Information and Price Dispersion: Evidence from Retail Gasoline *

Dieter Pennerstorfer† Philipp Schmidt-Dengler‡ Nicolas Schutz§
Christoph Weiss¶ Biliana Yontcheva¶

March 5, 2014

Abstract

We examine the relationship between information and price dispersion in the retail gasoline market. We first show that the clearinghouse models in the spirit of Stahl (1989) generate an inverted-U relationship between information and price dispersion. Past empirical studies of this relationship have relied on (intertemporal) variation in internet usage and adoption to measure the number of consumers that have access to the clearinghouse. We construct a new measure of information based commuter data from Austria. Regular commuters can freely sample gasoline prices on their commuting route, giving us spatial variation in the share of informed consumers. We use detailed information on gas station level price to construct various measures of price dispersion. Our empirical estimates of the relationship are in line with the theoretical predictions.

Keywords: Search, Price Dispersion, Retail Gasoline, Commuter Data
JEL Classification: D43, D83, L13

*We thank Tomaso Duso and seminar participants at DIW Berlin, St. Gallen, the University of Queensland, Queensland University of Technology, Vienna University of Economics and Business, WIFO, and the 2014 Winter Marketing-Economics Summit for helpful comments. Schmidt-Dengler is also affiliated with CEPR, CES-Ifo, and ZEW.

†Austrian Institute of Economic Research

‡University of Mannheim, also affiliated with CEPR, CES-Ifo, and ZEW.

§University of Mannheim

¶Vienna University of Economics and Business

1 Introduction

Price competition in homogeneous goods markets rarely yields results in market outcomes in line with the "law of one price." To the contrary, price dispersion is ubiquitous and differences in location, cost or services attributed to seemingly homogeneous goods cannot fully explain observed price dispersion. In his seminal paper on "The Economics of Information," Stigler (1961) offered the first search-theoretic rationale for price dispersion. In fact, Stigler claims 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 when consumers are not fully informed about prices (see Baye et al. (2006)).

The present paper examines the relationship between information and price dispersion. We first derive the global relationship between information and price dispersion in a "clearinghouse model" as introduced by Varian (1980) and further developed by Stahl (1989). Consumers are aware of sellers' (randomized) pricing strategy, but differ in the degree of information. For some, obtaining an additional price quote is costly. Others are aware of all prices charged in the relevant market: they have access to the "clearinghouse." At the very extremes, this model predicts no price dispersion. If no consumer has access to the clearinghouse, all firms will charge the monopoly price. Conversely, if all consumers are fully informed, this corresponds to Bertrand competition, and price equals marginal cost. While the existing literature has observed that price dispersion is not a monotone function of the fraction of informed consumers (see Conclusion 3 in Baye et al. (2006)), we prove that the model generates an inverse-U relationship globally.

We then test this prediction. Price dispersion has been observed and analyzed in a large number of markets (Baye et al. (2006)). These studies examine a variety of issues, including the difference between online and offline price dispersion, the effect of the number of sellers, the relationship between dispersion and purchase frequency, and the dynamics of online price dispersion. Empirical studies focusing on the impact of consumer information on price dispersion, however, are rare; the challenge here is to find a good measure for the fraction of informed consumers. Sorensen (2000) finds empirical evidence that purchase frequency (of drugs) is negatively correlated with both price-cost margins and dispersion, which is interpreted evidence in support of search models. Analyzing price dispersion in the market for life insurances, Brown and Goolsbee (2002) use variation in the share of consumers searching on the Internet over a six year period 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 decrease later on. Tang et al. (2010) examine the impact of changes in shopbot use over time on pricing behavior in the Internet book market. They observe that an increase in shopbot use is correlated with a decrease in price dispersion over time.

While analysis of price dispersion in online markets versus offline markets has provided useful insights, we argue that it may be preferable to look at the relationship between information and price dispersion in an offline market. First, Ellison and Ellison (2005) and Ellison and Ellison (2009) question the extent to which the Internet has actually reduced consumer search costs. They provide evidence that firms in online markets often engage in "bait and switch" as well as "obfuscation" strategies that frustrate consumer search and make search more costly.[1] Second, Baye and Morgan (2001) stress that consumers' and firms' decisions to use Internet shopbots are endogenous. Consumers' expected gains from obtaining information from shopbots will increase with the dispersion of prices in the market which implies that a correlation between the share of internet users and price dispersion cannot be given a causal interpretation.

