE OF INFORMED CONSUMERS

Variable	Mean	Std. Dev.	Min.	Max.
μ	0.577	0.147	0.192	0.967

We approximate the number of uninformed consumers in the market (U_i) with the number of employed individuals who live in the station's municipality and do not regularly commute over long distances by car.[17] We can then calculate a station-specific proxy for the share of informed consumers in station i's market:

$$\mu_i = \frac{I_i}{U_i + I_i}.$$

Table 1 shows summary statistics on the share of informed consumers. The mean value of our information measure lies close to the 60% mark.[18] This skewness toward larger values indicates that commuter flows account for a significant fraction of the gasoline stations' potential customers. In contrast to other empirical studies on the effects of information on price dispersion, we observe large cross-sectional variation, with the share of informed consumers ranging from 19% to 97%, thus covering a substantial range of feasible values. This significant spatial variation allows us to test the global predictions derived in Section 2. Only very low values of μ are not part of our sample.

In general, the share of commuters is below average in very rural areas (surrounded by other rural municipalities) and in larger towns or cities with many residents employed within the city boundaries. Consumers are best informed in suburban municipalities, where a large share of employed individuals commute to the agglomeration area nearby. Additionally, gasoline stations located in those municipalities often face many transit commuters, passing by those municipalities when commuting to the city.

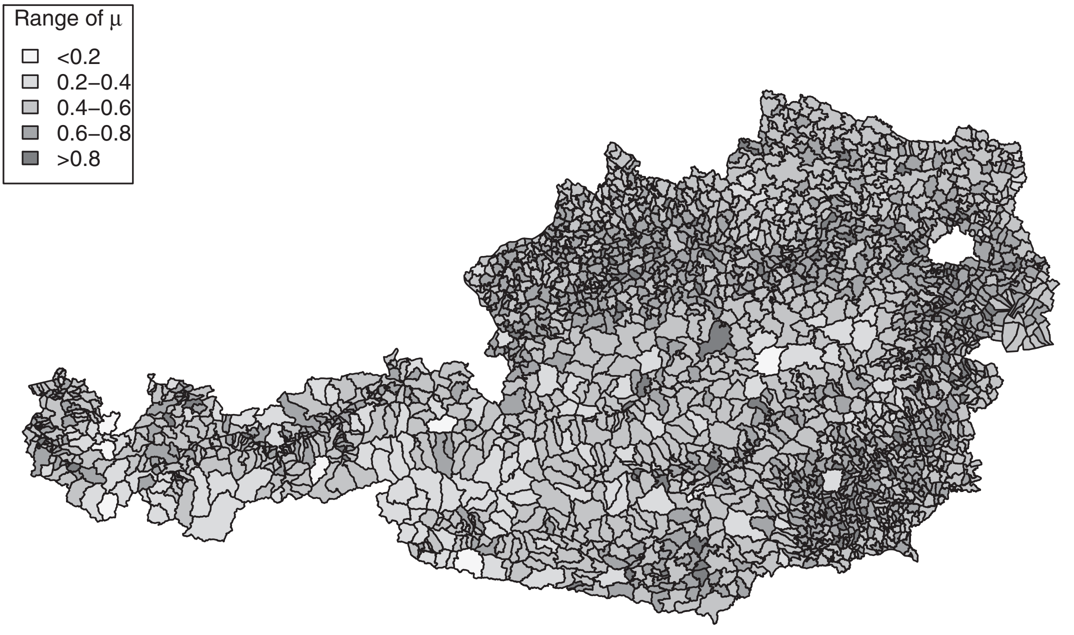
The distribution of our information measure over the entire country is illustrated in Figure 3. Figure 4 highlights symptomatic differences in the composition of the information measure: The figures show the locations of stations in a medium-sized town (depicted by the shaded area) and its surrounding municipalities. The share of informed consumers μ for stations located in the town is mainly driven by in-commuters (Figure 4a), whereas the share of out-commuters is higher for stations located outside (Figure 4b). Transit commuters are negligible for stations inside the town (Figure 4c), and are of heterogeneous importance for stations located outside, depending on whether a particular station is located on a busy commuting route. The overall share of informed consumers μ is somewhat smaller for stations located inside the town (Figure 4d).

3.2. *Diesel Prices and Stations.* Our empirical analysis focuses on the retail diesel market in Austria.[19] This market is particularly suitable for our purpose: Diesel is a fairly homogeneous product with the main source of differentiation being spatial location, which is easily controlled for. Moreover, as consumers visit gasoline stations primarily to purchase fuel, our analysis is unlikely to be confounded by consumers purchasing multiple products (see Hosken et al., 2008).

[17] We follow this approach due to lack of better data on, for example, passenger vehicle registrations at the municipality level. Given the localized character of competition and the assumed lack of mobility for uninformed consumers, a more narrow definition of U_i would be preferable, especially for very large municipalities.

[18] Although we do not have evidence from Austria to validate our measure externally, the abovementioned survey from Germany (Dewenter et al., 2012, table 8) shows that 59% of respondents compare prices either "always" or "most of the time," whereas the remaining 41% compare prices either "rarely" or "never."

[19] Unlike in North America, diesel-engine vehicles are most popular, accounting for more than 50% of registered passenger vehicles in Austria in 2005 (Statistik Austria, 2006).



NOTES: The figure illustrates the share of informed consumers μ at the municipal level. For municipalities with multiple stations, we compute the average value of μ across all stations in the municipality. In municipalities without gasoline stations, the number of informed consumers is approximated by the sum of in- and out-commuters. Data on Vienna are excluded.

FIGURE 3

REGIONAL VARIATION IN THE SHARE OF INFORMED CONSUMERS

We use quarterly data on diesel prices at the gasoline station level from October 1999 to March 2005. Prices from each station were collected by the Austrian Chamber of Labor ("Arbeiterkammer") within three days in each time period, on weekdays. We merge the price data with information on the geographical location of all 2,814 gasoline stations as well as their characteristics: the number of pumps, whether the station has service bays, a convenience store, etc.[20] Retail prices are nominal and measured in euro cents per liter, including fuel tax (a per unit tax) and value added tax. Overall, these taxes amount to about 55% of the total diesel price. Unfortunately, the Austrian Chamber of Labor did not obtain prices for all active gasoline stations in each quarter. As there is no systematic pattern for whether a particular station was sampled in a given quarter, we are not concerned with selection issues. We do control for unsampled competitors in a given market in the price-dispersion regressions.

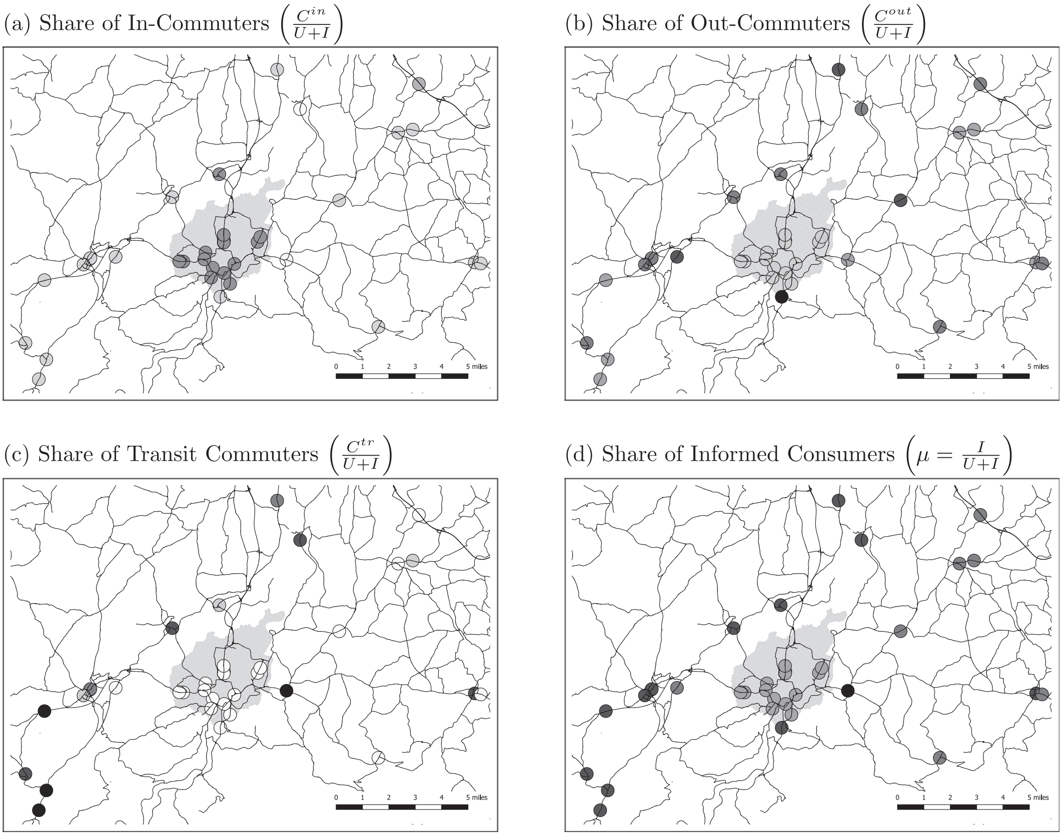
In order to characterize the spatial distribution of suppliers and measure distances between gasoline stations, we collect information about the structure of the road network. Using data from ArcData Austria and the ArcGIS extension WIGeoNetwork, the geographical location of the gasoline stations is linked to information on the Austrian road system.[21]

3.3. *Measuring Price Dispersion.* We now describe how we calculate measures of dispersion. Below we explain how we construct "residual" prices, define local markets and various measures of price dispersion, and investigate temporal price variability.

