Information and Price Dispersion: Theory and Evidence*

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Abstract

We study the empirical importance of consumer information in generating price dispersion. Limited information is the key element generating price dispersion in models of homogeneous-goods markets. We show that in these models, the global relationship between information and price dispersion is an inverse-U shape. We test this mechanism using a new measure of information based on precise commuter data from Austria. Commuters sample gasoline prices on their commuting route, providing us with spatial variation in the share of informed consumers. Using gasoline station level prices we construct dispersion measures. 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.

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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, Morgan, and Scholten, 2006).

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, Morgan, and Scholten, 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, 2013). Several countries have introduced restrictions on price setting,[1] as well as transparency regimes requiring retailers to report to an online platform.[2]

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).[3] Consumers differ in their degree of informedness: For some, obtaining an additional price quote is costly;

[1]This includes Australia (Byrne and de Roos, 2017), Austria (Obradovits, 2014), and Canada (Carranza, Clark, and Houde, 2015).

[2]This includes Australia (Byrne and de Roos, 2017), Chile (Luco, 2019), Germany (Dewenter, Heimeshoff, and Lüth, 2017), and Italy (Rossi and Chintagunta, 2018).

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

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 non-commuters, 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 inverted-U shaped relationship between information and price dispersion. Those 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: (a) Firms' abilities to obfuscate consumers' search and learning efforts are limited in this market; (b) unlike other measures of information, commuting is not correlated with firms' ability to monitor each other and collude;[4] (c) gasoline is a homogeneous product and seller characteristics can be adequately controlled for; (d) we observe substantial variation in our measure of the share of informed consumers, enabling us to test the global prediction derived from theory; (e) 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.

Our paper 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.[5] The literature has observed that price dispersion is not a monotone function of the fraction of informed consumers (see Baye, Morgan, and Scholten, 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 Tappata (2009)'s earlier result 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 measure used by Tappata (2009).

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

[5]In the Stahl (1989) model, the equilibrium price distribution is common knowledge, and the non-shoppers 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, Moraga-Gonzalez, and Wildenbeest, 2005), recall is costly (Janssen and Parakhonyak, 2014), non-shoppers do not know the firms' underlying production costs (Janssen, Pichler, and Weidenholzer, 2011), non-shoppers only know the support of the price distribution (Parakhonyak, 2014), and search costs are heterogeneous (Stahl, 1996; Chen and Zhang, 2011).

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, Smith, and Montgomery (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.[6] 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 paper 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.[7] Chandra and

[6]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).

[7]Daily data in Loy, Steinhagen, Weiss, and Koch (2018) on a sub-sample of 282 gasoline stations in Austria

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 paper is organized as follows. Section 2 presents the clearinghouse model and derives testable prediction on the relationship between consumer information and 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 Stahl (1989)'s search model, which subsumes Varian (1980)'s 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 Section 2.1. Further results on heterogeneous consumer demand, the role of market structure, and alternative measures of price dispersion are stated in Section 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

between January 2003 and December 2004 shows 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 rather than search costs per purchase. Our theoretical predictions are robust to different purchase frequency (see Remark 2 in Section 2).

to as "informed" consumers or "shoppers," observes all prices through the clearinghouse and buy 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 $s>0$.

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 $\left[\underline{p},\overline{p}\right]$ and setting $\bar{p}$:

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

The first term on the left-hand side corresponds to the profits made on shoppers (which the firm serves with probability $(1-F(p))^{N-1}$, whereas the second term corresponds to the profits stemming from the firm's $(1-\mu)/N$ non-shoppers. Manipulating condition (1) yields:

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

for all $p\in\left[\underline{p},\overline{p}\right]$. 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 non-shoppers' optimal search behavior, which satisfies a stationary reservation price property. The reservation price ρ is such that non-shoppers are indifferent between purchasing at ρ, and paying the search cost to receive a new price quote drawn from F:

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

Janssen, Moraga-Gonzalez, and Wildenbeest (2005) and Janssen, Pichler, and Weidenholzer (2011) show that $\overline{p}=\min(\rho,v)$, where $\rho\equiv c+s/(1-A)$ and $A=\int_0^1\frac{dz}{1+\frac{\mu}{1-\mu}Nz^{N-1}}\in(0,1)$. The upper bound of the support is therefore given by $\overline{p}\in(\rho,v)$.

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 non-shoppers 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 non-shoppers' 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 non-shopper 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 non-shoppers, resulting in zero profits.[8]

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 below illustrates how s and the possibility to search in the Stahl (1989) model affects the price distribution relative to the Varian (1980) model.

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:

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

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

towards lower prices (see Stahl, 1989).

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

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

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

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

An immediate observation is that the relationship between information and price dispersion is non-monotonic. This holds as the value of information vanishes when μ tends to zero or one, whereas VOI is strictly positive for every μ in $(0, 1)$.[9,10] The following proposition, which delivers a second testable prediction, characterizes the global relationship between

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

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

[10]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 5. Janssen, Moraga-Gonzalez, and Wildenbeest (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 non-shoppers drops out of the market when μ is low—a prediction that appears unappealing in our empirical application to retail gasoline.

information and price dispersion:

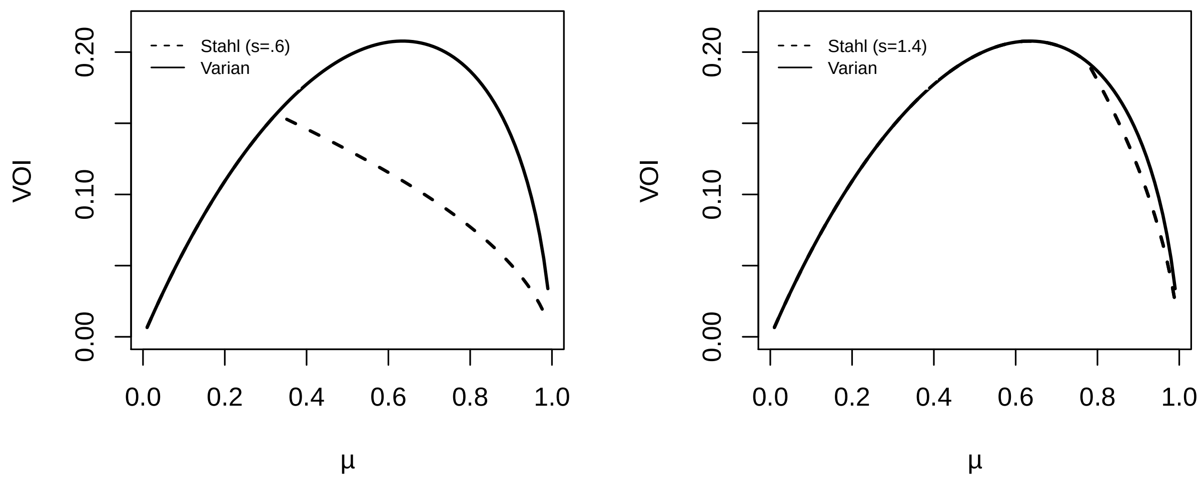
Proposition 1. *There is an inverse U-shaped relationship between price dispersion* $E(p - p_{\min})$ *and the proportion of informed consumers* μ*: There exists a* $\overline{\mu} \in (0,1)$ *such that price dispersion is increasing in* μ *on* $(0, \overline{\mu})$ *and decreasing in* μ *on* $(\overline{\mu},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

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 $s \geq v - c$. 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 $\mu \geq \widehat{\mu}$, then $\overline{p} = \rho$ and VOI simplifies to $s\left(\frac{A}{1-A} - \frac{1-\mu}{\mu}\right)$, which is indeed strictly decreasing in μ by Lemma A, stated and proven in Appendix A. This concludes the proof of the proposition.

We now provide a brief sketch of the proof of Lemma A. We first argue that $s\left(\frac{A}{1-A} - \frac{1-\mu}{\mu}\right)$ 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 sub solution 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 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 towards 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 non-shoppers, 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.

Figure 1: Illustration of Proposition 1



Notes: The relationship between μ and VOI induced by the Varian (1980) model, where non-shoppers 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 $v - c = 2$.

2.2 Further Results

Heterogeneous demand. In our empirical application to retail gasoline, where shoppers are proxied by commuters, shoppers' and non-shoppers' 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 non-shoppers:

Remark 2. *Consider the following modification of Stahl (1989)'s model: A shopper is willing to pay* v *with probability* $\phi \in (0, 1]$*, and* 0 *with complementary probability* $1-\phi$*; a non-shopper is willing to pay* v *(resp. 0) with probability* $\psi \in (0, 1]$ *(resp.* $1-\psi$*). 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:

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

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

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

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 $\text{VOI}(\mu)$ be the value of information in the Stahl model. The value of information in the heterogeneous-demand model is $\widetilde{\text{VOI}}(\mu)=\text{VOI}\left(\nu(\mu)\right)$. As $\nu(\cdot)$ is strictly increasing and $\text{VOI}(\cdot)$ 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. □

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 sub solutions of a certain differential equation. See Appendix C.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 C.2.2 for analytical proofs for low N. Simulations suggest that the result also holds for higher N. □

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, Orzen, and Sefton, 2006; Janssen, Pichler, and Weidenholzer, 2011).[11] 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, Orzen, and Sefton (2006) and Janssen, Pichler, and Weidenholzer (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.[12]

[11] 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 C.3 for details and further comparative statics.

[12] In Appendix C.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 C.1.3).

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 non-commuters.[13] (Recall 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.

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 2381 administrative units in Austria. All commuters are assigned to an

[13] 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 non-commuters (46%) always fuel at the same station, while this is the case for only 29% of all commuters. A descriptive analysis is provided in Dewenter, Haucap, and Heimeshoff (2012). We thank Ralf Dewenter for providing us with those numbers.

origin-destination pair of municipalities based on their home and workplace addresses.[14] 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 3373 (1575) 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 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

[14] 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.

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.

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 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.[15] Specifically, we assign the commuter flow from municipality o to municipality d to station i whenever

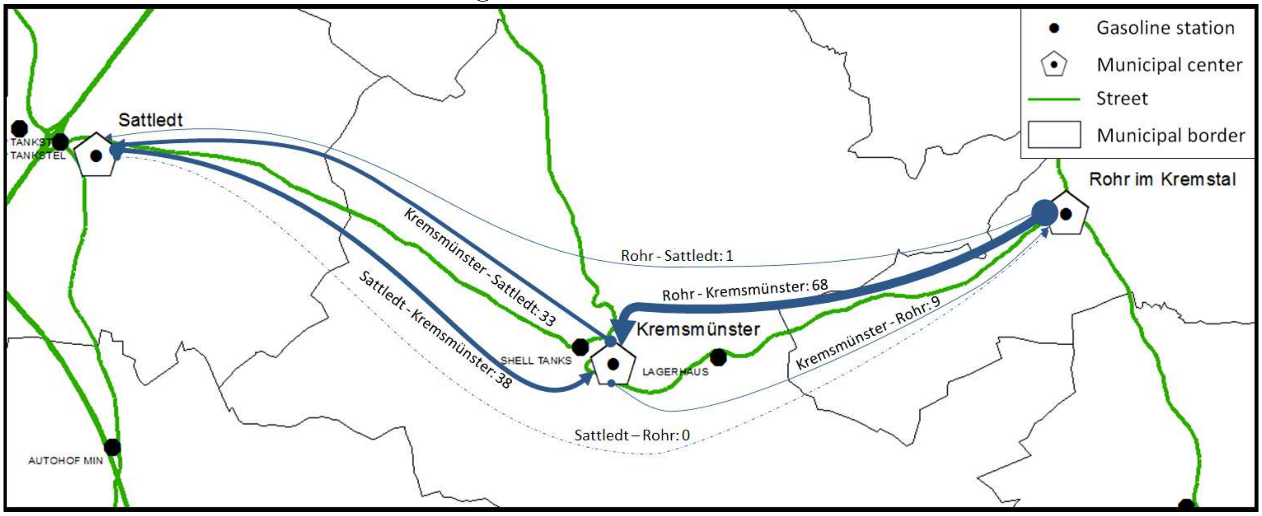
$$dist_{oi} + dist_{id} - dist_{od} < \overline{dist}, \tag{6}$$

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 ($\overline{dist} = 250$ meters) 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. 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 B. 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

[15]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 $\overline{dist} = 250$ meters means that a station is on the commuting path if it is located less than 125 meters off the optimal route.

Figure 2: Commuter Flows



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 1 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 kilometers). This distance is compared to the distance from Rohr to the station (5.2 kilometers) 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 kilometers, which is 100 meters more than he would travel otherwise. As 100 meters is within our critical distance, we count the commuter as one of the informed consumers in the Lagerhaus station's market.

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):

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

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.[16] We can then calculate a station-specific proxy for the share of

[16]We follow this approach due to lack of better data on, e.g., 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.