Our paper follows a different approach. We adopt an alternative interpretation of the "clearinghouse" by employing spatial variation in commuting behavior. Commuters are able to freely sample all price quotes for gasoline along their commute. Using detailed data on commuting behavior from the Austrian census, we construct the share of commuters passing by an individual gas station. We use this as our measure of the fraction of informed consumers. We combine this with data on retail gasoline prices at the station level to test the relationship between consumer information and price dispersion. To the best of our knowledge, this is the first attempt to create a measure of informed consumers not related to internet usage or access. We believe that our setting is closer in spirit to the seminal clearinghouse models of Varian (1980) and Stahl (1989) for the following reasons: (a) firms' abilities to obfuscate consumers search and learning efforts are limited in this market, (b) gasoline is a homogeneous product and seller characteristics can be adequately controlled, (c) we observe substantial variation in our measure of the share of informed consumers enabling us to test the global prediction derived from theory, and (d) the consumers' decisions to commute - and thus to become better informed - is not determined by regional differences in price dispersion which allows a causal interpretation of our empirical results.

[1] According to Ellison and Ellison (2005) "the Internet makes it easy for e-retailers to offer complicated menus of prices (for example, with different options for shipping), to make price offers that search engines will misinterpret (like products bundled together), to personalize prices and to make the process of examining an offer sufficiently time consuming so that customers will not want to do it many times" (p. 153). They conclude that "whether the Internet will prove to aid search or obfuscation more is not clear a priori" (p. 153) and that "Knowledgeable economists would also not have put much faith in how the Internet would lead literally to the 'Law of One Price' " (p. 149)

Our empirical findings are surprisingly robust. For all commonly used measures of price dispersion, we cannot reject the null-hypothesis of an inverted-U relationship. This result is also robust to different market definitions. As a further robustness check we also test a key implication of the model: Price levels decline with the fraction of informed consumers.

The remainder of the paper is organized as follows. Section 2 presents the clearinghouse model and derives the testable prediction regarding the relationship between information and price dispersion. Section 3 describes the industry, the retail price data, and our construction of a measure of informed consumers from the information on commuting behavior in the Census. Section 4 presents the empirical results. Section 5 concludes.

2 Information and Price Dispersion in Clearinghouse Models

In this section, we present Stahl (1989)'s search model with unit demand, which encompasses Varian (1980)'s model of sales as a special case. There is a finite number of 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 maximal willingness to pay $v > c$. A share $\mu \in (0, 1)$ of consumers are "informed" consumers who observe all prices through the clearinghouse. We sometimes refer to these consumers as "shoppers", because they sample all prices. These consumers buy at the lowest price provided that it does not exceed their willingness to pay v. The remaining fraction of consumers $(1 - \mu)$ is referred to as "non-shoppers". They engage in sequential search with costless recall: the first sample is free, thereafter each sample costs $s > 0$.

Equilibrium price distribution. It is well known that for any $\mu \in (0, 1)$ there is no pure strategy equilibrium, but that there exists a unique symmetric mixed strategy equilibrium. The equilibrium price distribution is given by

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

for all p in support $\left[\underline{p}, \bar{p}\right]$. Solving for $F(\underline{p}) = 0$, we obtain 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 is pinned down by the non-shoppers' optimal search behavior. Stahl (1989) shows that the optimal search rule is characterized by a reservation rice rule. He also shows that when there are $K \geq 1$ stores left, the reservation price rule is independent of the number of stores left. Let $\psi(r)$ be the expected net benefit of searching when facing a price of r:

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

Then the upper bound of the support is such that $\psi(\bar{p}) \leq 0$, because otherwise $\bar{p}$ would lead to zero profit. It must also hold that $\psi(\bar{p}) \geq 0$ if $\bar{p} < v$, because otherwise a firm could strictly increase its profit by charging a price of $\bar{p} + \varepsilon$. Since ψ is strictly increasing in $\bar{p}$, there exists a unique $\bar{p}$ which satisfies these conditions. Janssen et al. (2011) show that $\psi(r) = 0$ if and only if $r = \rho \equiv c + \frac{s}{1-\alpha}$, where $\alpha = \int_0^1 \frac{dz}{1+\frac{\mu}{1-\mu}Nz^{N-1}} \in (0,1)$. It follows that the upper bound of the support is given by $\bar{p} = \min(\rho, v)$.