3.3.1. *Residual prices.* Although diesel fuel is a homogeneous product, gasoline stations differ in their locations, the services they provide, and other characteristics. This heterogeneity

[20] The information on gasoline station characteristics was collected by the company Experian Catalist in August 2003. See http://www.catalist.com for company details.

[21] We further supplement the individual data with demographic data (e.g., population density) of the municipality where the gasoline station is located. This information is collected by the Austrian Statistical Office ("Statistik Austria").



NOTES: All panels show the same map section of Austria. The shaded area depicts the town of Steyr, a medium-sized town with about 40,000 inhabitants and 20,000 employees, surrounded by smaller municipalities. Major roads are indicated by solid lines. The circles, indicating the location of gas stations, are colored with different shades of gray, depending on the share of commuters associated with the respective station. Darker shades correspond to higher commuter shares.

FIGURE 4

COMPOSITION OF THE INFORMATION MEASURE

is likely to explain part of the price dispersion we observe in the data. The challenge is thus to obtain a measure of price dispersion that removes those sources of heterogeneity. We follow the literature by computing the residuals of a price equation and interpreting those residuals as the price of a homogeneous product.[22] In order to obtain "cleaned" prices, we exploit the panel nature of our data following Lach (2002) and run a two-way fixed effects panel regression of "raw" gasoline prices (p^r_{it}) on seller (ζ_i) and time (χ_t) fixed effects:

$$p^r_{it} = \alpha + \zeta_i + \chi_t + u_{it}. \tag{7}$$

We focus on the residual variation, interpreting the residual price $p_{it} \equiv \hat{u}_{it}$ as the price of a homogeneous product after controlling for time-invariant station-specific effects and fluctuations in prices common to all stations. We are aware of the risk of misspecification bias in this regression: The results are only valid "if station fixed effects are additively separable from stations' costs" (Chandra and Tappata, 2011, p. 693). We therefore also examine the robustness of our results to using raw prices.

[22] See, for example, Lach (2002), Barron et al. (2004), Bahadir-Lust et al. (2007), Hosken et al. (2008), or Lewis (2008). Wildenbeest (2011) shows how to account for vertical differentiation.

TABLE 2
DESCRIPTIVE STATISTICS ON MEASURES OF PRICE DISPERSION

	Two Miles		ROL 50%		Municipality	
Local Market Delineation	Mean	SD	Mean	SD	Mean	SD
Residual Prices						
VOI^M	0.725	(0.781)	0.874	(0.938)	0.847	(0.902)
VOI	0.723	(1.095)	0.874	(1.243)	0.847	(1.204)
Range	1.467	(1.526)	1.762	(1.783)	1.725	(1.771)
SD^M	0.539	(0.546)	0.584	(0.564)	0.571	(0.556)
AD	0.466	(0.608)	0.499	(0.648)	0.486	(0.632)
Raw Prices						
VOI^M	0.747	(0.960)	0.946	(1.216)	0.900	(1.123)
VOI	0.749	(1.355)	0.946	(1.609)	0.900	(1.536)
Range	1.546	(2.028)	2.010	(2.538)	1.951	(2.513)
SD^M	0.579	(0.736)	0.668	(0.812)	0.653	(0.819)
AD	0.498	(0.797)	0.560	(0.893)	0.548	(0.892)
Number of Rival Firms (N^c)	6.965	(6.415)	13.768	(19.144)	13.781	(19.145)
Number of Rival Firms with Prices (N^c_o)	4.428	(4.351)	7.893	(10.037)	7.920	(10.054)
Number of Obervations	14,851		13,980		14,037	
Descriptive Statistics for Trimmed Range Only:						
Residual Prices						
Trimmed Range	0.881	(0.921)	1.232	(1.164)	1.210	(1.149)
Raw Prices						
Trimmed Range	0.879	(1.226)	1.279	(1.525)	1.255	(1.529)
Number of Rival Firms (N^c)	10.560	(6.769)	22.695	(21.693)	22.682	(21.662)
Number of Rival Firms with Prices (N^c_o)	7.030	(4.505)	13.012	(10.946)	13.035	(10.943)
Number of Obervations	7,996		7,840		7,895	

NOTES: The sample is restricted to market quarters where at least two prices are observed. For the trimmed range, observations are restricted to market quarters where at least four prices are observed.

3.3.2. *Local markets.* We connect each station location to the Austrian road network. Local markets are defined at the station level. We use two distinct approaches to delineate markets. In the first specification, each local market contains the location itself and all rivals within a critical driving distance of two miles. Similar approaches have been used in earlier work on retail gasoline markets (see, e.g., Hastings, 2004; Chandra and Tappata, 2011).[23] We depart from the existing literature by using driving distances instead of Euclidean distances. Local markets are thus not characterized by circles, but by a delineated part of the road network.

In the second specification, we make use of our data on commuting patterns to define local markets: Two stations are considered to be part of the same local market if the share of potential consumers they have in common (the "relative overlap," ROL, between these two stations) exceeds a certain threshold. On average, this approach tends to lead to larger local markets than the critical driving distance approach (see Table 2), although this is not necessarily true for individual markets. A detailed description of the ROL approach and a comparison between the two approaches is provided in Appendix A.2.

3.3.3. *Measures of price dispersion.* Several measures of price dispersion have been proposed in the literature. We focus first on the "value of information" (VOI). As discussed in Section 2, this is a commonly used measure and Proposition 1 is based on this metric. The VOI in gas station i's local market, m_i, is the difference between the expected price and the expected minimum price in the market: $\text{VOI}_i = E(p^{m_i}) - E(p^{m_i}_{\min})$. Although the estimate of $E(p^{m_i}_{\min})$ is given by $p^{m_i}_{(1)}$ (the first-order statistic of prices sampled in market m_i), there are two possibilities to

[23] We face the common problem in the literature that our theoretical model delivers predictions for isolated markets, whereas the markets we define for our empirical analysis overlap with each other. We address this issue by extensively examining the robustness of our results to market definition.

construct $E(p^{m_i})$. A first possibility is to use station i's price as the expected price: $E(p^{m_i}) = p_i$ and $\text{VOI}_i = p_i - p^{m_i}_{(1)}$. Another possibility is to follow Chandra and Tappata (2011) and use the average local market price $\overline{p}^{m_i}$, so that $E(p^{m_i}) = \overline{p}^{m_i}$ and $\text{VOI}^M_i = \overline{p}^{m_i} - p^{m_i}_{(1)}$ (where the superscript M stands for "market").

Another common measure of price dispersion, explored in Subsection 2.2, is the sample range: the difference between the highest and the lowest price, that is, $\text{R}_i = p^{m_i}_{(N)} - p^{m_i}_{(1)}$. As this measure is strongly influenced by outliers, we also use the trimmed range $\text{TR}_i = p^{m_i}_{(N-1)} - p^{m_i}_{(2)}$, that is, the difference between the $(N-1)$-th and the second-order statistic. A disadvantage of the latter measure is that it can only be computed in local markets with at least four firms.

As VOI, R, and TR are based on extreme values, these measures depend heavily on the number of firms in the local market: Even if the price distribution is not affected by the number of firms, the expected values of these measures of price dispersion increase with the number of stations. Measures that are less dependent on the number of firms compare the price of a station (or of all stations) with the local market average. Similar to VOI, we can compare either the price of station i or the prices of all stations within a local market with the average (local) market price. In the former case, the measure is the absolute difference between the price of station i and the average market price, $\text{AD}_i = |p_i - \overline{p}^{m_i}|$. In the latter case, the measure is the standard deviation, $\text{SD}^{m_i}_i = \sqrt{\sum_{j\in m_i}(p_j - \overline{p}^{m_i})^2/(N^{m_i})}$, where N^{m_i} is the number of firms in station i's market.