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 percent mark.[17] This skewness towards 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 percent, 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.

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

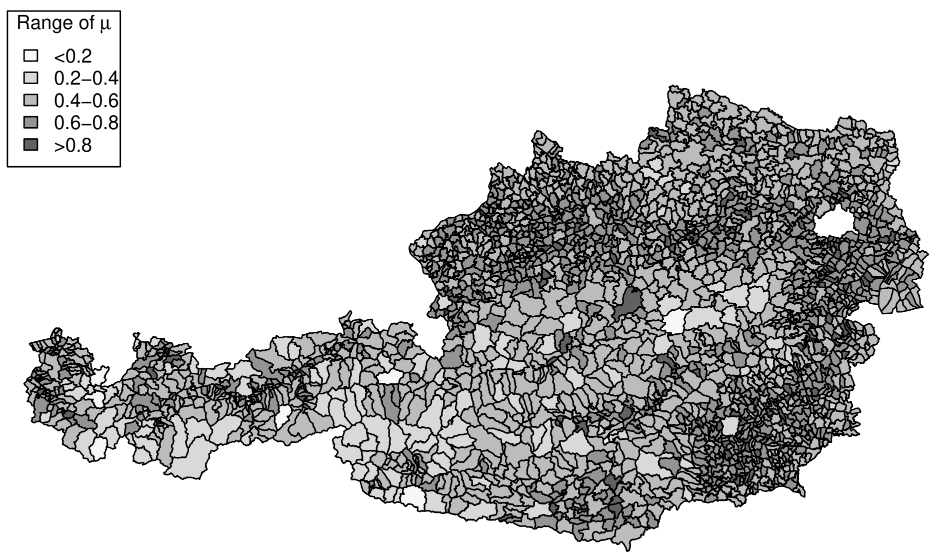
In general, the share of commuters is below average in very rural areas (surrounded by other rural municipalities) and in larger towns or cities with many residents employed within the city boundaries. Consumers are best informed in suburban municipalities, where a large share of employed individuals 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

[17] While we do not have evidence from Austria to validate our measure externally, the above mentioned survey from Germany (Dewenter, Haucap, and Heimeshoff, 2012, Table 8) shows that 59% of respondents compare prices either "always" or "most of the time", while the remaining 41% compare prices either "rarely" or "never."

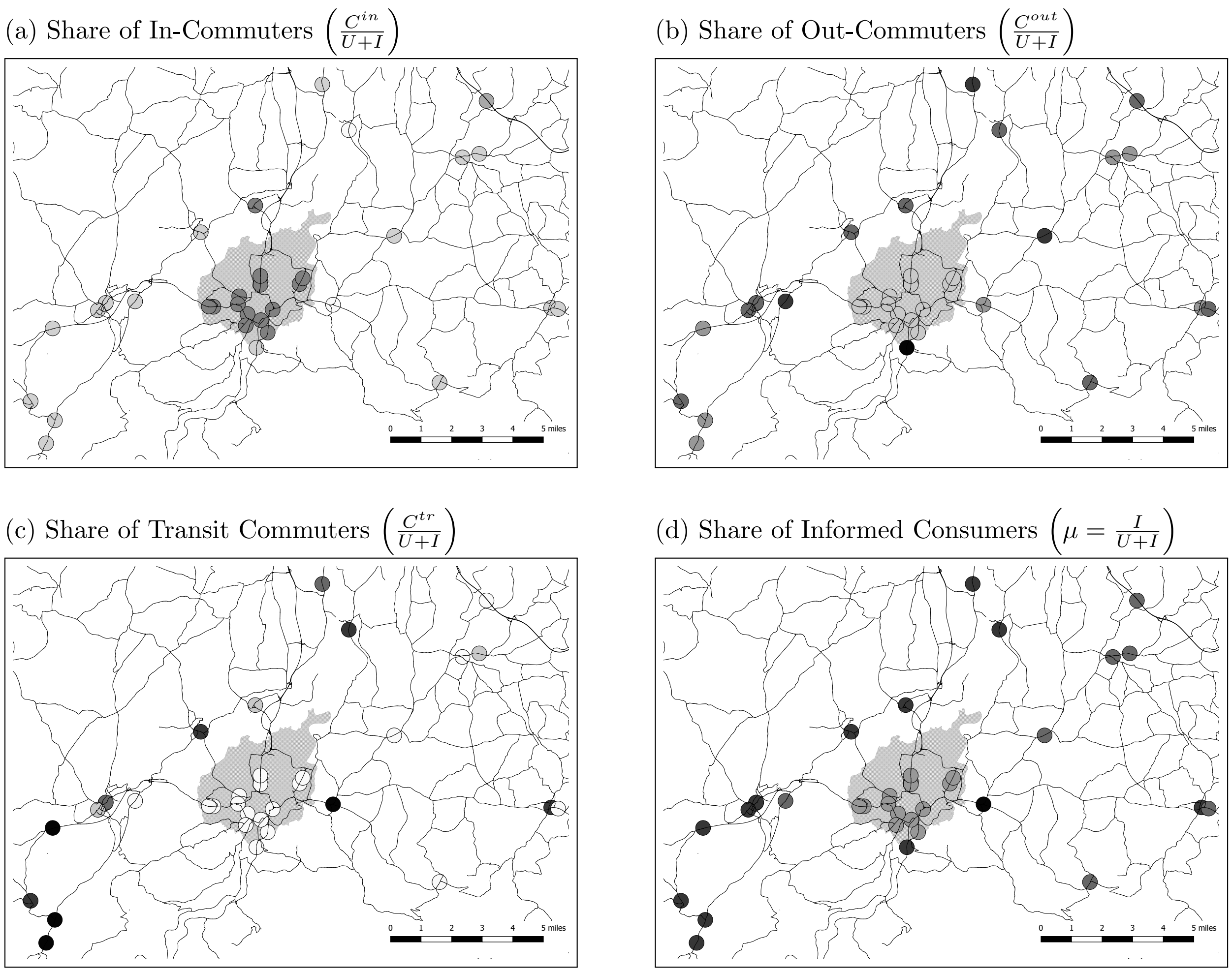
for stations located in the town is mainly driven by in-commuters (Figure 4a), whereas the share of out-commuters is higher for stations located outside (Figure 4b). Transit commuters are negligible for stations inside the town (Figure 4c), and are of heterogeneous importance for stations located outside, 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).

Figure 3: Regional Variation in the Share of Informed Consumers



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 4: Composition of the Information Measure



(a) Share of In-Commuters $\left(\frac{C^{in}}{U+I}\right)$

(b) Share of Out-Commuters $\left(\frac{C^{out}}{U+I}\right)$

(c) Share of Transit Commuters $\left(\frac{C^{tr}}{U+I}\right)$

(d) Share of Informed Consumers $\left(\mu = \frac{I}{U+I}\right)$

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.

3.2 Diesel Prices and Stations

Our empirical analysis focuses on the retail diesel market in Austria. 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, McMillan, and Taylor, 2008).

We use quarterly data on diesel prices at the gasoline station level from October 1999 to March 2005.[18] 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.[19] 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.

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.[20]

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

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

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

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.

Residual prices. Although diesel fuel is a homogeneous product, gasoline stations differ in their locations, the services they provide, and other characteristics. This heterogeneity 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.[21] 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.

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

[21] See e.g. Lach (2002), Barron, Taylor, and Umbeck (2004), Bahadir-Lust, Loy, and Weiss (2007), Hosken, McMillan, and Taylor (2008) or Lewis (2008). Wildenbeest (2011) shows how to account for vertical differentiation.

critical driving distance of two miles. Similar approaches have been used in earlier work on retail gasoline markets (see for example Hastings, 2004, and Chandra and Tappata, 2011).[22] We depart from the existing literature by using driving distances rather than 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 relative overlap approach and a comparison between the two approaches is provided in Appendix B.

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 value of information in gas station i's local market, m_i, is the difference between the expected price and the expected minimum price in the market: $\text{VOI}_i = E(p^{m_i}) - E(p^{m_i}_{\min})$. While 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 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 Section 2.2, is the sample range: The difference between the highest and the lowest price, i.e., $\text{R}_i = p^{m_i}_{(N)} - p^{m_i}_{(1)}$. As this measure is strongly influenced by outliers, we also use the trimmed range $\text{TR}_i = p^{m_i}_{(N-1)} - p^{m_i}_{(2)}$, i.e.,

[22] 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.

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, $\text{SD}_i^{m_i} = \sqrt{\sum_{j \in m_i}(p_j - \overline{p}^{m_i})^2/(N^{m_i})}$, 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, a relative overlap 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 where at least four prices are observed. Prices are least dispersed with the two-mile driving distance delineation, and most dispersed with the relative overlap definition. The standard deviation (SD) is less dependent on how the market is defined, as expected. While raw prices are more dispersed than cleaned prices, the difference appears small.

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

Table 2: Descriptive Statistics on Measures of Price Dispersion

Local market delineation	2 Miles		ROL 50%		Municipality	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
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)
# of rival firms (N^c)	6.965	(6.415)	13.768	(19.144)	13.781	(19.145)
# of rival firms with prices (N^c_o)	4.428	(4.351)	7.893	(10.037)	7.920	(10.054)
# of obs.	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)
# of rival firms (N^c)	10.560	(6.769)	22.695	(21.693)	22.682	(21.662)
# of rival firms with prices (N^c_o)	7.030	(4.505)	13.012	(10.946)	13.035	(10.943)
# of obs.	7,996		7,840		7,895	

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.

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 non-parametric 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 μ_i (Remark 1). To test this prediction, we estimate the following linear regression:

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

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 period fixed effects, depending on the model specification.

Table 3 presents the results. The first and second column contain results using the entire sample, whereas the third and fourth (fifth and sixth) column 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 column) or the crude oil price index (second, fourth and sixth column). 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 2 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 Section 2.2, although our clearinghouse model predicts a positive impact of N^c, models that are richer in their information structure (or that accounts 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.

Table 3: Regression results on price levels (delineation: 2 miles)

Dependent variable: Price level (diesel)	Full sample		Markets with at least 2 stations		Markets with at least 4 stations	
	(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)
# 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)
# of obs.	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

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
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 fixed time effects.

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 (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 inverted 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 2-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.[23] 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 Section 2.2.

To test formally for the presence of an inverted U-shaped relationship between information and price dispersion, we apply the statistical test suggested in Lind and Mehlum (2010).[24] 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 inverted U-shaped relationship

[23] 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.

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

Table 4: Regression results using residual prices to calculate dispersion and a market delineation of 2 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)
# 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)
# 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
# of obs.	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

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

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, Range, and Trimmed range measures, at the 5% level for the VOI and AD measures, and at the 10% level for the SD measure.

Using the relative overlap 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 Range and Trimmed Range and lowest for SD and AD. This is due to the fact that Range and Trimmed Range 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 inverted-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.

Robustness. To confirm that our results are driven neither by using residual rather than raw prices, nor by the specific product, nor by specific assumptions imposed on the error term, nor by the way in which we delineate local markets, nor by particular sub-samples, nor 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 D (available online) for detailed descriptions of the various model alterations, more thorough discussions, and tables of results.

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)
# 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)
# 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
# of obs.	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

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

First, we investigate the relationship between consumer information and price dispersion using raw rather than 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 relative overlap 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: (a) We do not weight commuter flows by the share of possible routes passing by a particular gasoline stations. (b) 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 assuming that commuters are perfectly informed about all prices. (c) 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. (d) We use different values for the critical distance $\overline{dist}$ when assigning commuter flows to gasoline stations.