Observe that if $s \geq v - c$, then non-shopper never find it profitable to search and our model is equivalent to Varian's model of sales. In this case, $\rho > v$ and $\bar{p} = v$ for all (μ, N), as in Varian (1980). Conversely, if $s < v - c$, then there exists a unique $\hat{\mu} \in (0,1)$ such that $\bar{p} = v$ if $\mu \leq \hat{\mu}$ and $\bar{p} = \rho$ if $\mu \geq \hat{\mu}$.[2] We thus have fully characterized the equilibrium price distribution in terms of the parameters (c, v, s, μ, N).

Expected Price. The expected price is given by

$$\begin{aligned} E(p) &= \int_{\underline{p}}^{min(\rho,v)} pdF(p), \\ &= c + \alpha * (min(\rho, v) - c). \end{aligned}$$

It is immediate, that the expected price is decreasing in the fraction of shoppers μ, as both α and ρ are decreasing in μ. In order to validate the model, we will test the following prediction due to Stahl (1989):

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

The intuition behind this result is very simple. As the proportion of shoppers increases, firms are increasingly tempted to attract shoppers by charging the lowest price. As a consequence, both the upper bound and the lower bound of the distribution shift down, and probability mass shifts down everywhere.

Price dispersion. Various measures of price dispersion have been used in the literature. We will focus on one common measure of price dispersion: the *Value of Information (VOI).* It corresponds to a consumer's expected benefit of becoming informed: the difference between

[2]This follows from the fact that ρ is strictly decreasing in μ and has limits $+\infty$ and $c + s$ in 0 and 1, respectively.

the expected price and the expected minimum price in the market:

$$E(p - p_{min}) = \int_{\underline{p}}^{\bar{p}} p \left[1 - N\left[1 - F(p)\right]^{N-1}\right] dF(p), \tag{2}$$

where $p_{min} = \min\{p_1, p_2, \ldots, p_N\}$. Substituting the equilibrium price distribution (1) into equation (2) and applying change of variables $z = 1 - F(p)$ yields

$$\begin{aligned} E(p - p_{min}) &= \int_0^1 \left(c + \frac{\bar{p} - c}{1 + \frac{\mu}{1-\mu} N z^{N-1}} \right) \left(1 - N z^{N-1}\right) dz, \\ &= (\bar{p} - c) \left(\alpha - \frac{1-\mu}{\mu}(1 - \alpha) \right). \end{aligned}$$

When μ is close enough to zero, $\bar{p} = v$ and the value of information goes to zero as μ goes to zero. Conversely, when μ is in the neighborhood of 1, $\bar{p}$ is equal to either $c + \frac{s}{1-\alpha}$ or $\bar{v}$. In both cases, the value of information goes to zero as μ goes to 1. We prove the following proposition:

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 value $\bar{\mu} \in (0, 1)$ such that price dispersion is increasing in μ on $(0, \bar{\mu})$ and decreasing in μ on $(\bar{\mu}, 1)$.*

Proof. It follows from Lemma 1 in Tappata (2009) that $\alpha - \frac{1-\mu}{\mu}(1 - \alpha)$ is strictly concave in μ. Combining this with the fact that $E(p - p_{min})$ goes to 0 as μ goes to 0 and 1 proves the proposition for the case $s \geq v - c$.

Next, assume $s < v - c$. Then $E(p - p_{min})$ is strictly concave on interval $(0, \hat{\mu}]$, and we now claim that it is strictly decreasing on $[\hat{\mu}, 1)$. If $\mu \geq \hat{\mu}$, then $v = \rho$ and $E(p - p_{min})$ simplifies to $s\left(\frac{\alpha}{1-\alpha} - \frac{1-\mu}{\mu}\right)$, which is strictly decreasing in μ by Lemma 1, stated and proven in Appendix A. This concludes the proof. □

To obtain intuition behind this result, consider starting at $\mu = 0$, where all firms charge the monopoly price v and there is zero 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, 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 $\mu \geq \hat{\mu}$, the reserve price ρ is binding, and therefore, both the upper bound and the lower bound of the distribution shift down: when firms are constrained by consumers' optimal search behavior, the support widens less as μ increases. Consequently, prices dispersion decreases for all $\mu \geq \hat{\mu}$.

To summarize, price dispersion is strictly concave on $(0, \hat{\mu})$ and strictly decreasing on $(\hat{\mu}, 1)$. It is therefore a strictly quasi-concave and single-peaked function of the fraction of shoppers μ.