Table 2 reports summary statistics for these price dispersion measures for different market delineations, namely, using a critical driving distance of two miles, an ROL threshold of 50%, and administrative boundaries (the municipality where the station is located). For each market delineation, the number of observations drops when calculating the trimmed range as the sample is restricted to market-quarters where at least four prices are observed. Prices are least dispersed with the two-mile driving distance delineation, and most dispersed with the ROL definition. The SD is less dependent on how the market is defined, as expected. Although raw prices are more dispersed than cleaned prices, the difference appears small.

3.3.4. *Temporal price variation.* One question that arises is whether price dispersion is caused by permanent price differences across firms, or whether firms indeed employ mixed strategies. We follow Chandra and Tappata (2011) and calculate a measure of rank reversals rr_{ij} for each pair of stations i and j (provided that i and j are located in the same local market and that we can observe the prices of both stations for at least two time periods). Let T_{ij} denote the number of periods where price information is available for both firms. Subscripts i and j are assigned to the two stations so that $p_{it} \geq p_{jt}$ for most time periods. The measure of rank reversals is defined as the proportion of observations with $p_{jt} > p_{it}$:

$$rr_{ij} = \frac{1}{T_{ij}} \sum_{t=1}^{T_{ij}} \mathbf{I}_{\{p_{jt} > p_{it}\}}.$$

Our results are in line with Chandra and Tappata (2011). When using raw prices, the station that is cheaper most of the time charges higher prices in 10.5% of all time periods. Our measure of rank reversals increases to 21.5% when analyzing cleaned prices instead of actual prices, suggesting that firms are indeed mixing.

4. TESTING THE RELATIONSHIP BETWEEN INFORMATION AND PRICES

In this section, we apply both parametric and nonparametric techniques to test the predictions derived in Section 2.

4.1. *Information and the Price Level.* The clearinghouse model presented in Section 2 predicts that prices p_{it} charged by gasoline station i decrease with the share of informed consumers

TABLE 3
REGRESSION RESULTS ON PRICE LEVELS (DELINEATION: TWO MILES)

Dependent Variable:	Full Sample		Markets with at Least Two Stations		Markets with at Least Four Stations	
Price Level (Diesel)	(1)	(2)	(3)	(4)	(5)	(6)
μ	−1.862***	−2.742***	−1.576***	−2.392***	−1.594***	−2.673***
	(0.315)	(0.329)	(0.373)	(0.393)	(0.519)	(0.520)
Number of Rival Firms (N^c)	−0.012	−0.018**	−0.008	−0.016*	−0.013	−0.024**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Time Fixed Effects	Yes	No	Yes	No	Yes	No
Brent Price in Euro		0.220***		0.221***		0.224***
		(0.006)		(0.007)		(0.011)
Constant	73.084***	74.095***	72.988***	74.151***	72.623***	74.197***
	(0.369)	(0.413)	(0.458)	(0.498)	(0.594)	(0.642)
Number of Observations	21,905	21,905	14,851	14,851	7,996	7,996
R^2	0.804	0.171	0.805	0.166	0.809	0.166

NOTES: Robust standard errors in parentheses. Random effects regressions include station- and region-specific characteristics, state fixed effects, as well as dummy variables for missing exogenous variables. Models (1), (3), and (5) include time fixed effects.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

μ_i (Remark 1). In order to test this prediction, we estimate the following linear regression:

$$p_{it} = \alpha + \tau\mu_i + X_{it}\psi + \kappa_{it}, \quad (8)$$

where X_{it} represents possible confounding factors at the station or regional level as well as over time. Specifically, X_{it} includes the number of rival stations in the local market as a measure of the competitive environment, and station-specific control variables, such as indicator variables for brand names (10), dummy variables for (other) station characteristics (whether the station has a service bay, a car wash facility, a shop, self-service or is open 24 hours a day, whether the station is dealer owned, or located on a highway), and the station's number of pumps. Regional variables include data on the population density and on tourism at the municipality level as well as state fixed effects (7). Fluctuations of crude oil prices are controlled for by including either price quotes for Brent crude oil or time fixed effects, depending on the model specification.

Table 3 presents the results. The first and second columns contain results using the entire sample, whereas the third and fourth (fifth and sixth) columns show results when restricting the sample to stations where the prices of at least one (three) rival firm(s) in the local market are available. All regressions include either time fixed effects (first, third, and fifth columns) or the crude oil price index (second, fourth, and sixth columns). The parameter estimates on the share of informed consumers μ are negative and statistically significant at the 1% level in all model specifications, suggesting that a larger share of informed consumers does reduce price levels. The point estimates vary between −2.7 and −1.6: Going from no informed consumers to all consumers being informed would therefore reduce prices by about two cents.

The parameter estimates on the number of rival firms N^c are always negative, but significantly different from zero in some specifications only. As discussed in Subsection 2.2, although our clearinghouse model predicts a positive impact of N^c, models that are richer in their information structure (or that account for the fact that the search cost s depends negatively on N) tend to predict a negative effect. As expected (and documented in the existing empirical literature, see Eckert, 2013), crude oil prices exert a positive and highly significant impact on retail price levels.

4.2. *Information and Price Dispersion.* Our prediction of an inverse-U–shaped relationship between price dispersion PD_{it} and the share of informed consumers μ_i in station i's market

TABLE 4
REGRESSION RESULTS USING RESIDUAL PRICES TO CALCULATE DISPERSION AND A MARKET DELINEATION OF TWO MILES

	(1) VOI^M	(2) VOI	(3) *Range*	(4) *Trimmed Range*	(5) *SD*	(6) *AD*
μ	1.705***	1.709***	2.994***	4.192***	0.913***	0.851***
	(0.300)	(0.460)	(0.586)	(0.555)	(0.237)	(0.264)
μ^2	−1.210***	−1.182***	−2.046***	−2.971***	−0.600***	−0.594***
	(0.249)	(0.388)	(0.489)	(0.460)	(0.200)	(0.225)
Number of Rival Firms with Prices (N_o^c)	0.064***	0.065***	0.122***	0.060***	0.018***	0.007***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
Number of Rival Firms (N^c)	0.004*	0.005	0.016***	0.024***	0.005***	0.004**
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	−0.575***	−0.605***	−1.075***	−1.616***	−0.232***	−0.095
	(0.109)	(0.173)	(0.221)	(0.220)	(0.088)	(0.101)
Lower Bound	0.214	0.214	0.214	0.329	0.214	0.214
Slope at Lower Bound	1.186	1.203	2.118	2.240	0.656	0.597
t	6.070	4.047	5.558	8.564	4.292	3.515
p	0.000	0.000	0.000	0.000	0.000	0.000
Upper Bound	0.967	0.967	0.967	0.967	0.967	0.967
Slope at Upper Bound	−0.637	−0.578	−0.965	−1.556	−0.247	−0.299
t	−3.320	−1.881	−2.553	−4.393	−1.567	−1.661
p	0.001	0.030	0.005	0.000	0.059	0.048
Overall Inverse-U Test						
t	3.32	1.88	2.55	4.39	1.57	1.66
p	0.001	0.030	0.005	0.000	0.059	0.048
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.704	0.723	0.732	0.706	0.761	0.716
Number of obervations	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.260	0.136	0.280	0.370	0.172	0.104

NOTES: Robust standard errors in parentheses. Regressions include station- and region-specific characteristics, state and time fixed effects, as well as dummy variables for missing exogenous variables.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

(Proposition 1) can be tested by estimating the following linear regression model:

$$PD_{it} = \alpha + \beta\mu_i + \gamma\mu_i^2 + X_{it}\theta + \eta_{it},$$

where X_{it} includes the same confounding factors at the station and at the regional level as in the regression on price levels above (see Equation (8)), as well as time fixed effects.

The main parameters of interest are β and γ. An inverse-U–shaped relationship between price dispersion and information would imply that $\beta > 0$ and $\gamma < 0$. According to the parameter estimates reported in Table 4 (where local markets are defined using a two-mile critical driving distance), this proposition is supported by the data: The parameter estimates for β (γ) are positive (negative) and statistically significant at the 1% level in all specifications. As the share of informed consumers increases, price dispersion first increases and then starts decreasing once μ exceeds a critical level, which lies between 0.70 and 0.76.

The number of rival firms N^c has a positive effect on all measures of price dispersion.[24] Although this result is broadly in line with the predictions of our theoretical model, one should keep in mind the concerns raised at the end of Subsection 2.2.