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

4.3 Semi-Parametric Evidence

In this section we show that our results on the relationship between information and the price level (resp. price dispersion) are not driven by the parametric restriction to a linear (resp. linear-quadratic) function. Given the large number of control variables, we follow a semi-parametric 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 (resp. price dispersion) and information μ. We estimate the following equations semi-parametrically:

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

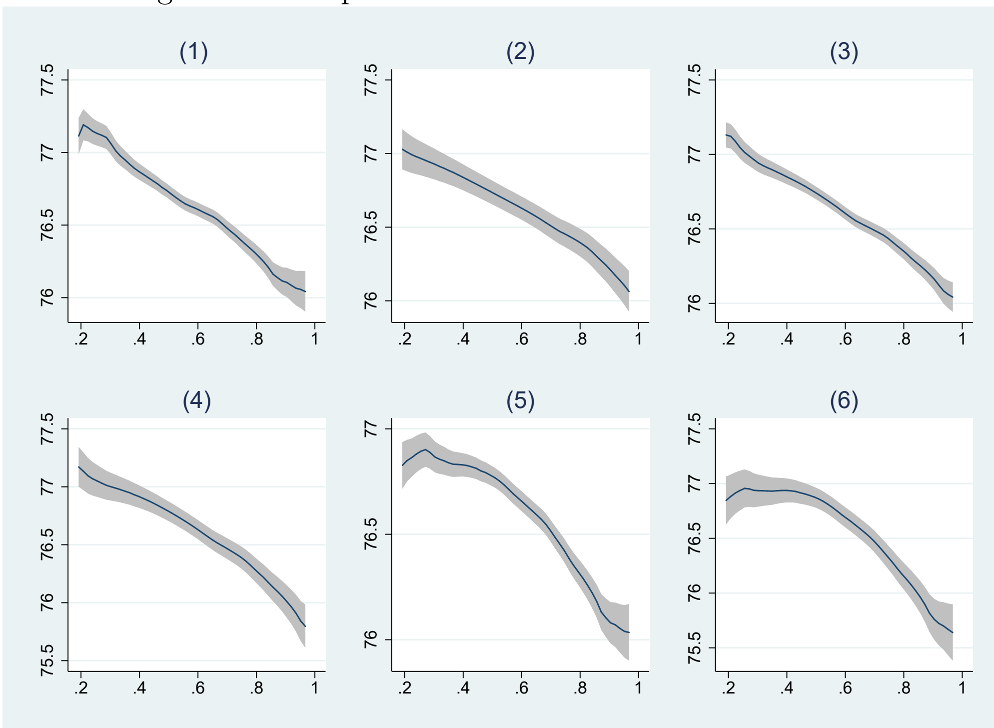
$$PD_{it} = \alpha + f(\mu_i) + X_{it}\theta + \eta_{it}. \tag{10}$$

We use the two-step procedure proposed by Robinson (1988). We first obtain non-parametric 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 non-parametrically to obtain an estimate of $g(\cdot)$. Similarly, we obtain an estimate of $f(\cdot)$.

The results obtained for the non-parametric 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 above. Figure 5 shows a strong, negative, and close-to-linear relationship between consumer information (horizontal axis) and the price level (vertical axis).

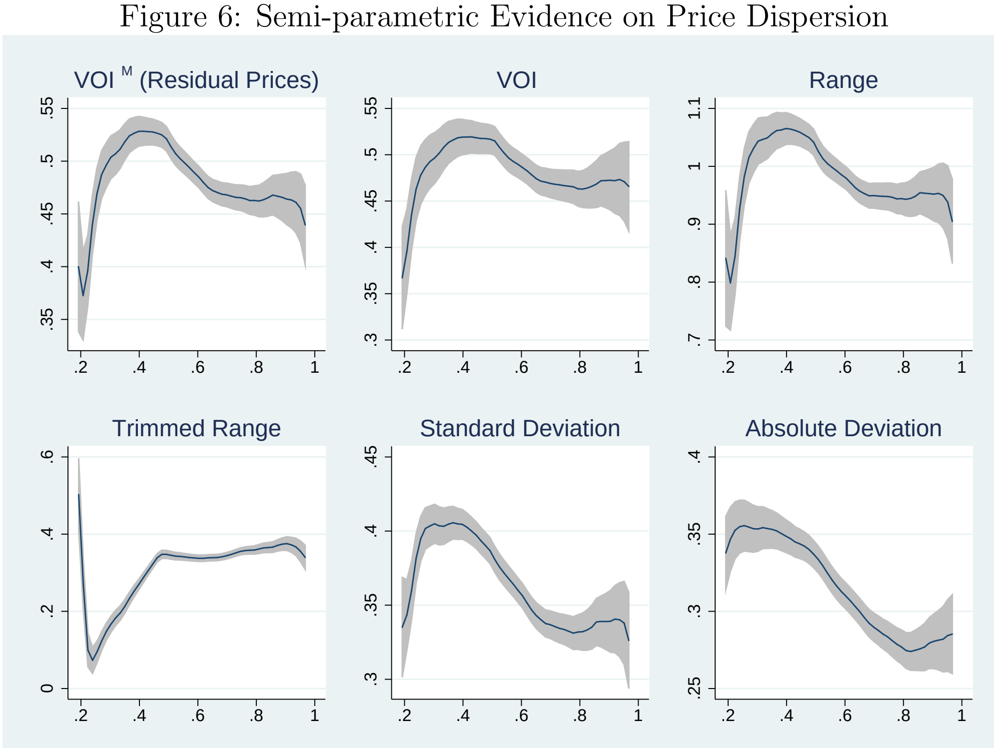
Figure 6 reports results obtained for the non-parametric component of the price dispersion regression (equation (10)). The restriction to a linear-quadratic function results in a peak further to the right than with a flexible functional form. Although the specific form of the relationship between information (horizontal axis) and different measures of price dispersion (vertical axis) depends on the measure of price dispersion, there is strong evidence in favor

Figure 5: Semi-parametric Evidence on the Price Level



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 specific specifications in Table 3.

Figure 6: Semi-parametric Evidence on Price Dispersion



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

of an inverted U shape of the relationship of interest.[25]

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. 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, e.g., 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

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

cents.[26] We distribute commuters equally among gas stations on their commuting path, and non-commuters 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 kilometers 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 non-commuters. Assuming a fuel consumption of 0.079 liters per kilometer, 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 consumers relative to a situation with no information. Overall, commuters save €36.4 million and non-commuters save €15 million per year. The implied individual savings are small, with average expenses reduced by €26.42 per commuter and €6.07 per non-commuter. As a share of total fuel expenses, this amounts to only 2.23% for commuters and 1.01% for non-commuters. 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.

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 $\mu = 0.6$, informed consumers obtain 72 percent of total surplus, whereas uninformed consumers receive 42 percent. 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

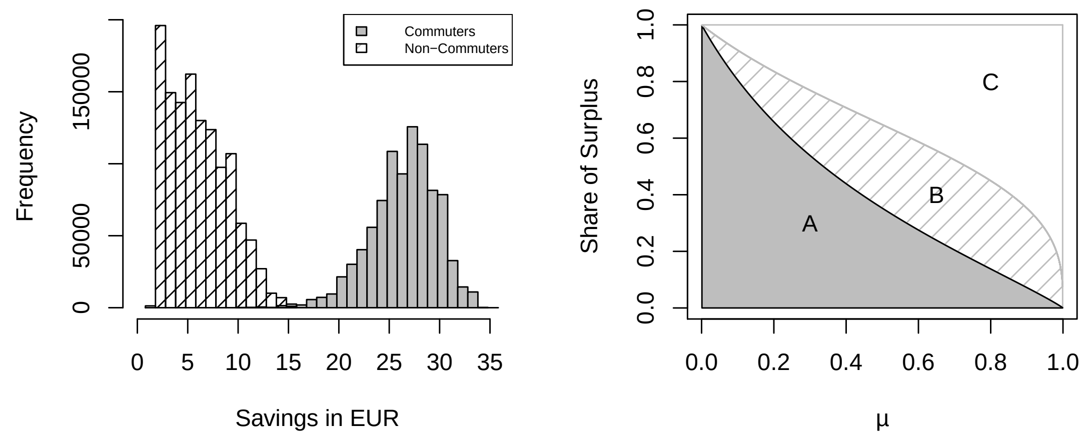
[26]This corresponds to the estimate in regression (4) in Table 3.

figure thus illustrates that while 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 Value of Information, $F(p - p_{\min})$, in the left panel of Figure 8 for the 5th, 50th and 95th percentile 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, while 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 non-monotonic relationship between information and price dispersion.

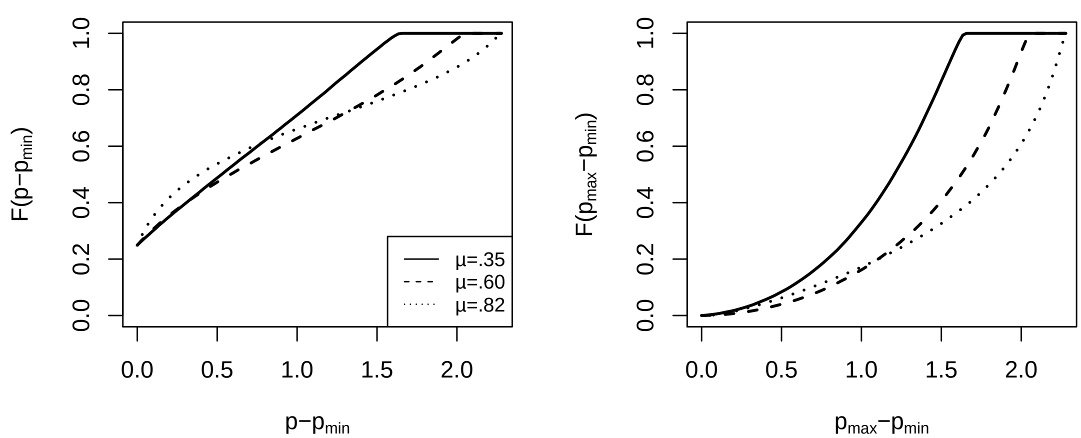
The right panel of Figure 8 shows the distribution of the range of prices, $F(p_{\max} - p_{\min})$. Here, the results are stronger and they can be interpreted as the benefit the 'unluckiest' consumer would derive from becoming informed. That benefit is at least one cent 76% of the time in the median 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.

Figure 7: Distribution of Savings



The left panel shows the savings distribution for commuters and non-commuters 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. Non-commuters receive Area C, commuters B plus C. Firms earn the residual area, depending on the type of consumer they face.

Figure 8: Distribution Functions for the Value of Information and Price Range



The left panel shows the distribution function of the value of information 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.

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Appendix

A Proof of Proposition 1

All we need to do is prove the following lemma:

Lemma A. *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 $B(x) \equiv \int_0^1 \frac{dz}{1+xNz^{N-1}} \in \left(\frac{1}{1+xN}, 1\right)$. 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

$$\begin{aligned} B'(x) &= -\int_0^1 \frac{Nz^{N-1}}{(1+xNz^{N-1})^2} dz, \\ &= \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B(x)\right), \end{aligned} \tag{11}$$

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

$$\phi(y,x) = \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - y\right), \tag{12}$$

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 (11), we see that $g'(x)$ is strictly negative if and only if $P(B(x)) < 0$, where

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

$P(\cdot)$ 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:

$$B(x) = 1 - x + \frac{2N^2}{2N-1}\frac{x^2}{2} - \frac{6N^3}{3N-2}\frac{x^3}{6} + o(x^3). \tag{13}$$

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 sub solution of differential equation $y' = \phi(y, x)$ on $[x^0, \infty)$. Γ is a sub solution 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

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

This expression is strictly negative if and only if

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

The left-hand side is in fact equal to $-4N^2(N-1)^4x^2$, 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 sub solution 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 $x>x^0$. □

B Constructing Variables

Weighting commuter flows. 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

$$dist_{oi} + dist_{ij} + dist_{jd} - min\left(dist_{oi} + dist_{id}, dist_{oj} + dist_{jd}\right) < \overline{dist}. \tag{14}$$

Multiple stations are on the same route if all pairs of stations comply with equation (14). If, for a particular commuter flow, at least one station complies with equation (6), then each potential route contains at least one station.[27] 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

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

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.

Relative overlap approach to market definition. As an alternative to delineating local markets based on an exogenously-chosen critical driving distance (2 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 *relative overlap* between i and j) exceeds a certain threshold. Non-commuters 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, i.e., if i and j both comply with equation (6).

The relative overlap between two stations i and j is defined as:

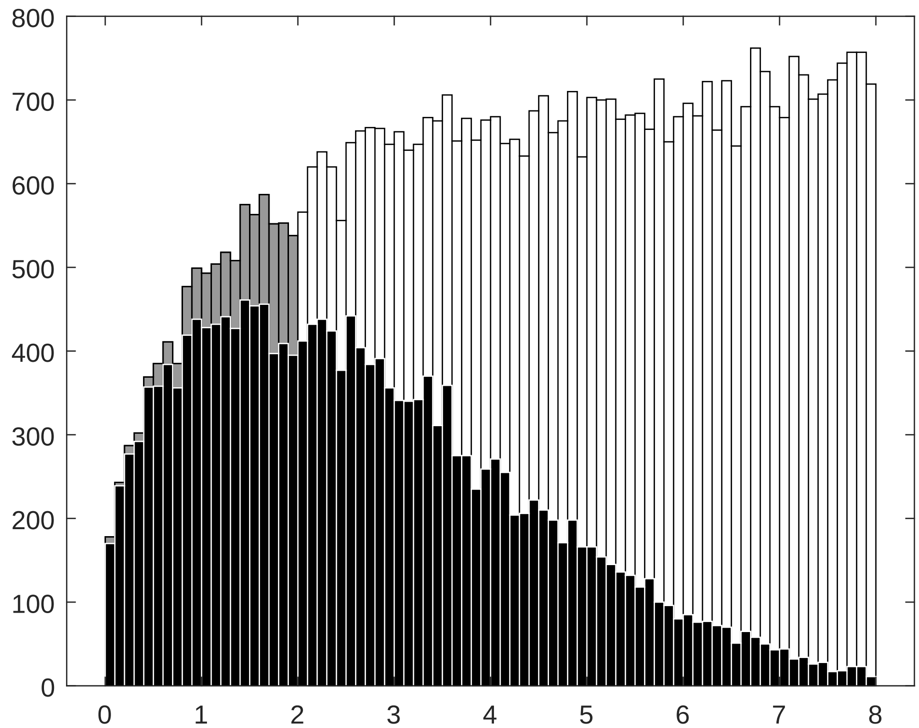
$$\text{ROL}_{ij} = \frac{Cons_i \wedge Cons_j}{Cons_i \vee Cons_j}$$

where $Cons_i \wedge Cons_j$ denotes the number of individuals (including both commuters and non-commuters) 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 9 contrasts the local markets obtained with a critical driving distance of two miles with those obtained with a ROL threshold of 50%. The histograms show the number of pairs 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 a ROL threshold of 50%.

The figure indicates that the relative overlap 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, while a 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.

Figure 9: Market Definition with a Threshold Distance of 2 miles and a Relative Overlap (ROL) of 50%



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 a relative overlap (ROL), which is the share of common (potential) consumers, above 50%.

C Further Theoretical Developments—For Online Publication Only

C.1 Standard Deviation of Prices

C.1.1 Formulas

In the following, it will be more convenient to work with the variable $x \equiv \mu/(1-\mu)$, which is a strictly increasing transformation of μ. We start by computing $E(p^2)$:

$$
\begin{aligned}
E(p^2) &= \int_{\underline{p}}^{\overline{p}} p^2 dF(p), \\
&= \int_0^1 \left(c + \frac{\overline{p}-c}{1+xNz^{N-1}}\right)^2 dz, \\
&= c^2 + 2c(\overline{p}-c)B(x) + (\overline{p}-c)^2 \underbrace{\int_0^1 \frac{dz}{(1+Nxz^{N-1})^2}}_{\equiv C(x)},
\end{aligned} \tag{15}
$$

where the second line follows by definition of $F(\cdot)$ (equation (2)) and the change of variables $z = 1 - F(p)$, and the function $B(x)$ was defined in Appendix A.

Combining equations (3) and (15) gives us a formula for the variance of prices:

$$
V(p) = E(p^2) - (E(p))^2 = (\overline{p}-c)^2 \left(C(x) - B(x)^2\right). \tag{16}
$$

Note that $C(x)$ can be simplified as follows:

$$
\begin{aligned}
C(x) &= \int_0^1 \left(\frac{1+xNz^{N-1}}{(1+xNz^{N-1})^2} - \frac{xNz^{N-1}}{(1+xNz^{N-1})^2}\right) dz, \\
&= B(x) - \frac{1}{N-1}\int_0^1 \frac{xN(N-1)z^{N-2}}{(1+xNz^{N-1})^2} \times z dz, \\
&= B(x) - \frac{1}{N-1}\left(-\left[\frac{z}{1+xNz^{N-1}}\right]_0^1 + \int_0^1 \frac{dz}{1+Nxz^{N-1}}\right), \\
&= B(x) + \frac{1}{N-1}\left(\frac{1}{1+xN} - B(x)\right),
\end{aligned} \tag{17}
$$

where the third line follows by integrating by parts. Combining equations (16) and (17), we obtain our final formula for $V(p)$:

$$V(p) = (\overline{p} - c)^2 \left(B(x) + \frac{1}{N-1} \left(\frac{1}{1+xN} - B(x) \right) - B(x)^2 \right). \tag{18}$$

The standard deviation of prices is $\text{SD}(p) = \sqrt{V(p)}$.

C.1.2 Proof of Proposition 2

Proof. Recall from Section 2.1 that, for given (v, c, s, N), there exists a threshold $\widehat{\mu} \in (0, 1]$ such that $\overline{p} = v$ if $\mu \leq \widehat{\mu}$ and $\overline{p} = \rho = c + s/(1 - A)$ if $\mu > \widehat{\mu}$. (If $s - c > v$, then we set $\widehat{\mu} = 1$.) Since $\mu \mapsto \mu/(1 - \mu)$ is strictly increasing, this implies that $\overline{p} = v$ if $x \leq \widehat{x}$ and $\overline{p} = c + s/(1 - B(x))$ if $x > \widehat{x}$, where $\widehat{x} \equiv \widehat{\mu}/(1 - \widehat{\mu}) \in (0, \infty]$. Combining this with equation (18) gives us a formula for the variance of prices as a function of x:

$$\text{Var}(x) = \begin{cases} (v - c)^2 \Psi(x) & \text{if } x \leq \widehat{x}, \\ s^2 \Phi(x) & \text{if } x > \widehat{x}, \end{cases}$$

where

$$\Psi(x) \equiv B(x) + \frac{1}{N-1} \left(\frac{1}{1+xN} - B(x) \right) - B(x)^2 \tag{19}$$

and

$$\Phi(x) \equiv \frac{\Psi(x)}{(1 - B(x))^2}. \tag{20}$$

Clearly,

$$\lim_{x \to 0} \text{Var}(x) = \lim_{x \to 0} \Psi(x) = \lim_{x \to \infty} \text{Var}(x) = \lim_{x \to \infty} \Psi(x) = \lim_{x \to \infty} \Phi(x) = 0.$$

All we need to do is show that $\text{Var}(x)$ is strictly quasi-concave in x. It will then immediately follow that the standard deviation of prices is inverse-U shaped in μ, since the square root and $\mu \mapsto \mu/(1-\mu)$ are both strictly increasing.

To prove that the piecewise-defined function $\mathrm{Var}(\cdot)$ is strictly quasi-concave, it is sufficient to show that $\Psi(\cdot)$ is strictly quasi-concave on $\mathbb{R}_{++}$ and $\Phi(\cdot)$ is strictly decreasing on $\mathbb{R}_{++}$, which we undertake next.

Claim 1: Ψ is strictly quasi-concave on $\mathbb{R}_{++}$.

Proof. Differentiating Ψ and using equation (11) yields $\Psi'(x) = Q(B(x))$, where

$$Q(Y) \equiv \frac{N-2-Nx+(1+Nx)\,(4-3N-N(N-2)x)\,Y+2(N-1)(1+Nx)^2Y^2}{(N-1)^2x(1+Nx)^2}.$$

$Q(\cdot)$ is a quadratic and strictly convex polynomial. Routine calculations show that

$$Q\left(\frac{1}{1+Nx}\right) < 0 < Q\,(1)\,.$$

Thus, Q has a unique root, $\Delta(x)$, in the interval $\left(\frac{1}{1+Nx},1\right)$:

$$\Delta(x) = \frac{3N-4+N(N-2)x+\sqrt{N\left(N+8x+6N(N-2)x+N(N-2)^2x^2\right)}}{4(N-1)(1+Nx)}.$$

Moreover, for every $Y \in \left(\frac{1}{1+Nx},1\right)$, $Q(Y)$ is strictly positive if $Y > \Delta(x)$ and strictly negative if $Y < \Delta(x)$. Since $B(x) \in \left(\frac{1}{1+Nx},1\right)$, this implies that $\Psi'(x)$ has the same sign as $B(x) - \Delta(x)$. The problem therefore reduces to studying the sign of $B - \Delta$.

We first show that $B(x) > \Delta(x)$ when x is close enough to 0. Applying Taylor's theorem to $\Delta(x)$ at the second order in the neighborhood of $x = 0^+$ yields:

$$\Delta(x) = 1 - x + \frac{4-2N(N-2)^2}{N}\frac{x^2}{2} + o(x^2).$$

Combining this with equation (13), we obtain:

$$B(x) - \Delta(x) = \underbrace{\left(\frac{2N^2}{2N-1} - \frac{4-2N(N-2)^2}{N}\right)}_{>0}\frac{x^2}{2} + o(x^2),$$

which implies that $B(x) > \Delta(x)$ for x close enough to zero. Next, we study the sign of $B - \Delta$ for higher values of x.

Recall from Appendix A that B solves the differential equation $y' = \phi(y, x)$ (see equations (11) and (12)). We now study whether Δ is a sub solution or a super solution of that differential equation. We are therefore interested in the sign of

$$\xi(x) \equiv \Delta'(x) - \phi\left(\Delta(x), x\right).$$

Using Mathematica, we show analytically that the equation $\xi(x) = 0$ has a unique solution on $(0, \infty)$:

$$x^* \equiv \frac{N - 1 + \sqrt{2 + N(N-2)}}{N}.$$

Moreover, $\xi(x) < 0$ if $x < x^*$ and $\xi(x) > 0$ if $x > x^*$. This means that Δ is a sub solution of $y' = \phi(y, x)$ on $(0, x^*)$ and a super solution on (x^*, ∞).

Since B and Δ are, respectively, a solution and a sub solution of the same differential equation and $B(x) > \Delta(x)$ for x small enough, we have that $B(x) > \Delta(x)$ for every $x \in (0, x^*)$.

Next, we turn our attention to the interval (x^*, ∞). Since B and Δ are, respectively, a solution and a super solution of the same differential equation on (x^*, ∞), they intersect at most once in that interval. Suppose first that they never intersect. Then, Ψ is strictly monotone on (x^*, ∞). If Ψ is increasing on that interval, then $\lim_{x\to\infty} \Psi(x) \geq \Psi(x^*) > 0$, which is a contradiction. Therefore, Ψ is strictly decreasing on $[x^*, \infty)$, and therefore strictly quasi-concave on $(0, \infty)$.

Suppose instead that B and Δ do intersect at some $\widetilde{x} \in (x^*, \infty)$. The fact that B and Δ

are a solution and a super solution of the same differential equation implies that $B(x) > \Delta(x)$ for every $x \in (x^*, \widetilde{x})$ and $B(x) < \Delta(x)$ for every $x \in (\widetilde{x}, \infty)$. It follows that Ψ is strictly increasing on $(0, \widetilde{x})$, strictly decreasing on $(\widetilde{x}, \infty)$, and therefore strictly quasi-concave on $(0, \infty)$. This concludes the proof of Claim 1.

Claim 2: Φ is strictly decreasing on $\mathbb{R}_{++}$.

Proof. Differentiating Φ and using equation (11) yields $\Phi'(x) = \widetilde{Q}(B(x))$, where

$$\widetilde{Q}(Y) \equiv \frac{N\left(1 - x - \left(2 + (2N-1)x + N(N-2)x^2\right)Y + (1+Nx)^2Y^2\right)}{(N-1)^2 x(1+Nx)^2(1-Y)^3}.$$

The denominator of $\widetilde{Q}$ is everywhere strictly positive. The numerator of $\widetilde{Q}$ is a quadratic polynomial in Y, which is negative at $Y = 1/(1+Nx)$ and positive at $Y = 1$. That polynomial therefore has one and only one root in the interval $\left(\frac{1}{1+Nx}, 1\right)$:

$$\Lambda(x) = \Bigg(x\sqrt{N^4x^2 - 4N^3(x-1)x + N^2\left(4x^2 - 6x + 4\right) + 4N(x-1) + 1} \\ + (2N-1)x + (N-2)Nx^2 + 2\Bigg) \Big/ \left(2(1+Nx)^2\right).$$

Moreover, $\Phi'(x)$ has the same sign as $B(x) - \Lambda(x)$. Hence, all we need to do is show that $B(x) < \Lambda(x)$ for every $x > 0$.

We start by showing that this is the case when x is small. In the neighborhood of $x = 0^+$, we have:

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

Combining this with equation (13), we obtain:

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

Routine calculations show that the coefficient on x^3 is strictly positive, implying that $B(x) <$

$\Lambda(x)$ for x sufficiently small.

Using Mathematica, we prove analytically that, for every $x > 0$,

$$\Lambda'(x) - \phi\left(\Lambda(x), x\right) > 0.$$

It follows that Λ is a super solution of the differential equation $y' = \phi(y, x)$ on the interval $(0, \infty)$. Since B is a solution of the same differential equation and $B(x) < \Lambda(x)$ for x small, this implies that $B(x) < \Lambda(x)$ for every $x > 0$. Hence, Φ is strictly decreasing, which concludes the proof of Claim 2. □

C.1.3 Impact of N

We make the dependence of B on N explicit by writing $B(x, N)$. We know from Janssen and Moraga-Gonzalez (2004) that $B(x, N)$ is strictly increasing in N. Moreover, $B(x, N) \underset{N\to\infty}{\longrightarrow} 1$. Since $\overline{p} = \max(v, c + s/(1 - B(x, N)))$, this implies the existence of a cutoff $\widehat{N} > 0$ such that for every $N \geq 2$,

$$\overline{p} = \begin{cases} c + \frac{s}{1-B(x,N)} & \text{if } N \leq \widehat{N}, \\ v & \text{if } N > \widehat{N}. \end{cases}$$

(Note that $\widehat{N}$ may be strictly less than 2.) The variance of prices is therefore given by

$$\text{Var}(N) = \begin{cases} s^2\Phi(x, N) & \text{if } N \leq \widehat{N}, \\ (v - c)^2\Psi(x, N) & \text{if } N > \widehat{N}, \end{cases}$$

where the functions Ψ and Φ are as defined in equations (19) and (20).