In order to test formally for the presence of an inverse-U–shaped relationship between information and price dispersion, we apply the statistical test suggested in Lind and Mehlum

[24] We also control for the number of rival firms where prices are observed in a particular period, N_o^c, as some measures of price dispersion (such as the sample range) increase mechanically if the number of price observations increases, holding fixed the number of rival firms N^c in the market.

TABLE 5
REGRESSION RESULTS USING RESIDUAL PRICES TO CALCULATE DISPERSION AND A MARKET DELINEATION OF 50% RELATIVE OVERLAP

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed Range*	(5) *SD*	(6) *AD*
μ	3.363***	3.154***	5.575***	8.499***	1.301***	1.344***
	(0.411)	(0.602)	(0.768)	(0.862)	(0.305)	(0.357)
μ^2	−2.739***	−2.614***	−4.517***	−6.881***	−1.073***	−0.997***
	(0.343)	(0.507)	(0.648)	(0.768)	(0.257)	(0.298)
Number of Rival Firms with Prices (N_o^c)	0.044***	0.043***	0.090***	0.056***	0.010***	0.005***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)
Number of Rival Firms (N^c)	0.005***	0.004***	0.007***	0.012***	0.001***	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Constant	−0.599***	−0.538**	−0.979***	−3.087***	−0.060	−0.039
	(0.143)	(0.213)	(0.272)	(0.282)	(0.106)	(0.128)
Overall Inverse-U Test						
t	7.20	4.71	6.14	7.25	3.79	2.45
p	0.000	0.000	0.000	0.000	0.000	0.007
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.614	0.603	0.617	0.618	0.607	0.674
Number of Observations	13,980	13,980	13,980	7,840	13,980	13,980
R^2	0.335	0.194	0.378	0.543	0.169	0.097

NOTES: Robust standard errors in parentheses. Regressions include station- and region-specific characteristics, state and time fixed effects, as well as dummy variables for missing exogenous variables.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

(2010).[25] This test calculates the slope of the estimation equation at both ends of the distribution of the explanatory variable (μ). A positive slope for low values of the information measure and a negative slope after a certain threshold ($\bar{\mu}$) would imply an inverse-U–shaped relationship between information and price dispersion. The test is an intersection-union test as the null hypothesis is that the parameter vector is contained in a union of specified sets.

The results are reported in Table 4. At the lower bound of our set of observations, the slope is positive and significantly different from zero at the 1% level for all measures of price dispersion. At the upper bound, the slope is negative in all specifications. It is significantly different from zero at the 1% level for the VOI^M, R, and TR measures, at the 5% level for the VOI and AD measures, and at the 10% level for the SD measure.

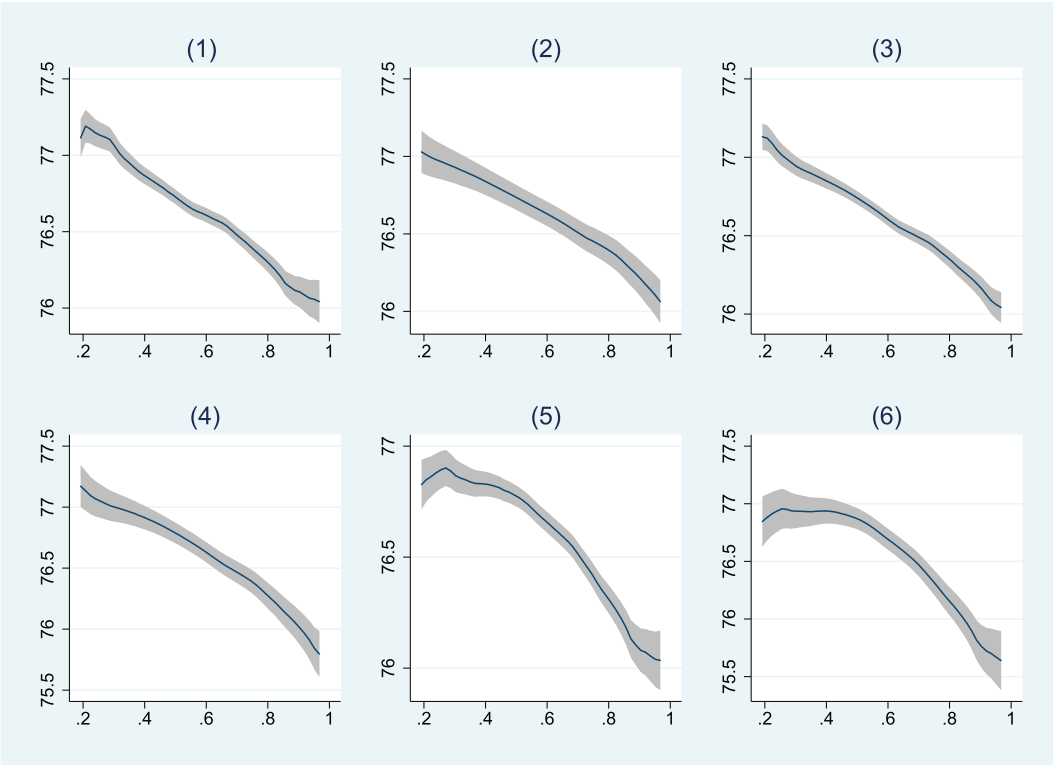
Using the ROL approach to market definition delivers even stronger results. With an ROL threshold of 50%, the parameter estimates on μ (μ^2) are positive (negative) and statistically significant, and the intersection-union test is rejected at a 1% significance level for all measures of price dispersion. These results are summarized in Table 5.

Comparing the magnitude of the coefficient estimates on μ and μ^2 across the models, we find that the (absolute values of the) parameters are largest for R and TR and lowest for SD and AD. This is due to the fact that R and TR are more dispersed than SD and AD, as the first two measures (and, to a lesser extent, VOI^M and VOI) are more affected by extreme values in the local price distribution.

The inverse-U–shaped relationship between our measures of informed consumers and price dispersion suggests that price dispersion is significantly smaller in markets where firms have mainly either informed or uninformed consumers. For markets with intermediate levels of consumer information, our findings clearly reject the law of one price.

4.2.1. *Robustness.* In order to confirm that our results are not driven by using residual instead of raw prices, by the specific product, by specific assumptions imposed on the error term, by the

[25] Lind and Mehlum (2010) argue that although a positive linear and a negative quadratic term supports a concave relationship between two variables, it is not sufficient to guarantee an inverse-U–shaped relationship since the relationship may be concave but still monotone in the relevant range.



NOTES: This figure presents Nadaraya–Watson estimates of the function $g(\mu_i)$ in Equation (9) and 95% confidence bands using an Epanechnikov kernel. The panels correspond to the six parametric specifications in Table 3.

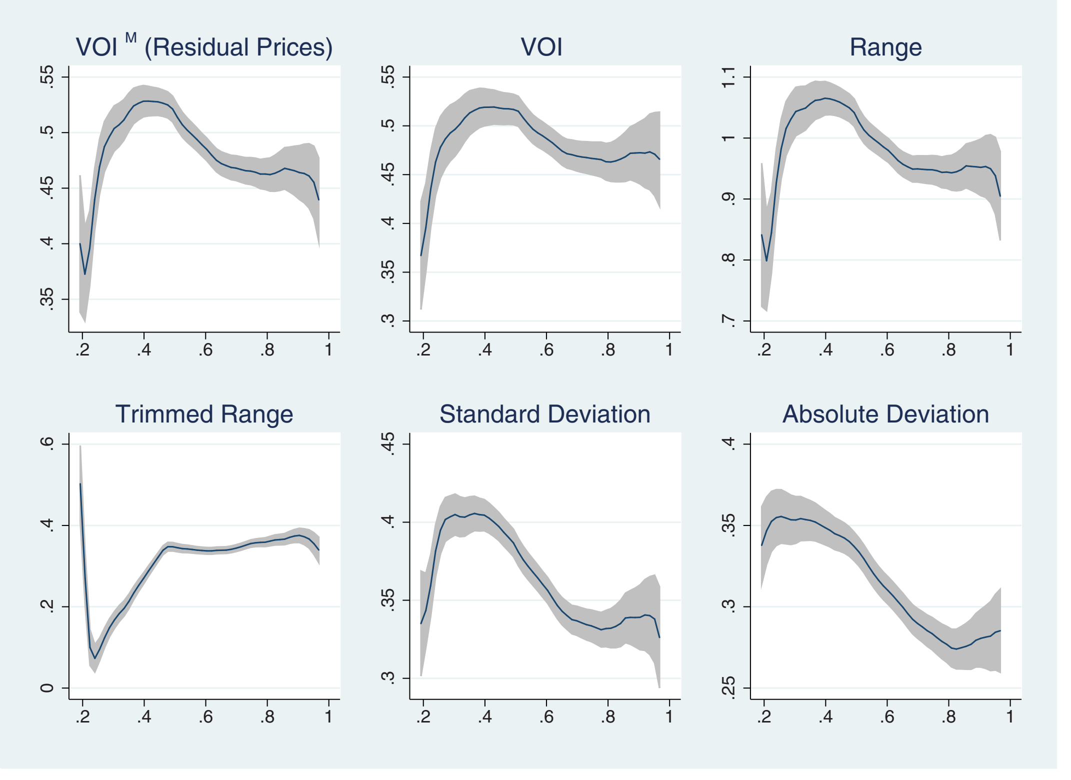
FIGURE 5

SEMIPARAMETRIC EVIDENCE ON THE PRICE LEVEL [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

way in which we delineate local markets, by particular subsamples, or by the approach used to calculate the measure of consumer information μ, we have carried out a number of robustness checks. Below, we summarize the results of these robustness exercises, referring the reader to Appendix S2 (available online) for detailed descriptions of the various model alterations, more thorough discussions, and tables of results.