Numerical simulations suggest that $\Psi(x, N)$ is inverse-U shaped in N, whereas $\Phi(x, N)$ is increasing in N. This implies that $\text{Var}(N)$ is inverse-U shaped.

C.2 Expected Sample Range

C.2.1 Formulas

The expected sample range is

$$R = E\left(p_{\max}\right) - E\left(p_{\min}\right).$$

The cumulative distribution function of the maximum price is $F(p)^N$. This implies that

$$\begin{aligned}
E\left(p_{\max}\right) &= \int_{\underline{p}}^{\overline{p}} pNF(p)^{N-1}dF(p), \\
&= \int_0^1 \left(c + \frac{\overline{p} - c}{1 + xNz^{N-1}}\right) N(1-z)^{N-1}dz, \\
&= c + (\overline{p} - c)N \int_0^1 \frac{(1-z)^{N-1}}{1 + Nxz^{N-1}}dz,
\end{aligned}$$

where we have used the change of variables $z = 1 - F(p)$ to obtain the second line. Moreover,

$$E(p_{\min}) = c + (\overline{p} - c)N \int_0^1 \frac{z^{N-1}}{1 + Nxz^{N-1}}dz,$$

as shown in Section 2.1.

The expected sample range is therefore given by

$$R = (\overline{p} - c)N \int_0^1 \frac{(1-z)^{N-1} - z^{N-1}}{1 + Nxz^{N-1}}dz. \tag{21}$$

C.2.2 Supporting Analytical and Numerical Evidence for Remark 3

The argument at the beginning of Section C.1.2 and equation (21) imply that the expected sample range can be written as follows as a function of $x = \mu/(1-\mu)$:

$$R(x) = \begin{cases} (v - c)N\chi(x) & \text{if } x \leq \widehat{x}, \\ sN\psi(x) & \text{if } x > \widehat{x}, \end{cases}$$

where

$$\chi(x) = \int_0^1 \frac{(1-z)^{N-1} - z^{N-1}}{1 + Nxz^{N-1}} dz \quad \text{and} \quad \psi(x) = \frac{\chi(x)}{1 - B(x)}.$$

Clearly, $\lim_{x\to 0} R(x) = \lim_{x\to\infty} R(x) = 0$. Numerical simulations suggest that $\chi(x)$ is inverse-U shaped in x and ψ is strictly decreasing in x. This implies that $R(x)$ is inverse-U shaped in x, and that the expected sample range is inverse-U shaped in the fraction of informed consumers.

Next, we prove analytically that, when N is low, χ and ψ do behave as numerical simulations suggest:

Lemma B. *If $N \in \{2, 3, 4\}$, then χ is inverse-U shaped in x.*

Proof. We prove the result by showing that $\widetilde{\chi} : \mu \in (0, 1) \mapsto \chi(\mu/(1-\mu))$ is strictly concave. Differentiating $\widetilde{\chi}$ twice yields:

$$\begin{aligned}
\widetilde{\chi}''(\mu) &= -2N \int_0^1 \frac{z^{N-1}\left(1 - Nz^{N-1}\right)\left((1-z)^{N-1} - z^{N-1}\right)}{\left(1 - \mu + \mu N z^{N-1}\right)^3} dz, \\
&= \frac{-2N}{(1-\mu)^3} \underbrace{\int_0^1 \frac{z^{N-1}\left(1 - Nz^{N-1}\right)\left((1-z)^{N-1} - z^{N-1}\right)}{\left(1 + Nxz^{N-1}\right)^3} dz}_{\equiv \zeta(x)}, \text{ where } x = \frac{\mu}{1-\mu}.
\end{aligned}$$

All we need to do is show that $\zeta(x) > 0$ for every $x > 0$. We do so by exploiting the symmetry properties of the integrand:

$$\begin{aligned}
\zeta(x) = &\int_0^{\frac{1}{2}} \frac{z^{N-1}\left(1 - Nz^{N-1}\right)\left((1-z)^{N-1} - z^{N-1}\right)}{\left(1 + Nxz^{N-1}\right)^3} dz \\
&+ \int_{\frac{1}{2}}^1 \frac{z^{N-1}\left(1 - Nz^{N-1}\right)\left((1-z)^{N-1} - z^{N-1}\right)}{\left(1 + Nxz^{N-1}\right)^3} dz, \\
= &\int_0^{\frac{1}{2}} \frac{z^{N-1}\left(1 - Nz^{N-1}\right)\left((1-z)^{N-1} - z^{N-1}\right)}{\left(1 + Nxz^{N-1}\right)^3} dz \\
&+ \int_0^{\frac{1}{2}} \frac{(1-y)^{N-1}\left(1 - N(1-y)^{N-1}\right)\left(y^{N-1} - (1-y)^{N-1}\right)}{\left(1 + Nx(1-y)^{N-1}\right)^3} dy, \\
= &\int_0^{\frac{1}{2}} \underbrace{\left((1-z)^{N-1} - z^{N-1}\right)}_{>0} \left(\frac{z^{N-1}\left(1 - Nz^{N-1}\right)}{\left(1 + Nxz^{N-1}\right)^3} - \frac{(1-z)^{N-1}\left(1 - N(1-z)^{N-1}\right)}{\left(1 + Nx(1-z)^{N-1}\right)^3} \right) dz,
\end{aligned}$$

where the second equality follows by the change of variables $y = 1 - z$. The next step is to show that the the term inside parentheses on the last line is strictly positive for every $z \in (0, 1/2)$. Since

$$1 - Nz^{N-1} > 0 \quad \text{and} \quad \left(1 + Nxz^{N-1}\right)^3 < \left(1 + Nx(1-z)^{N-1}\right)^3$$

for every such z, a sufficient condition is that

$$z^{N-1}\left(1 - Nz^{N-1}\right) - (1-z)^{N-1}\left(1 - N(1-z)^{N-1}\right) > 0$$

for every $z \in (0, 1/2)$. Routine calculations show that this condition is satisfied whenever $N \in \{2, 3, 4\}$. □

Lemma C. *If $N = 2$, then ψ is strictly decreasing in x.*

Proof. When $N = 2$, a closed-form expression is available for ψ:

$$\psi(x) = \frac{(1+x)\log(1+2x) - 2x}{x\left(2x - \log(1+2x)\right)}.$$

Routine calculations show that this ψ is strictly decreasing in x. □

C.2.3 Impact of N

We prove the following proposition:

Proposition A. *The expected sample range is strictly increasing in the number of firms.*

Proof. The argument at the beginning of Section C.1.3 and equation (21) imply that the expected sample range, $R(N)$, is given by:

$$R(N) = \begin{cases} \frac{s}{1-B(x,N)} N \int_0^1 \frac{(1-z)^{N-1} - z^{N-1}}{1+xNz^{N-1}} dz & \text{if } N \leq \widehat{N}, \\ (v-c) N \int_0^1 \frac{(1-z)^{N-1} - z^{N-1}}{1+xNz^{N-1}} dz & \text{if } N > \widehat{N}. \end{cases}$$

Since $B(x,N)$ is strictly increasing in N and

$$\frac{s}{1-B(x,N)} \leq v-c \quad \forall N \leq \widehat{N},$$

all we need to do is show that

$$N\int_0^1 \frac{(1-z)^{N-1}-z^{N-1}}{1+xNz^{N-1}}dz$$

is strictly increasing in $N \geq 2$. We know from Morgan, Orzen, and Sefton (2006) that the term

$$N\int_0^1 \frac{z^{N-1}}{1+xNz^{N-1}}dz,$$

is strictly decreasing in N. This term corresponds to the expected minimum price in the Varian model, up to additive and multiplicative constants c and $v-c$. We want to show that

$$\mathcal{I}(N) \equiv N\int_0^1 \frac{(1-z)^{N-1}}{1+xNz^{N-1}}dz,$$

which corresponds to the expected maximum price in the Varian model, is strictly increasing in N.

Note that for every $N \geq 2$, $\mathcal{I}(N+1)-\mathcal{I}(N)$ is equal to

$$\begin{aligned}
&\int_0^1 \frac{(1-z)^{N-1}\left((N+1)(1-z)\left(1+xNz^{N-1}\right)-N\left(1+x(N+1)z^N\right)\right)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz,\\
&=\int_0^1 \frac{(1-z)^{N-1}\left(1-(N+1)z+N(N+1)xz^{N-1}(1-2z)\right)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz,\\
&=\underbrace{\int_0^1 \frac{(1-z)^{N-1}(1-(N+1)z)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz}_{\equiv\mathcal{J}(N)}+N(N+1)x\underbrace{\int_0^1 \frac{(1-z)^{N-1}z^{N-1}(1-2z)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz}_{\equiv\mathcal{K}(N)}.
\end{aligned}$$

All we need to do is show that $\mathcal{J}(N)$ and $\mathcal{K}(N)$ are both strictly positive.

$$\begin{aligned}
\mathcal{J}(N) &= \int_0^{\frac{1}{N+1}} \frac{(1-z)^{N-1}\left(1-(N+1)z\right)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz + \int_{\frac{1}{N+1}}^{1} \frac{(1-z)^{N-1}\left(1-(N+1)z\right)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz,\\
&> \int_0^{\frac{1}{N+1}} \frac{(1-z)^{N-1}\left(1-(N+1)z\right)}{\left(1+\frac{xN}{(N+1)^{N-1}}\right)\left(1+\frac{x(N+1)}{(N+1)^N}\right)}dz + \int_{\frac{1}{N+1}}^{1} \frac{(1-z)^{N-1}\left(1-(N+1)z\right)}{\left(1+\frac{xN}{(N+1)^{N-1}}\right)\left(1+\frac{x(N+1)}{(N+1)^N}\right)}dz,\\
&= \frac{1}{\left(1+\frac{xN}{(N+1)^{N-1}}\right)\left(1+\frac{x(N+1)}{(N+1)^N}\right)} \int_0^{\frac{1}{N+1}} (1-z)^{N-1}\left(1-(N+1)z\right)dz,\\
&= 0.
\end{aligned}$$

Moreover,

$$\begin{aligned}
\mathcal{K}(N) &= \int_0^{\frac{1}{2}} \frac{(1-z)^{N-1}z^{N-1}(1-2z)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz + \int_{\frac{1}{2}}^{1} \frac{(1-z)^{N-1}z^{N-1}(1-2z)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz,\\
&= \int_0^{\frac{1}{2}} \frac{(1-z)^{N-1}z^{N-1}(1-2z)}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)}dz - \int_0^{\frac{1}{2}} \frac{y^{N-1}(1-y)^{N-1}(1-2y)}{\left(1+xN(1-y)^{N-1}\right)\left(1+x(N+1)(1-y)^N\right)}dy,\\
&= \int_0^{\frac{1}{2}} \overbrace{\left(\frac{1}{\left(1+xNz^{N-1}\right)\left(1+x(N+1)z^N\right)} - \frac{1}{\left(1+xN(1-z)^{N-1}\right)\left(1+x(N+1)(1-z)^N\right)}\right)}^{>0}\\
&\quad \times \underbrace{(1-z)^{N-1}z^{N-1}(1-2z)}_{>0}\,dz,\\
&> 0.
\end{aligned}$$

It follows that $\mathcal{I}(\cdot)$ is strictly increasing and that the expected sample range is strictly increasing in N. $\square$

C.3 Interaction Between μ and N

Expected price. We are interested in the sign of $\partial^2 E(p)/\partial N \partial\mu$. This is equivalent to studying the sign of $\partial^2 E(p)/\partial N \partial x$, with $x = \mu/(1-\mu)$.

If $\overline{p} = v$ (which, as argued in Sections 2.1 and C.1.3, arises if s is high and/or x is low and/or N is high), then the expected price is proportional to B, and so $\partial^2 E(p)/\partial N \partial x$ has the same sign as $\partial^2 B/\partial N \partial x$. Note that

$$\frac{\partial^2 B}{\partial x \partial N} = \frac{\partial}{\partial N}\frac{\partial B}{\partial x} = \frac{\partial}{\partial N}\left(\frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B\right)\right),$$

where we have used equation (11). Numerical simulations suggest that

$$N \mapsto \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B\right)$$

is strictly increasing if x is small, and J-shaped if x is large. Therefore, when $\overline{p} = v$, $\partial^2 E(p)/\partial N \partial x$ is negative when x is large and N is small, and positive otherwise.