First, we investigate the relationship between consumer information and price dispersion using raw instead of residual prices. Second, we perform the same regressions using regular gasoline instead of diesel. Third, the (implicit) assumption that all observations are independent from one another may be violated as our measures of price dispersion are calculated by comparing the price of a gasoline station with prices charged by other stations in the local market. We provide a sensitivity analysis that addresses this issue by accounting for potential spatial correlation of the residuals within local markets. Fourth, we define local markets using administrative boundaries (municipalities) and a smaller critical distance (1.5 miles instead of 2 miles). When using the ROL approach to defining local markets, we use different thresholds to decide whether two stations are in the same local market. Fifth, we analyze alternative samples by excluding larger municipalities as well as stations located on highways, by including gasoline stations located in Vienna, and by restricting attention to local markets with at least three gasoline stations.

Last, we use alternative ways to calculate our measure of consumer information μ: (1) We do not weight commuter flows by the share of possible routes passing by a particular gasoline stations. (2) We consider different levels of informedness, based on the number of stations sampled by each commuter relative to the total number of stations in a local market, instead of



NOTES: This figure presents Nadaraya–Watson estimates of the function $f(\mu_i)$ in Equation (10) and 95% confidence bands using an Epanechnikov kernel.

FIGURE 6

SEMIPARAMETRIC EVIDENCE ON PRICE DISPERSION [COLOR FIGURE CAN BE VIEWED AT WILEYONLINELIBRARY.COM]

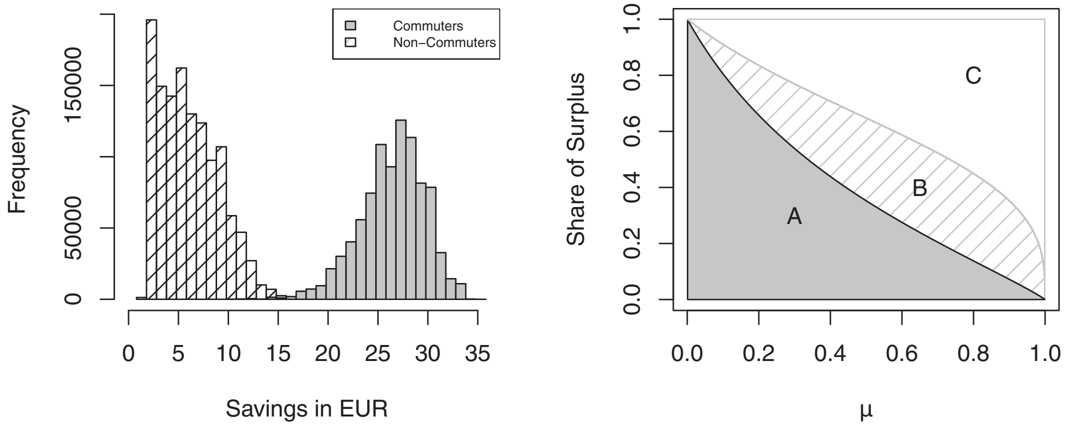
assuming that commuters are perfectly informed about all prices. (3) We account for the fact that long-distance commuters (may) drive through many local markets and therefore pass by a larger number of gasoline stations. As commuters passing by many gasoline stations are less likely to visit a particular one, these commuter flows receive lower weights when calculating this alternative measure of consumer information. (4) We use different values for the critical distance $\overline{dist}$ when assigning commuter flows to gasoline stations.

The main result of our analysis—an inverse-U–shaped relationship between consumer information and price dispersion—remains unaffected by these modifications.

4.3. *Semiparametric Evidence.* In this section, we show that our results on the relationship between information and the price level (respectively, price dispersion) are not driven by the parametric restriction to a linear (respectively, linear–quadratic) function. Given the large number of control variables, we follow a semiparametric approach: We still restrict attention to a linear specification for the vector of controls, but do not impose any parametric restrictions on the relationship between price levels (respectively, price dispersion) and information μ. We estimate the following equations semiparametrically:

$$p_{it} = \alpha + g(\mu_i) + X_{it}\psi + \kappa_{it}, \tag{9}$$

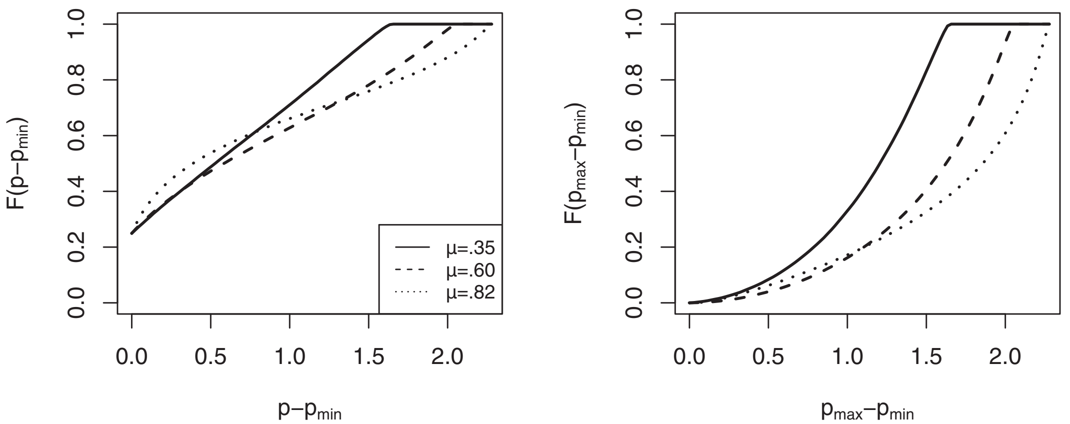
$$PD_{it} = \alpha + f(\mu_i) + X_{it}\theta + \eta_{it}. \tag{10}$$



NOTES: The left panel shows the savings distribution for commuters and noncommuters implied by the clearinghouse model, taking into account variation in market structure and information. The right panel shows the distribution of surplus in a market with four firms as a function of μ. Noncommuters receive Area C, commuters B plus C. Firms earn the residual area, depending on the type of consumer they face.

FIGURE 7

DISTRIBUTION OF SAVINGS



NOTES: The left panel shows the distribution function of the VOI and the right panel of the price range. In both panels, the distribution functions are shown for four firms and the 5th, 50th, and 95th percentiles of μ.

FIGURE 8

DISTRIBUTION FUNCTIONS FOR THE VALUE OF INFORMATION (VOI) AND PRICE RANGE

We use the two-step procedure proposed by Robinson (1988). We first obtain nonparametric estimates of $E(p\,|\mu)$ and $E(X|\mu)$ and then regress $p - E(p\,|\mu)$ on $X - E(X|\mu)$ to obtain a consistent estimate of ψ. We then regress $p - E(X|\mu)\widehat{\psi}$ on μ nonparametrically to obtain an estimate of $g(\cdot)$. Similarly, we obtain an estimate of $f(\cdot)$.

The results obtained for the nonparametric component of the price-level regression (Equation (9)) are illustrated in Figure 5. The samples and included explanatory variables correspond to the specifications reported in Table 3. Figure 5 shows a strong, negative, and close-to-linear relationship between consumer information (horizontal axis) and the price level (vertical axis).