If instead $\overline{p} < v$, then the expected price is proportional to $B/(1-B)$, and so $\frac{\partial^2 E(p)}{\partial N \partial x}$ has the same sign as $\frac{\partial^2}{\partial x \partial N}\frac{B}{1-B}$. Note that

$$\frac{\partial^2}{\partial x \partial N}\frac{B}{1-B} = \frac{\partial}{\partial N}\left(\frac{\partial B}{\partial x}\frac{1}{(1-B)^2}\right) = \frac{\partial}{\partial N}\left(\frac{1}{(1-B)^2}\frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B\right)\right),$$

where the second equality follows by equation (11). Numerical simulations suggest that the term inside parentheses is strictly decreasing in N, implying that the cross-partial derivative is strictly negative whenever $\overline{p} < v$.

Value of information. We are interested in the sign of $\partial^2 \mathrm{VOI}/\partial N \partial \mu$, or, equivalently, $\partial^2 \mathrm{VOI}/\partial N \partial x$ with $x = \mu/(1-\mu)$.

If $\overline{p} = v$, then VOI is proportional to $B - \frac{1-B}{x}$, and so $\partial^2 \mathrm{VOI}/\partial N \partial x$ has the same sign as $\frac{\partial^2}{\partial x \partial N}\left(B - \frac{1-B}{x}\right)$. Using equation (11), we find that

$$\frac{\partial^2}{\partial x \partial N}\left(B - \frac{1-B}{x}\right) = \frac{\partial}{\partial N}\left(\left(1 + \frac{1}{x}\right)\frac{1}{x(N-1)}\left(\frac{1}{1+xN} - B\right) + \frac{1-B}{x^2}\right).$$

Numerical simulations suggest that the function inside parentheses is:

- increasing in N when x is small,

- inverse U-shaped in N when x is intermediate,
- U-shaped in N when x is high.

This means that $\partial^2\text{VOI}/\partial N \partial x$ is negative when x is intermediate and N is high, or when x is high and N is small, and positive otherwise.

If instead $\overline{p} < v$, then the value of information is proportional to $\frac{B}{1-B} - \frac{1}{x}$. It follows that $\partial^2\text{VOI}/\partial N \partial x$ has the same sign as $\frac{\partial^2}{\partial x \partial N} \frac{B}{1-B}$, which, as shown numerically above, is everywhere strictly negative. Hence, $\partial^2\text{VOI}/\partial N \partial x$ is strictly negative whenever $\overline{p} < v$.

D Further Sensitivity Analysis—For Online Publication Only

In this Online Appendix, we carry out a number of robustness checks. We alter the baseline model specification along several dimensions: (i) By calculating measures of price dispersion using raw (rather than residual) prices; (ii) by using regular gasoline instead of diesel; (iii) by explicitly accounting for spatial correlation in the data; (iv) by using alternative approaches to local market delineation; (v) by analyzing alternative samples; and (vi) by using alternative definitions when calculating the share of informed consumers μ.

Raw prices (Table 6). The regression results explaining price dispersion using raw rather than residual prices are summarized in Table 6. The qualitative results hardly change: The coefficient estimates on μ are positive and statistically significant in all specifications, while the parameter estimates on μ^2 are negative for all measures of price dispersion and statistically significant at the 5%-level (at the 10%-level) in five out of six (in all) models. Although the parameters are not estimated with the same level of precision as with cleaned prices, the null hypothesis of no inverse U shape is rejected at common significance levels in four out of six specifications.

Regular gasoline (Table 7). In the main text, we focused on diesel as this is the most prevalent fuel for cars in Austria. The regression results using regular (unleaded) gasoline instead of diesel are reported in Table 7. The parameter estimates on μ (μ^2) are positive (negative) and statistically significant at the 5%-significance level in all specifications. As with diesel, we find the expected concave relationship in almost all model specifications when using regular gasoline. The intersection-union test of Lind and Mehlum (2010) is rejected at the 5%- (10%) significance level in four (five) out of six model specifications. While we find strong statistical evidence for an upward-sloping relationship between price dispersion and consumer information at low levels of μ, the downward-sloping relationship at high levels of

μ is not significantly negative in all specifications.

Accounting for spatial correlation (Table 8). So far, we have treated all observations as independent from each other. However, the measures of price dispersion are calculated by comparing the price of a gasoline station with prices charged by other stations in the local market, which may jeopardize the assumption that observations are independent. A natural approach to tackle this issue is to cluster the residuals at the local market level. This approach, however, is not feasible in our case of overlapping markets.

Another way to account for contemporaneous correlation of the residuals η_{it} within local markets is to allow for a spatially autoregressive process (see Anselin, 1988, for an overview). We thus obtain an estimate of the variance-covariance matrix of the residuals, $\boldsymbol{VC}_\eta$, accounting for spatial correlation.

We assume that the residual vector $\boldsymbol{\eta}$ takes the form $\boldsymbol{\eta} = \lambda \boldsymbol{W}\boldsymbol{\eta} + \boldsymbol{\nu}$, where λ is the spatial autocorrelation parameter, the matrix $\boldsymbol{W}$ describes the structure of spatial dependence, and $\boldsymbol{\nu}$ is the remaining error vector. The matrix $\boldsymbol{W}$ is constructed as follows: The variable $w^*_{it,js}$ is equal to one whenever i and j are in the same local market, $i \neq j$, and $t = s$, and zero otherwise.[28] The matrix $\boldsymbol{W}$ is row-normalized with typical element $w_{it,js} = \frac{w^*_{it,js}}{\sum_j w^*_{it,jt}}$.[29] The variance-covariance matrix of $\boldsymbol{\eta}$ becomes

$$\boldsymbol{VC}_\eta(\lambda) = (\boldsymbol{I} - \lambda \boldsymbol{W})^{-1} \boldsymbol{\Sigma}_\nu (\boldsymbol{I} - \lambda \boldsymbol{W}')^{-1},$$

where $\boldsymbol{\Sigma}_\nu$ is the variance-covariance matrix of the remaining error ν_{it}.

We apply a GMM procedure based on the OLS residuals to obtain a consistent estimate of

[28] One caveat is that the structure of the matrix $\boldsymbol{VC}_\eta$ is (partly) determined by the matrix of weights $\boldsymbol{W}$, which has to be (exogenously) specified by the researcher. When constructing the matrix of weights, we use the same approach as when calculating the measures of price dispersion: Namely, only contemporaneous observations are considered and all rival firms in the local market receive the same weight (regardless of their exact location relative to the central station of the local market).

[29] Row-normalization is commonly used when specifying spatially autocorrelated residuals. It facilitates interpretation as $\sum_j w_{it,jt}\eta_{jt}$ is the (spatially weighted) average of residuals of other stations located in the same local market as station i, and it ensures that $\boldsymbol{I} - \lambda \boldsymbol{W}$ is non-singular as long as $\lambda \in (-1, 1)$. See Bell and Bockstael (2000) for a discussion.

the spatial autocorrelation parameter λ (Kelejian and Prucha, 1999) and adjust the variance-covariance matrix as described above.[30]

The results are reported in Table 8. The parameter estimates are negligibly affected as the sample size is slightly smaller.[31] While the size of the standard errors of the parameter estimates increases by a small amount, the interpretation of the results remains unaffected: The parameter estimates of the linear and quadratic terms of μ take the expected signs and are statistically different from zero at the 5%-significance level, and the implied critical level lies between 0.70 and 0.76.[32]

Local market delineation (Tables 9–12). We explore various alternatives to the market delineation approaches used in our baseline specifications.

We begin by defining local markets using administrative boundaries (municipalities) and a different critical driving distance (1.5 instead of 2 miles). The results on these alterations are reported in Table 9–10. In all (all but one) model specifications, the parameter estimates on μ (μ^2) are positive (negative) and statistically different from zero at the 5%-significance level. The intersection-union test of Lind and Mehlum (2010) is rejected at the 5%-significance level for all measures of price dispersion when market delineation is based on municipality boundaries, but only in three (out of six) specifications when markets are defined using a critical distance of 1.5 miles. In those model specifications where the test fails to reject the null-hypothesis, the peak of the inverse-U appears rather late (at values of μ of about 0.75), resulting in the downward-sloping part at high levels of μ no longer being statistically significant. Nevertheless, the concave relationship between consumer information and price dispersion is supported by virtually all model specifications, while the inverse-U relationship

[30]We allow for heteroskedasticity of unknown form in the remaining error ν_{it} as suggested by White (1980).

[31]The sample size is slightly reduced when we account for the spatial dependence structure in the residuals, as we exclude stations that are located in a market with no other stations in the sample (to enable the row-normalization of $\boldsymbol{W}$). This can occur as we exclude stations located in Vienna in the entire analysis. Thus, if a station has only rival stations in the local market that are located in Vienna, we can calculate the value of price dispersion for this station (and include this observation in the baseline specifications), but exclude this observation here.

[32]We will not formally test for an inverse-U shape as we are not aware of a test in the spirit of Lind and Mehlum (2010) in the presence of spatial correlation.

is endorsed by 9 out of 12 specifications.

In the main text, we used an ROL threshold of 50% when delineating local markets using the relative overlap approach. As a robustness exercise, we use threshold levels of 10% (Table 11) and 90% (Table 12). As in the main text (see Table 5), the parameter estimates on μ (μ^2) are positive (negative) and statistically different from zero at the 1%-significance level for all measures of price dispersion. In addition, the intersection-union test is rejected at the 1%-significance level in all specifications, endorsing the interpretation of an inverse-U relationship between consumer information and price dispersion.

Alternative samples (Tables 13–16). In Table 13, We exclude all stations located in the three largest Austrian cities (besides Vienna), namely, Graz, Linz and Salzburg, leaving only stations located in municipalities with fewer than 120,000 inhabitants in the sample. We do so as our measure of information is based on commuter flows between municipalities, which is less precise in very large cities. In Table 14, we exclude all stations located on highways, as competition between firms on and off highways can be expected to be lower than suggested by the distance between these competitors.[33] Evaluating these subsamples hardly affects the results, as reported in Tables 13–14: the parameter estimates on μ and μ^2 take the expected signs and are significantly different from zero at the 1%-significance level for all measures of price dispersion and for both subsamples. Additionally, the intersection-union test is rejected (at least) at the 5%-level in all specifications.

Throughout the paper, we have excluded stations located in Vienna, as Vienna has more than 1.5 million inhabitants and is therefore more than six times as large as the second biggest city. Our data on commuting behavior within Vienna is therefore only a rough guess. However, including Vienna does not change the main findings: The parameter estimates on μ and μ^2 always take the expected sign, and for all measures of dispersion (except the absolute distance, AD) the parameter estimates are significantly different from zero. The

[33]Note that this problem is mitigated as we use driving distance: Even if the Euclidean distance between one station on a highway and one station off that highway is small, those stations will not be in the same local market if there is no exit close-by.

intersection-union test, however, is rejected only once (twice) at the 1%- (10%-) significance level. These results are reported in Table 15.

We also follow Chandra and Tappata (2011) and restrict our sample to stations in local markets with three or more firms only (i.e. to stations with at least two competitors where prices are observed in the particular period). These results are summarized in Table 16. The sign and the statistical significance of the parameter estimates on μ and μ^2 and the intersection-union test support our main result of an inverse-U shaped relationship between consumer information and price dispersion.

Alternative ways to calculate μ (Tables 17–22). In our last set of robustness checks, we provide alternative ways of constructing μ. In the first alteration, we refrain from weighting commuter flows by the number of potential routes when calculating the share of informed consumers μ. Formally, all transit commuters receive the weight $\omega_{i,od} = 1$ provided station i complies with equation (6). As summarized in Table 17, the parameter estimates on μ and μ^2 take the expected signs and are statistically significant at the 1%-significance level for all measures of price dispersion. The intersection-union test again supports our main result of an inverse-U shaped relationship between consumer information and price dispersion.

In the second alteration, we relax the assumption that all commuters are perfectly informed about all prices, and assign instead different degrees of informedness τ to long-distance commuters. The degree of informedness depends on the number of stations sampled by each commuter flow in relation to the number of competitors in the local market. The measure of information endowment μ_i^{degree} is calculated as

$$\mu_i^{degree} = \frac{U_i \tau_i^U + \sum_o \sum_{d \neq o} \omega_{i,od} C_{od} \tau_{i,od}^I}{U_i + I_i}$$

where:

- $\omega_{i,od}$ is the weight assigned to the commuter flow from o to d, as described in Appendix B;

- $I_i = \sum_o \sum_{d \neq o} \omega_{i,od} C_{od}$ is the weighted number of commuters for station i;
- $\tau^I_{i,od}$ measures the degree of informedness of commuters from o to d passing by station i;
- τ^U_i measures the degree of informedness of non-commuters.