Figure 6 reports results obtained for the nonparametric component of the price dispersion regression (Equation (10)). The restriction to a linear–quadratic function results in a peak further to the right than with a flexible functional form. Although the specific form of the relationship between information (horizontal axis) and different measures of price dispersion (vertical axis) depends on the measure of price dispersion, there is strong evidence in favor of an inverse-U shape for the relationship of interest.[26]

5. CONCLUDING REMARKS

We have studied, both theoretically and empirically, the relationship between consumer information and prices. We have shown that classic clearinghouse models generate an inverse-U–shaped relationship between the share of informed consumers and price dispersion, and a decreasing relationship between consumer information and price levels. In order to test those theoretical predictions, we have constructed a novel measure of the share of informed consumers in the market for retail gasoline. This measure relies on detailed data on commuting patterns and on the idea that commuters can freely sample prices at gasoline stations along their commuting path. Our approach thus differs from earlier approaches, which have primarily relied on Internet usage or on a comparison of online and offline markets to examine the effect of consumer information on prices. We have found robust statistical evidence supporting our theoretical predictions, thus validating the information mechanism in clearinghouse models.

It is worth emphasizing that our new measure captures variation in information on the consumers' side but not on the firms' side of the market. Our empirical setting therefore comes very close to the thought experiment of varying the share of informed consumers in a classic clearinghouse model. In many other real-world settings, however, more transparency on the consumers' side, for example, due to price comparison apps, also makes it easier for firms to monitor each other's prices. In such settings, increased transparency may thus facilitate collusion, resulting in higher prices.

We conclude by illustrating the quantitative implications of price dispersion generated by the heterogeneity of consumer information. We restrict attention to the Varian model, which does not require an estimate of the search cost s. The model implies a fixed surplus equaling willingness to pay per liter less marginal cost per liter $v - c$, which we set equal to 2.4 euro cents.[27] We distribute commuters equally among gas stations on their commuting path, and noncommuters equally among gas stations in their municipality of residence. According to the Austrian Micro-Census carried out in the years 2003 and 2004, households drove 52.5 billion km per year. From our commuting data, we obtain the share of this distance that was driven for commuting purposes, namely, 25%. The remaining driving distance is distributed equally among commuters and noncommuters. Assuming a fuel consumption of 0.079 L/km, also obtained from the Micro-Census, we can compute total annual fuel consumption for each type of consumer.

We begin by computing the savings of each type of consumer relative to a situation with no information. Overall, commuters save € 36.4 million and noncommuters save € 15 million per year. The implied individual savings are small, with average expenses reduced by € 26.42 per commuter and € 6.07 per noncommuter. As a share of total fuel expenses, this amounts to only 2.23% for commuters and 1.01% for noncommuters. These figures almost double when we consider net fuel prices, as taxes account for more than 50% of fuel costs.

The left panel in Figure 7, which illustrates the distribution of savings for the two consumer groups, shows that savings vary substantially within groups as well. This is driven by variation both in the share of informed consumers and in market structure.

In order to illustrate the effect of information alone, the right panel of Figure 7 shows how surplus is distributed between sellers, informed and uninformed consumers in a market with the median number of firms, $N = 4$, as a function of the share of informed consumers μ. The share of surplus uninformed consumers receive in expectation is given by Area C, whereas informed consumers receive B plus C. Firms earn the gray Area A from facing informed consumers and A plus B from dealing with uninformed consumers. At the sample median value of $\mu = 0.6$,

[26] We are not aware of a nonparametric test for an inverse-U shape corresponding to the parametric test of Lind and Mehlum (2010). Recently, Kostyshak (2015) suggested a critical-bandwidth approach in nonparametric regression.

[27] This corresponds to the estimate in regression (4) in Table 3.

informed consumers obtain 72% of total surplus, whereas uninformed consumers receive 42%. For low values of μ, informed consumers benefit from increasing information; for larger μ, the increase in surplus of the uninformed is more pronounced. The figure thus illustrates that although the effect of information accounts for a small share of total expenses, the impact on the distribution of surplus is substantial, even when the share of informed consumers is small.

Finally, we illustrate the distribution of the benefit of being informed across purchases in a market with the median number of firms, $N = 4$. Specifically, we plot the cumulative distribution function of the VOI, $F(p - p_{\min})$, in the left panel of Figure 8 for the 5th, 50th, and 95th percentiles of μ. The figure illustrates that the maximal benefit from being informed (1.37,1.71,1.89 for the three values of μ, respectively) is larger in markets with more informed consumers. This is due to the minimum price being lower in such markets. The distributions have a mass point at zero, as an uninformed consumer obtains the lowest price in a four-firm market with probability 1/4. For the median μ (0.6), the value of being informed is worth at least one cent per liter 37% of the time, although this is only the case 29% of the time in markets with the 5th-percentile μ (0.35). The absence of a dominance relationship between the three distributions reflects the nonmonotonic relationship between information and price dispersion.

The right panel of Figure 8 shows the distribution of the range of prices, $F(p_{\max} - p_{\min})$. Here, the results are stronger and they can be interpreted as the benefit the "unluckiest" consumer would derive from becoming informed. That benefit is at least one cent 76% of the time in the median market, whereas this is only the case 50% of the time when μ is at the 5th percentile. Overall, these simulation results demonstrate that consumer information can have substantial distributional effects across consumer groups, within consumer groups, and across purchases.

APPENDIX

A.1. *Proof of Proposition 1.* All we need to do is prove the following lemma:

LEMMA A.1. *For all* $\mu \in (0, 1)$ *and* $N \geq 2$, *let* $A(\mu) = \int_0^1 \frac{dz}{1+\frac{\mu}{1-\mu}Nz^{N-1}}$. *Then,* $\mu \in (0, 1) \mapsto \frac{A(\mu)}{1-A(\mu)} - \frac{1-\mu}{\mu}$ *is strictly decreasing.*

PROOF. For all $x > 0$ and $N \geq 2$, let $B(x) \equiv \int_0^1 \frac{dz}{1+xNz^{N-1}} \in (\frac{1}{1+xN}, 1)$. Clearly, $A(\mu) = B(\mu/(1-\mu))$ for every μ, and $\frac{A(\mu)}{1-A(\mu)} - \frac{1-\mu}{\mu}$ is strictly decreasing in μ on (0, 1) if and only if $g(x) \equiv \frac{B(x)}{1-B(x)} - \frac{1}{x}$ is strictly decreasing in x on $(0, \infty)$.

Note that

$$B'(x) = -\int_0^1 \frac{Nz^{N-1}}{(1 + xNz^{N-1})^2} dz$$

$$= \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B(x)\right), \tag{A.1}$$

where the second line follows by integrating by parts. Therefore, if we define

$$\phi(y, x) = \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - y\right), \tag{A.2}$$

then B is a solution of the differential equation $y' = \phi(y, x)$ on the interval $(0, \infty)$.

For all $x > 0$, $g'(x) = \frac{B'(x)}{(1-B(x))^2} + \frac{1}{x^2}$. Using Equation (A.1), we see that $g'(x)$ is strictly negative if and only if $P(B(x)) < 0$, where

$$P(Y) \equiv x(1 - Y(1 + xN)) + (1 - Y)^2(N - 1)(1 + xN) \;\; \forall Y \in \mathbb{R}.$$

$P(\cdot)$ is strictly convex and $P(1) < 0 < P(1/(1+xN))$. Hence, there exists a unique root $\Gamma(x) \in (1/(1+xN), 1)$ such that $P(\cdot)$ is strictly positive on $(1/(1+xN), \Gamma(x))$ and strictly negative on $(\Gamma(x), 1)$. $\Gamma(x)$ is given by

$$\Gamma(x) = 1 + \frac{x}{2(N-1)}\left(1 - \sqrt{1 + \frac{4N(N-1)}{1+xN}}\right).$$

Since $B(x) \in (1/(1+xN), 1)$, it follows that $g'(x) < 0$ if and only if $B(x) > \Gamma(x)$.

Next, we show that $B(x) > \Gamma(x)$ when x is in the neighborhood of 0. Applying Taylor's theorem to $\Gamma(x)$ for $x \to 0^+$, we obtain:

$$\Gamma(x) = 1 - x + \frac{2N^2}{2N-1}\frac{x^2}{2} - \frac{6N^3(1-3N+3N^2)}{(2N-1)^3}\frac{x^3}{6} + o(x^3),$$

where $o(x^3)$ is Landau's little-o. Differentiating B three times under the integral sign and applying Taylor's theorem for $x \to 0^+$, we obtain:

$$B(x) = 1 - x + \frac{2N^2}{2N-1}\frac{x^2}{2} - \frac{6N^3}{3N-2}\frac{x^3}{6} + o(x^3). \tag{A.3}$$

It follows that

$$B(x) - \Gamma(x) = x^3\left(N^3\frac{17N^3 - 27N^2 + 15N - 3}{(2N-1)^3(3N-2)} + o(1)\right).$$

Since $N^3\frac{17N^3-27N^2+15N-3}{(2N-1)^3(3N-2)} > 0$ for all $N \geq 2$, there exists $x^0 > 0$ such that $B(x) - \Gamma(x) > 0$ for all $x \in (0, x^0]$.