In line with the assumption maintained throughout the paper that non-commuters are uninformed, we set $\tau^U_i = 0$. To capture the idea that a commuter that samples more prices is likely to be better informed, we set $\tau^I_{i,od} = \frac{\delta_{i,od}}{N^{m_i}} \in [\frac{1}{N^{m_i}}, 1]$, where N^{m_i} is the number of firms in station i's local market and

$$\delta_{i,od} = \min(\text{average \# of stations observed by the commuter flow } C_{od}, N^{m_i}).$$

Thus, commuters that observe fewer prices than there are firms in market m_i are less-than-perfectly informed, in the sense that $\tau^I_{i,od} < 1$.

The regression results using the variable μ^{degree} are summarized in Table 18. For all measures of price dispersion the parameter estimates on the linear and the quadratic term on μ^{degree} take the expected signs and are significantly different from zero at the 1%-significance level. Additionally, the intersection-union test is rejected at the 1%-significance level for all measures of price dispersion, suggesting an inverted-U shaped relationship between consumer information and price dispersion.

In the third alteration, reported in Table 19, we assume that non-commuters have information on one price quote (i.e., $\tau^U_i = \frac{1}{N^{m_i}}$). Again, the parameter estimates for μ^{degree} and $(\mu^{degree})^2$ take the expected signs and are significantly different from zero at the 1%-significance level, and the intersection-union test is rejected at the 1%-significance level for all measures of price dispersion. Note that the absolute size of the parameter estimates on μ^{degree} and $(\mu^{degree})^2$ increases considerably: As we assign a lower degree of informedness to commuters on average (compared to the baseline specification, see Table 4) and a higher degree of informedness to non-commuters, the dispersion of the measure of information endowment becomes smaller, causing the parameter estimates to increase in absolute value.

In the fourth alteration, we account for the following: First, commuters passing by a large number of gasoline stations (compared to non-commuters and commuters passing by a smaller number of stations) are less likely to visit a particular station. Second, the probability that a non-commuter refuels at a given gasoline station declines with the number of stations located in the municipality. In this specification, we assign weights to each commuter based on the probability of his/her buying from a particular station if he/she randomly and uniformly chooses a commuting route $R_{od} \in \mathcal{R}_{od}$, and then randomly and uniformly buys from one of the stations in R_{od}. The weights $\omega_{i,od}^{alternative}$ for a commuter flow from o to d for station i can be expressed as follows:

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

The weighted number of informed consumers for station i can therefore be calculated as $I_i^{alternative} = \sum_o \sum_{d \neq o} \omega_{i,od}^{alternative} C_{od}$. Similarly, the weighted number of uninformed consumers, $U_i^{alternative}$, is the ratio of the number of non-commuters to the number of stations in the municipality. Having constructed $I_i^{alternative}$ and $U_i^{alternative}$, we can compute

$$\mu^{alternative\ weights} = \frac{I_i^{alternative}}{I_i^{alternative} + U_i^{alternative}}$$

for each gasoline station i.

The regression results using the variable $\mu^{alternative\ weights}$ are reported in Table 20. Again, for all measures of price dispersion, the parameter estimates on the linear term have positive signs, whereas the estimated coefficients on the quadratic term have negative signs. All parameter estimates on $\mu^{alternative\ weights}$ are significantly different from zero. The quadratic term $(\mu^{alternative\ weights})^2$ is significant in all but one specification (VOI). The higher variance of the quadratic term in this specification of μ results in the intersection-union test being rejected at the 5%-significance level for half of the measures of price dispersion.

In our fifth and final set of alterations, we experiment with different values of the critical driving distance $\overline{dist}$, which is used to determine whether a commuter flow passes by a given gasoline station. In the main specification, we used a critical distance of $\overline{dist} = 250$ meters, meaning that a commuter flow from municipality o to municipality d is assigned to station i if the driving distance from o to d passing through station i is less than 250 meters longer than traveling from o to d directly.

We use alternative critical distances of $\overline{dist} = 50$ meters (see Table 21) and $\overline{dist} = 500$ meters (see Table 22). Using a very narrow critical distance of 50 meters results in the parameter estimates of μ and μ^2 taking the expected sign, but being smaller in absolute value than in our baseline specification. The estimated coefficients on the linear term are statistically significant at the 1%- (5%-) level for five (all) measures of price dispersion, and the parameter estimates on the quadratic term are statistically significant at the 1%- (10%-) level in four (all) model specifications. The intersection-union test, however, is rejected only twice (four times) at the 5%- (10%-) significance level. This may be due to the fact that the mapping of gasoline stations is not accurate enough to assign transit commuters correctly to gasoline stations if a very small value of $\overline{dist}$ is chosen.

By contrast, the intersection-union test is rejected for all measures of price dispersion at the 5%-significance level when using $\overline{dist} = 500$ meters. As reported in Table 22, the parameter estimates take the expected signs and are significantly different from zero at the 1%-significance level for μ and μ^2 for all measures of price dispersion, supporting again our main finding of an inverse-U shaped relationship between consumer information and price dispersion.

Table 6: Regression results using raw prices to calculate dispersion and a market delineation of 2 miles

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ	1.325***	1.811***	2.264***	5.973***	0.806**	0.992***
	(0.382)	(0.541)	(0.796)	(0.746)	(0.323)	(0.341)
μ^2	-0.885***	-1.211***	-1.422**	-4.370***	-0.504*	-0.692**
	(0.320)	(0.462)	(0.665)	(0.621)	(0.274)	(0.290)
# of rival firms with prices (N_o^c)	0.011***	0.010*	0.126***	0.066***	0.016***	0.003
	(0.004)	(0.006)	(0.009)	(0.006)	(0.003)	(0.003)
# of rival firms (N^c)	0.046***	0.050***	0.031***	0.039***	0.012***	0.011***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.002)	(0.003)
Constant	-0.767***	-1.697***	-1.669***	-2.813***	-0.474***	-0.420***
	(0.136)	(0.205)	(0.299)	(0.292)	(0.119)	(0.133)
Overall inverse-U test						
t	1.55	1.43	0.94	5.18	0.78	1.50
p	0.061	0.076	0.172	0.000	0.219	0.067
Extremum ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.749	0.748	0.796	0.683	0.800	0.716
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.238	0.160	0.270	0.373	0.178	0.131

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 7: Regression results using residual prices to calculate dispersion for gasoline and a market delineation of 2 miles

	(1) VOI^M	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	1.763***	1.806***	4.166***	3.178***	1.190***	0.834***
	(0.314)	(0.468)	(0.570)	(0.598)	(0.235)	(0.265)
μ^2	-1.151***	-1.150***	-2.794***	-2.043***	-0.765***	-0.505**
	(0.257)	(0.395)	(0.478)	(0.498)	(0.198)	(0.228)
# of rival firms with prices (N_o^c)	0.057***	0.057***	0.107***	0.059***	0.018***	0.008***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.008***	0.009**	0.016***	0.025***	0.004***	0.003*
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.029	-0.054	-0.442**	-1.245***	0.007	0.102**
	(0.122)	(0.181)	(0.219)	(0.228)	(0.089)	(0.104)
Overall inverse-U test						
t	2.37	1.33	3.31	2.02	1.85	0.77
p	0.009	0.092	0.001	0.022	0.032	0.221
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.766	0.785	0.746	0.778	0.778	0.826
# of obs.	14,656	14,656	14,656	7,803	14,656	14,656
R^2	0.241	0.133	0.263	0.354	0.167	0.105

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 8: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles accounting for spatial autocorrelation in the residuals

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	1.792 ***	1.811 ***	3.181 ***	4.095 ***	1.027 **	0.911 **
	(0.505)	(0.504)	(1.043)	(0.552)	(0.408)	(0.359)
μ^2	-1.259 ***	-1.247 ***	-2.156 **	-2.902 ***	-0.672 **	-0.619 **
	(0.417)	(0.424)	(0.859)	(0.451)	(0.340)	(0.299)
# of rival firms with prices (N_o^c)	0.063 ***	0.065 ***	0.121 ***	0.060 ***	0.018 ***	0.007
	(0.007)	(0.006)	(0.013)	(0.005)	(0.004)	(0.004)
# of rival firms (N^c)	0.005	0.006	0.017 *	0.024 ***	0.006 **	0.005 *
	(0.005)	(0.004)	(0.010)	(0.003)	(0.003)	(0.003)
Constant	-0.577 ***	-0.605 ***	-1.081 ***	-2.153 ***	-0.244	-0.070
	(0.186)	(0.188)	(0.398)	(0.212)	(0.157)	(0.135)
λ	0.803 ***	0.143 ***	0.843 ***	0.789 ***	0.855 ***	0.520 ***
	(0.004)	(0.008)	(0.004)	(0.005)	(0.004)	(0.009)
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.712	0.726	0.738	0.706	0.764	0.736
# of obs.	14,634	14,634	14,634	7,927	14,634	14,634
R^2	0.264	0.140	0.285	0.371	0.174	0.105

Standard errors in parentheses obtained from a variance-covariance matrix of the residuals accounting for a spatially autoregressive process in the residuals $^{***}(p < .01)$, $^{**}(p < .05)$, $^{*}(p < .1)$

Regressions include station- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. λ is estimated using GMM based on residuals of OLS regression.

Table 9: Regression results using residual prices to calculate dispersion and a market delineation based on municipal borders

	(1) VOI^M	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	3.435***	3.485***	5.713***	12.122***	1.352***	1.032***
	(0.413)	(0.605)	(0.786)	(0.824)	(0.318)	(0.350)
μ^2	-2.986***	-3.048***	-5.007***	-10.485***	-1.185***	-0.855***
	(0.343)	(0.511)	(0.657)	(0.707)	(0.270)	(0.296)
# of rival firms with prices (N_o^c)	0.047***	0.047***	0.094***	0.058***	0.012***	0.005***
	(0.002)	(0.003)	(0.004)	(0.002)	(0.001)	(0.001)
# of rival firms (N^c)	-0.001	-0.001	-0.002	0.009***	-0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Constant	-0.682***	-0.729***	-1.142***	-3.655***	-0.125	0.027
	(0.143)	(0.211)	(0.276)	(0.285)	(0.109)	(0.123)
Overall inverse-U test						
t	8.02	5.58	7.00	13.98	4.12	2.61
p	0.000	0.000	0.000	0.000	0.000	0.005
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.575	0.572	0.571	0.578	0.571	0.604
# of obs.	14,037	14,037	14,037	7,895	14,037	14,037
R^2	0.340	0.194	0.376	0.543	0.182	0.104

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 10: Regression results using residual prices to calculate dispersion and a market delineation of 1.5 miles

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ	1.397***	1.229***	2.742***	4.914***	0.841***	0.625**
	(0.290)	(0.462)	(0.582)	(0.585)	(0.241)	(0.266)
μ^2	-0.988***	-0.829**	-1.870***	-3.729***	-0.550***	-0.436*
	(0.247)	(0.403)	(0.498)	(0.510)	(0.208)	(0.233)
# of rival firms with prices (N_o^c)	0.091***	0.093***	0.179***	0.091***	0.035***	0.022***
	(0.005)	(0.007)	(0.009)	(0.006)	(0.003)	(0.004)
# of rival firms (N^c)	0.002	0.002	0.014**	0.025***	0.006**	-0.000
	(0.003)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
Constant	-0.446***	-0.441**	-0.913***	-2.388***	-0.195**	-0.032
	(0.107)	(0.175)	(0.223)	(0.214)	(0.092)	(0.104)
Overall inverse-U test						
t	2.60	1.12	2.19	5.21	1.32	1.13
p	0.005	0.131	0.014	0.000	0.094	0.130
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.707	0.742	0.733	0.659	0.765	0.717
# of obs.	13,464	13,464	13,464	6,141	13,464	13,464
R^2	0.237	0.119	0.256	0.330	0.172	0.110

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 11: Regression results using residual prices to calculate dispersion and a market delineation of 10% relative overlap

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	6.149***	5.820***	11.236***	11.984***	3.020***	1.979***
	(0.412)	(0.621)	(0.736)	(0.681)	(0.260)	(0.320)
μ^2	-3.992***	-3.702***	-7.053***	-7.664***	-1.819***	-1.128***
	(0.340)	(0.516)	(0.608)	(0.556)	(0.214)	(0.264)
# of rival firms with prices (N_o^c)	0.050***	0.049***	0.101***	0.082***	0.011***	0.006***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
# of rival firms (N^c)	0.009***	0.009***	0.017***	0.017***	0.005***	0.003***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Constant	-1.799***	-1.735***	-3.485***	-4.486***	-0.806***	-0.422***
	(0.140)	(0.211)	(0.253)	(0.229)	(0.091)	(0.109)
Overall inverse-U test						
t	6.13	3.42	5.26	6.89	3.13	1.02
p	0.000	0.000	0.000	0.000	0.001	0.155
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.770	0.786	0.797	0.782	0.830	0.877
# of obs.	19,374	19,374	19,374	14,540	19,374	19,374
R^2	0.298	0.162	0.345	0.431	0.211	0.114

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 12: Regression results using residual prices to calculate dispersion and a market delineation of 90% relative overlap