Next, we show that $B(x) - \Gamma(x) > 0$ for all $x > x^0$. We establish this by showing that Γ is a subsolution of differential equation $y' = \phi(y, x)$ on $[x^0, \infty)$. Γ is a subsolution of this differential equation if and only if $\Gamma'(x) < \phi(\Gamma(x), x)$ for all $x \geq x^0$. $\Gamma'(x) - \phi(\Gamma(x), x)$ is given by

$$N\frac{\sqrt{(1+Nx)(1+4N(N-1)+Nx)}((x+2)N-1) - \left(1+4N(N-1)+2N^3x+N^2x^2\right)}{2(N-1)^2(1+Nx)\sqrt{(1+Nx)(1+4N(N-1)+Nx)}}.$$

This expression is strictly negative if and only if

$$(1+Nx)(1+4N(N-1)+Nx)((x+2)N-1)^2 - \left(1+4N(N-1)+2N^3x+N^2x^2\right)^2 < 0.$$

Simplifying the left-hand side yields $-4N^2(N-1)^4x^2$, which is indeed strictly negative.

We can conclude: B is a solution of differential equation $y' = \phi(y, x)$ on $[x^0, \infty)$, Γ is a subsolution of the same differential equation, and $B(x^0) > \Gamma(x^0)$; by lemma 1.2 in Teschl (2012), $B(x) > \Gamma(x)$ for all $x > x^0$. ■

A.2. *Constructing Variables.*

A.2.1. *Weighting commuter flows.* In order to calculate the number of potential routes, we have to identify which stations are on the same route. Two stations i and j that comply with Equation (6) are on one route from o to d if the optimal route between the two municipalities, which passes through both stations, is not excessively longer than the optimal route from o to d passing through one station only.

We order stations i and j so that $dist_{oi} \leq dist_{oj}$. (Recall that $dist_{kl}$ is the length of the optimal route between two locations k and l.) We view stations i and j as being on the same route if

$$dist_{oi} + dist_{ij} + dist_{jd} - min(dist_{oi} + dist_{id}, dist_{oj} + dist_{jd}) < \overline{dist}. \tag{A.4}$$

Multiple stations are on the same route if all pairs of stations comply with Equation (A.4). If, for a particular commuter flow, at least one station complies with Equation (6), then each potential route contains at least one station.[28] Two potential routes between o and d are viewed as separate if at least one station located on one route is not included in the other (and vice versa).

The weight of a commuter flow from o to d assigned to station i, $\omega_{i,od}$, equals the share of potential routes that include station i (and equals zero if i does not comply with Equation (6)). More formally, let $\mathcal{R}_{od}$ be the set of potential routes for a commuter flow from o to d. A potential route $R_{od} \in \mathcal{R}_{od}$ for this commuter flow enumerates all the gasoline stations that are passed by along this route. The weight assigned to station i for the commuter flow from o to d is defined as:

$$\omega_{i,od} = \frac{1}{|\mathcal{R}_{od}|} \sum_{R_{od} \in \mathcal{R}_{od}} \mathbf{1}_{i \in R_{od}}.$$

As the shortest path algorithm is applied to transit commuters only, we set $\omega_{i,od} = 1$ if station i is located in either municipality o or d. The aggregated weighted number of commuters for station i is given by

$$I_i = \sum_{o} \sum_{d \neq o} \omega_{i,od} C_{od},$$

where C_{od} is the commuter flow from o to d.

A.2.2. *ROL approach to market definition.* As an alternative to delineating local markets based on an exogenously chosen critical driving distance (two miles in our baseline specification) or on administrative boundaries, we exploit our data on commuting patterns to decide whether two stations are part of the same local market.

Two stations i and j are viewed as being part of the same local market if the share of common potential consumers for both stations (ROL_{ij}, the ROL between i and j) exceeds a certain threshold. Noncommuters are considered to be potential consumers for i and j if the two stations are located in the same municipality. A commuter flow between o and d gives rise to overlapping potential consumers for i and j if it passes by both stations, that is, if i and j both comply with Equation (6).

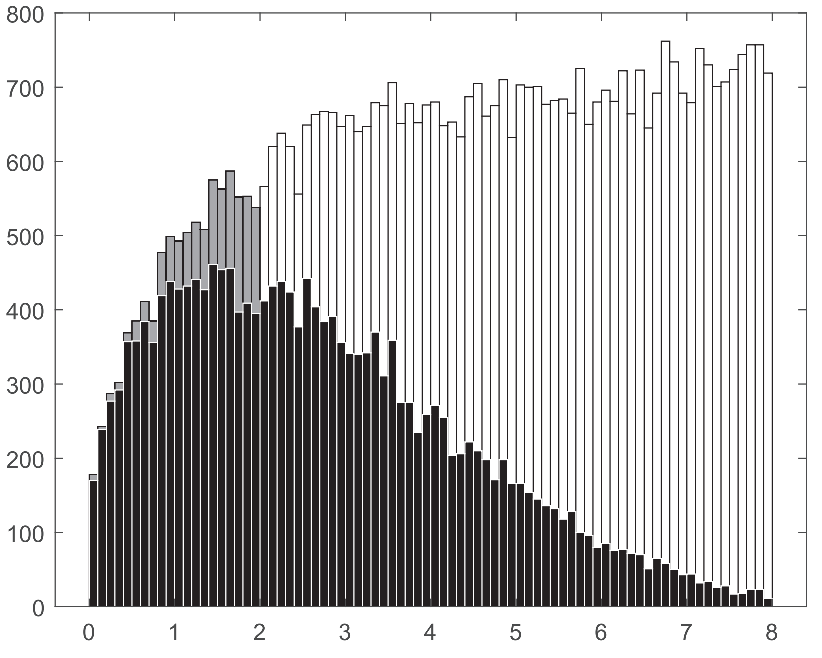
The ROL between two stations i and j is defined as:

$$\text{ROL}_{ij} = \frac{Cons_i \wedge Cons_j}{Cons_i \vee Cons_j},$$

where $Cons_i \wedge Cons_j$ denotes the number of individuals (including both commuters and noncommuters) that are potential consumers for *i and j*, and $Cons_i \vee Cons_j$ the number of individuals that are potential consumers for *i and/or j*. We again construct a local market for each station: Station i's market contains station i itself and all other stations $j \neq i$ for which ROL_{ij} exceeds a critical value.

Figure A.1 contrasts the local markets obtained with a critical driving distance of two miles with those obtained with an ROL threshold of 50%. The histograms show the number of pairs

[28] We do not consider routes without stations when calculating these weights.



NOTES: The figure shows the number of pairs of stations within bins of 0.1 miles driving distance. Gray bars indicate the number of station pairs within a distance of up to two miles. White bars depict all station pairs within a distance between two and eight miles. Black bars illustrate the number of pairs with an ROL, which is the share of common (potential) consumers, above 50%.

FIGURE A.1

MARKET DEFINITION WITH A THRESHOLD DISTANCE OF TWO MILES AND A RELATIVE OVERLAP (ROL) OF 50%

of stations within bins of 0.1 miles driving distance for the entire cross section of gas stations in Austria. The gray bars indicate all station pairs within a distance of up to two miles, whereas the white bars depict all station pairs between two and eight miles. When delineating local markets with a critical driving distance of two miles, all station pairs within that distance are considered to be in the same market, as depicted by the gray bars. The black bars illustrate the local markets obtained with an ROL threshold of 50%.

The figure indicates that the ROL approach to market definition gives rise to virtually all the station pairs within a one-mile distance being in the same local market. However, it excludes about 20 % of all the station pairs with a distance from one to two miles, while including some pairs that are located further apart. Thus, although an ROL threshold of 50% results in larger markets on average, there are many pairs of stations that are part of the same local market in one market definition but not in the other, and vice versa.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Table S2.1: Regression results using raw prices to calculate dispersion and a market delineation of 2 miles
Table S2.2: Regression results using residual prices to calculate dispersion for gasoline and a market delineation of 2 miles
Table S2.3: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles accounting for spatial autocorrelation in the residuals

Table S2.4: Regression results using residual prices to calculate dispersion and a market delineation based on municipal borders
Table S2.5: Regression results using residual prices to calculate dispersion and a market delineation of 1.5 miles
Table S2.6: Regression results using residual prices to calculate dispersion and a market delineation of 10% relative overlap
Table S2.7: Regression results using residual prices to calculate dispersion and a market delineation of 90% relative overlap
Table S2.8: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, excluding 3 largest towns (apart from Vienna)
Table S2.9: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, excl. highway stations
Table S2.10: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, including Vienna
Table S2.11: Regression results using residual prices and a market delineation of 2 miles, prices of at least 2 competitors observed
Table S2.12: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, no route-weights
Table S2.13: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, using different degrees of informedness
Table S2.14: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, using different degrees of informedness (locals are assumed to sample 1 station)
Table S2.15: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, using alternative weights
Table S2.16: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 50$m
Table S2.17: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 50$m

REFERENCES

ALBÆK, S., P. MØLLGAARD, AND P. B. OVERGAARD, "Government-Assisted Oligopoly Coordination? A Concrete Case," *The Journal of Industrial Economics* 45 (1997), 429–43.

BAHADIR-LUST, S., J.-P. LOY, AND C. R. WEISS, "Are They Always Offering the Lowest Price? An Empirical Analysis of the Persistence of Price Dispersion in a Low Inflation Environment," *Managerial and Decision Economics* 28 (2007), 777–88.

BARRON, J. M., B. A. TAYLOR, AND J. R. UMBECK, "Number of Sellers, Average Prices, and Price Dispersion," *International Journal of Industrial Organization* 22 (May 2004), 1041–66.

BAYE, M. R., AND J. MORGAN, "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets," *American Economic Review* 91 (June 2001), 454–74.

———, ———, AND P. SCHOLTEN, "Information, Search and Price Dispersion," in T. Hendershott, ed. *Economics and Information Systems* (Amsterdam: Elsevier Science Ltd, 2006), 323–77.

BROWN, J. R., AND A. GOOLSBEE, "Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry," *Journal of Political Economy* 110 (2002), 481–507.

BYRNE, D. P., AND N. DE ROOS, "Consumer Search in Retail Gasoline Markets," *The Journal of Industrial Economics* 65 (2017), 183–93.

CARRANZA, J. E., R. CLARK, AND J.-F. HOUDE, "Price Controls and Market Structure: Evidence from Gasoline Retail Markets," *The Journal of Industrial Economics* 63 (2015), 152–98.

CHANDRA, A., AND M. TAPPATA, "A Note on Sequential Search Models," Supplementary notes for *Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets*, mimeo, available at https://sites.google.com/site/marianotappata/research, 2008.

———, "Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets," *The RAND Journal of Economics* 42 (2011), 681–704.

CHEN, Y., AND T. ZHANG, "Equilibrium Price Dispersion with Heterogeneous Searchers," *International Journal of Industrial Organization* 29 (2011), 645–54.

Dewenter, R., J. Haucap, and U. Heimeshoff, "Maßnahmen zur Steigerung des Wettbewerbs auf den Kraftstoffmärkten in Deutschland," Technical Report, ADAC, April 2012.

———, U. Heimeshoff, and H. Lüth, "The Impact of the Market Transparency Unit for Fuels on Gasoline Prices in Germany," *Applied Economics Letters* 24 (2017), 302–05.

Eckert, A., "Empirical Studies of Gasoline Retailing: A Guide to the Literature," *Journal of Economic Surveys* 27 (2013), 140–66.

Ellison, G., and S. F. Ellison, "Lessons About Markets from the Internet," *Journal of Economic Perspectives* 19 (2005), 139–58.

———, "Search, Obfuscation, and Price Elasticities on the Internet," *Econometrica* 77 (2009), 427–52.

Friberg, R. "Price Transparency and Market Integration," in J. Forssbæck and L. Oxelheim, eds., *The Oxford Handbook of Economic and Institutional Transparency* (New York: Oxford University Press, Oxford Handbooks Online, 2014), 1–20.

Hastings, J. S., "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California," *American Economic Review* 94 (2004), 317–28.

Hosken, D. S., R. S. McMillan, and C. T. Taylor, "Retail Gasoline Pricing: What Do We Know?," *International Journal of Industrial Organization* 26 (2008), 1425–36.

Janssen, M. C. W., and A. Parakhonyak, "Consumer Search Markets with Costly Revisits," *Economic Theory* 55 (2014), 481–514.

———, P. Pichler, and S. Weidenholzer, "Oligopolistic Markets with Sequential Search and Production Cost Uncertainty," *The RAND Journal of Economics* 42 (2011), 444–70.

———, ———, and M. R. Wildenbeest, "Truly Costly Sequential Search and Oligopolistic Pricing," *International Journal of Industrial Organization* 23 (April 2005), 451–66.

Kaplan, G., and G. Menzio, "The Morphology of Price Dispersion," *International Economic Review* 56 (2015), 1165–1206.

Kostyshak, S., "Non-Parametric Testing of U-shaped Relationships," Mimeo, Princeton University, 2015.

Lach, S., "Existence and Persistence of Price Dispersion: An Empirical Analysis," *Review of Economics and Statistics* 84 (August 2002), 433–44.

———, and J. L. Moraga-González, "Asymmetric Price Effects of Competition," *The Journal of Industrial Economics* 65 (2017), 767–803.

Lewis, M., "Price Dispersion and Competition with Spatially Differentiated Sellers," *Journal of Industrial Economics* 56 (September 2008), 654–78.

Lind, J. T., and H. Mehlum, "With or Without U? An Appropriate Test for a U-Shaped Relationship," *Oxford Bulletin of Economics and Statistics* 72 (2010), 109–19.

Loy, J.-P., C. Steinhagen, C. Weiss, and B. Koch, "Price Transmission and Local Market Power: Empirical Evidence from the Austrian Gasoline Market," *Applied Economics* 50 (2018), 5728–46.

Luco, F., "Who Benefits from Information Disclosure? The Case of Retail Gasoline," *American Economic Journal: Microeconomics* 11 (May 2019), 277–305.

Marvel, H. P., "The Economics of Information and Retail Gasoline Price Behavior: An Empirical Analysis," *Journal of Political Economy* 84 (1976), 1033–60.

Morgan, J., H. Orzen, and M. Sefton, "An Experimental Study of Price Dispersion," *Games and Economic Behavior* 54 (July 2006), 134–58.

Obradovits, M., "Austrian-Style Gasoline Price Regulation: How It May Backfire," *International Journal of Industrial Organization* 32 (2014), 33–45.

OECD, "Competition in Road Fuel," OECD Policy Roundtable, 2013.

Parakhonyak, A., "Oligopolistic Competition and Search Without Priors," *The Economic Journal* 124 (May 2014), 594–606.

Robinson, P. M., "Root-N-Consistent Semiparametric Regression," *Econometrica* 56 (1988), 931–54.

Rossi, F., and P. K. Chintagunta, "Price Uncertainty and Market Power in Retail Gasoline: The Case of an Italian Highway," *Marketing Science* 37 (2018), 753–70.

Sengupta, A., and S. N. Wiggins, "Airline Pricing, Price Dispersion, and Ticket Characteristics On and Off the Internet," *American Economic Journal: Economic Policy* 6 (2014), 272–307.

Sorensen, A. T., "Equilibrium Price Dispersion in Retail Markets for Prescription Drugs," *Journal of Political Economy* 108 (2000), 833–50.

Stahl, D. O., "Oligopolistic Pricing with Sequential Consumer Search," *American Economic Review* 79 (1989), 700–12.

———, "Oligopolistic Pricing with Heterogeneous Consumer Search," *International Journal of Industrial Organization* 14 (1996), 243–68.

Statistik Austria, "Kfz-Bestand 2005," available at http://www.statistik.at/web_de/static/kfz-bestand_2005_021489.pdf, last accessed July, 19, 2013 (2006).

Stigler, G. J., "The Economics of Information," *Journal of Political Economy* 69 (May 1961), 213–25.

Tang, Z., M. D. Smith, and A. Montgomery, "The Impact of Shopbot Use on Prices and Price Dispersion: Evidence from Online Book Retailing," *International Journal of Industrial Organization* 28 (2010), 579–90.

Tappata, M., "Rockets and Feathers: Understanding Asymmetric Pricing," *The RAND Journal of Economics* 40 (2009), 673–87.

Teschl, G., *Ordinary Differential Equations and Dynamical Systems* (Providence, RI: American Mathematical Society, 2012).

Varian, H. R., "A Model of Sales," *American Economic Review* 70 (1980), 651–59.

Wildenbeest, M. R., "An Empirical Model of Search with Vertically Differentiated Products," *The RAND Journal of Economics* 42 (2011), 729–57.