	(1) VOI^M	(2) VOI	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	4.691***	4.485***	7.470***	16.137***	1.486***	1.380***
	(0.494)	(0.725)	(0.916)	(1.386)	(0.374)	(0.422)
μ^2	-4.038***	-3.940***	-6.430***	-14.871***	-1.349***	-1.108***
	(0.427)	(0.636)	(0.801)	(1.389)	(0.333)	(0.366)
# of rival firms with prices (N_o^c)	0.050***	0.049***	0.101***	0.066***	0.014***	0.009***
	(0.002)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
# of rival firms (N^c)	0.003***	0.003**	0.004**	0.009***	0.000	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)	(0.001)
Constant	-0.886***	-0.845***	-1.327***	-4.241***	-0.075	0.018
	(0.166)	(0.242)	(0.308)	(0.367)	(0.124)	(0.143)
Overall inverse-U test						
t	8.79	5.82	7.35	8.41	3.87	2.38
p	0.000	0.000	0.000	0.000	0.000	0.009
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.581	0.569	0.581	0.543	0.551	0.623
# of obs.	11,261	11,261	11,261	6,655	11,261	11,261
R^2	0.392	0.239	0.436	0.572	0.203	0.107

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 13: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, excluding 3 largest towns (apart from Vienna)

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	2.379***	2.450***	4.894***	4.069***	1.457***	1.213***
	(0.307)	(0.472)	(0.598)	(0.597)	(0.247)	(0.276)
μ^2	-1.657***	-1.670***	-3.388***	-2.711***	-0.980***	-0.854***
	(0.252)	(0.394)	(0.495)	(0.483)	(0.206)	(0.232)
# of rival firms with prices (N_o^c)	0.043***	0.048***	0.096***	0.069***	0.014***	0.004
	(0.005)	(0.007)	(0.009)	(0.006)	(0.003)	(0.004)
# of rival firms (N^c)	0.013***	0.011*	0.031***	0.007	0.009***	0.008**
	(0.004)	(0.006)	(0.007)	(0.005)	(0.003)	(0.003)
Constant	-0.765***	-0.767***	-1.637***	-1.625***	-0.401***	-0.218**
	(0.112)	(0.179)	(0.227)	(0.241)	(0.092)	(0.106)
Overall inverse-U test						
t	4.31	2.53	4.39	3.29	2.75	2.41
p	0.000	0.006	0.000	0.001	0.003	0.008
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.718	0.734	0.722	0.750	0.744	0.710
# of obs.	13,116	13,116	13,116	6,366	13,116	13,116
R^2	0.216	0.108	0.233	0.342	0.161	0.106

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 14: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, excl. highway stations

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ	1.801***	1.870***	3.165***	4.260***	0.993***	0.912***
	(0.300)	(0.460)	(0.587)	(0.555)	(0.237)	(0.264)
μ^2	-1.291***	-1.312***	-2.191***	-3.024***	-0.668***	-0.650***
	(0.249)	(0.388)	(0.489)	(0.460)	(0.200)	(0.225)
# of rival firms with prices (N_o^c)	0.063***	0.065***	0.121***	0.060***	0.018***	0.007***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.005*	0.006	0.017***	0.024***	0.006***	0.004**
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.589***	-0.626***	-1.103***	-2.178***	-0.243***	-0.103
	(0.109)	(0.174)	(0.221)	(0.208)	(0.088)	(0.102)
Overall inverse-U test						
t	3.63	2.18	2.84	4.48	1.90	1.92
p	0.000	0.015	0.002	0.000	0.029	0.028
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.698	0.713	0.722	0.705	0.742	0.702
# of obs.	14,625	14,625	14,625	7,926	14,625	14,625
R^2	0.262	0.138	0.282	0.374	0.173	0.104

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 15: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, including Vienna

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ	1.214***	1.092**	2.479***	3.192***	0.622***	0.387
	(0.296)	(0.460)	(0.575)	(0.549)	(0.221)	(0.261)
μ^2	-0.781***	-0.657*	-1.525***	-2.151***	-0.354*	-0.211
	(0.248)	(0.391)	(0.485)	(0.464)	(0.191)	(0.225)
# of rival firms with prices (N_o^c)	0.054***	0.053***	0.132***	0.093***	0.019***	0.007***
	(0.003)	(0.005)	(0.005)	(0.004)	(0.002)	(0.002)
# of rival firms (N^c)	0.011***	0.012***	0.016***	0.013***	0.004***	0.004**
	(0.002)	(0.003)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.027	-0.008	-0.093	-1.067***	0.153*	0.281***
	(0.110)	(0.176)	(0.216)	(0.210)	(0.081)	(0.100)
Overall inverse-U test						
t	1.54	0.58	1.24	2.65	0.40	0.12
p	0.062	0.282	0.108	0.004	0.344	0.451
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.777	0.831	0.813	0.742	0.879	0.914
# of obs.	17,993	17,993	17,993	11,000	17,993	17,993
R^2	0.422	0.237	0.474	0.607	0.265	0.121

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 16: Regression results using residual prices and a market delineation of 2 miles, prices of at least 2 competitors observed

	(1) VOI^M	(2) VOI	(3) $Range$	(4) $Trimmed\ range$	(5) SD	(6) AD
μ	2.592***	2.580***	4.415***	4.192***	1.188***	1.255***
	(0.433)	(0.664)	(0.839)	(0.555)	(0.313)	(0.375)
μ^2	-1.893***	-1.861***	-3.121***	-2.971***	-0.801***	-0.939***
	(0.356)	(0.560)	(0.694)	(0.460)	(0.260)	(0.318)
# of rival firms with prices (N_o^c)	0.052***	0.054***	0.099***	0.060***	0.010***	0.002
	(0.004)	(0.006)	(0.007)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.008***	0.008**	0.023***	0.024***	0.008***	0.006***
	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)
Constant	-0.887***	-0.894***	-1.635***	-1.616***	-0.343***	-0.193
	(0.160)	(0.256)	(0.327)	(0.220)	(0.121)	(0.149)
Overall inverse-U test						
t	3.97	2.31	3.08	4.39	1.80	2.23
p	0.000	0.010	0.001	0.000	0.036	0.013
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.685	0.693	0.707	0.706	0.742	0.668
# of obs.	10,685	10,685	10,685	7,996	10,685	10,685
R^2	0.244	0.125	0.262	0.370	0.189	0.112

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 17: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, no route-weights

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
$\mu^{no\ weights}$	1.753***	1.847***	3.212***	3.438***	1.030***	1.012***
	(0.283)	(0.429)	(0.553)	(0.488)	(0.220)	(0.244)
$(\mu^{no\ weights})^2$	-1.223***	-1.280***	-2.195***	-2.305***	-0.689***	-0.713***
	(0.222)	(0.342)	(0.435)	(0.386)	(0.175)	(0.196)
# of rival firms with prices (N_o^c)	0.064***	0.065***	0.122***	0.059***	0.018***	0.008***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# 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	-0.614***	-0.670***	-1.183***	-1.425***	-0.281***	-0.159
	(0.109)	(0.172)	(0.222)	(0.213)	(0.088)	(0.100)
Overall inverse-U test						
t	3.99	2.60	3.46	3.76	2.47	2.62
p	0.000	0.005	0.000	0.000	0.007	0.004
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.717	0.721	0.732	0.746	0.747	0.710
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.260	0.136	0.280	0.369	0.172	0.105

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 18: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, using different degrees of informedness

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ^{degree}	2.447***	2.601***	4.407***	4.842***	1.440***	1.408***
	(0.299)	(0.450)	(0.585)	(0.541)	(0.232)	(0.257)
$(\mu^{degree})^2$	-1.894***	-1.989***	-3.362***	-3.594***	-1.087***	-1.093***
	(0.237)	(0.361)	(0.466)	(0.440)	(0.188)	(0.207)
# of rival firms with prices (N_o^c)	0.064***	0.066***	0.123***	0.060***	0.018***	0.008***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.004*	0.005	0.015***	0.024***	0.005***	0.004**
	(0.003)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.785***	-0.860***	-1.471***	-1.834***	-0.380***	-0.257***
	(0.111)	(0.171)	(0.223)	(0.222)	(0.088)	(0.099)
Overall inverse-U test						
t	7.14	4.71	6.25	6.41	4.77	4.61
p	0.000	0.000	0.000	0.000	0.000	0.000
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.646	0.654	0.655	0.674	0.662	0.644
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.261	0.137	0.281	0.370	0.172	0.105

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 19: 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)

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ^{degree}	4.666***	4.922***	8.195***	6.882***	2.756***	2.218***
	(0.411)	(0.621)	(0.801)	(0.708)	(0.299)	(0.346)
$(\mu^{degree})^2$	-3.448***	-3.606***	-6.053***	-4.896***	-2.035***	-1.640***
	(0.287)	(0.436)	(0.563)	(0.534)	(0.214)	(0.246)
# of rival firms with prices (N_o^c)	0.068***	0.070***	0.129***	0.063***	0.021***	0.009***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.007**	0.008**	0.019***	0.030***	0.006***	0.005**
	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.002)
Constant	-1.633***	-1.755***	-2.917***	-2.700***	-0.878***	-0.582***
	(0.163)	(0.251)	(0.323)	(0.291)	(0.120)	(0.141)
Overall inverse-U test						
t	10.50	7.42	9.54	7.46	8.73	5.99
p	0.000	0.000	0.000	0.000	0.000	0.000
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.677	0.683	0.677	0.703	0.677	0.676
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.265	0.139	0.284	0.372	0.175	0.106

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 20: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, using alternative weights

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
$\mu^{alternative\ weights}$	0.900***	0.902***	1.759***	3.398***	0.892***	1.123***
	(0.281)	(0.460)	(0.535)	(0.642)	(0.234)	(0.262)
$(\mu^{alternative\ weights})^2$	-0.625**	-0.542	-1.132*	-2.801***	-0.725***	-1.042***
	(0.303)	(0.507)	(0.579)	(0.679)	(0.255)	(0.287)
# of rival firms with prices (N_o^c)	0.062***	0.063***	0.118***	0.058***	0.017***	0.007***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.002	0.002	0.011***	0.019***	0.004**	0.003
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.221***	-0.250*	-0.488***	-1.098***	-0.125*	-0.063
	(0.079)	(0.128)	(0.154)	(0.187)	(0.066)	(0.074)
Overall inverse-U test						
t	1.05	0.32	0.79	3.02	1.96	3.02
p	0.147	0.374	0.215	0.001	0.025	0.001
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.719	0.832	0.777	0.607	0.616	0.539
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.259	0.136	0.280	0.368	0.172	0.105

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 21: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 50$m

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*AD*
μ	1.424***	1.639***	2.484***	4.296***	0.661***	0.645**
	(0.308)	(0.469)	(0.596)	(0.594)	(0.244)	(0.266)
μ^2	-0.955***	-1.109***	-1.576***	-3.062***	-0.368*	-0.416*
	(0.262)	(0.403)	(0.508)	(0.504)	(0.210)	(0.230)
# of rival firms with prices (N_o^c)	0.063***	0.065***	0.122***	0.060***	0.018***	0.007***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	0.004*	0.005	0.015***	0.024***	0.005***	0.004**
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.485***	-0.578***	-0.913***	-1.637***	-0.154*	-0.029
	(0.109)	(0.172)	(0.218)	(0.224)	(0.088)	(0.099)
Overall inverse-U test						
t	2.00	1.52	1.37	4.03	0.27	0.83
p	0.023	0.064	0.086	0.000	0.394	0.204
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.745	0.739	0.788	0.701	0.899	0.776
# of obs.	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

Robust standard errors in parentheses. $^{***}(p < .01)$, $^{**}(p < .05)$, $^{*}(p < .1)$
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.

Table 22: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 500\text{m}$

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *AD*
μ	1.774***	1.818***	3.073***	3.971***	0.980***	1.026***
	(0.307)	(0.467)	(0.601)	(0.549)	(0.241)	(0.267)
μ^2	-1.273***	-1.281***	-2.129***	-2.777***	-0.664***	-0.755***
	(0.251)	(0.389)	(0.494)	(0.452)	(0.201)	(0.224)
# of rival firms with prices (N_o^c)	0.064***	0.065***	0.122***	0.059***	0.018***	0.008***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# 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	-0.602***	-0.643***	-1.107***	-1.558***	-0.254***	-0.150
	(0.112)	(0.178)	(0.229)	(0.221)	(0.091)	(0.104)
Overall inverse-U test						
t	3.66	2.21	2.82	4.09	1.98	2.50
p	0.000	0.014	0.002	0.000	0.024	0.006
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.697	0.710	0.722	0.715	0.738	0.679
# of obs.	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

Robust standard errors in parentheses. ***($p < .01$), **($p < .05$), *($p < .1$)
Regressions include station- and region-specific characteristics, state and time fixed effects as well as dummy variables for missing exogenous variables.