3 Industry Background and Data

3.1 Gasoline Prices and Stations

Our empirical analysis focuses on the retail gasoline market in Austria. The retail gasoline market is particularly suitable for our purpose: Retail gasoline is a fairly homogeneous product with the main source of differentiation being spatial location, which is easily controlled for. Further, consumers primarily visit gas stations to purchase gasoline, so that our analysis is less likely to be confounded by consumers purchasing multiple products (see Hosken et al. (2008)).

We use quarterly data on diesel prices at the gas station level[3] from October 1999 to March 2005. Prices from each station were collected within three days at each time period by the Austrian Chamber of Labor ("Arbeiterkammer") on weekdays. We merge the price data with information on the geographical location of all 2,814 gas stations as well as their characteristics: the number of pumps, whether the station has service bays, a convenience store etc..[4] Retail prices are nominal and measured in Euro cents per liter, including fuel tax (a per unit tax) and value added tax. In total, 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 every quarter. As there is no systematic pattern with respect to whether a particular station was sampled in a given year, we are not concerned with selection issues. We will however control for unsampled competitors in a given market in the price-dispersion regressions.

To characterize the spatial distribution of suppliers and to 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 individual gasoline stations is linked to information on the Austrian road system.[5]

[3] 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).

[4] The information on gas station characteristics have been collected by the company Experian Catalist in August 2003, see `http://www.catalist.com` for company details.

[5] 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).

This allows us to generate accurate measures of distance as well as the commuting behaviour across the road network.

3.2 Commuters as Informed Consumers

The main idea behind our measure of information is that commuters can freely sample prices along their daily commuting path.[6] We therefore rely on the fraction of long-distance commuters as a measure of the "shoppers" on 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. We define individuals who travel by car as a driver on a daily basis to work and go beyond the border of their own municipality as long-distance commuters. Our estimate of the share of informed consumers faced by a gas station depends on the relative size of this group compared to the total size of the station's market.

Commuter flows

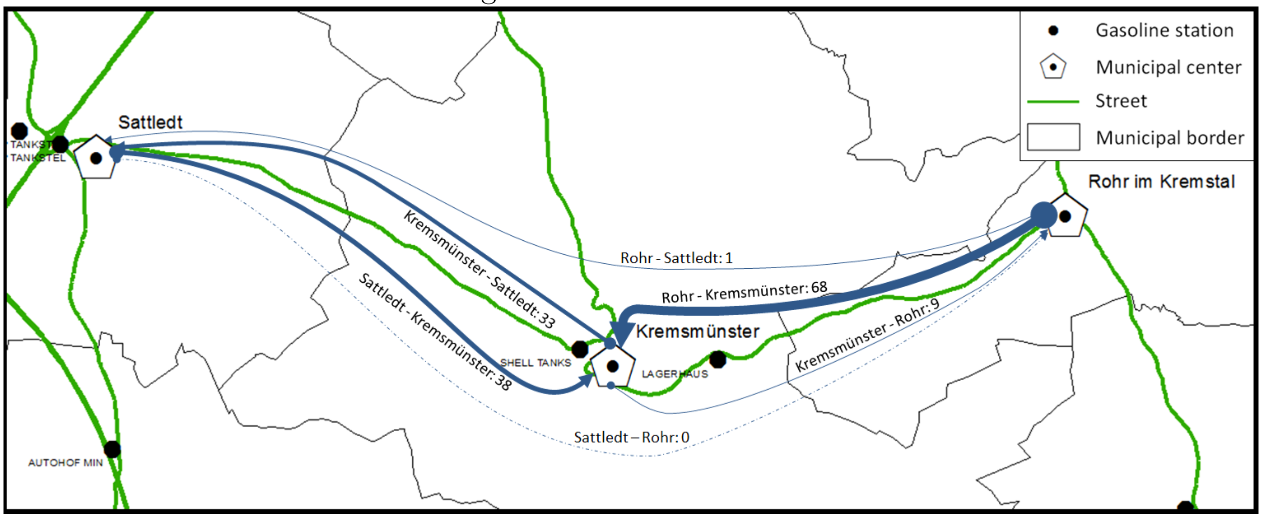
According to the 2001 census, 2,051,000 people in Austria go to work by car on a daily basis. For 1,396,426 of these people, the commute involves regular travel beyond the boundaries of their home municipality. We will refer to these consumers as informed consumers. The Austrian Statistical Office provides detailed information on the number of individuals commuting from a given "origin-municipality" o to a different "destination-municipality" d for each of the 2381 administrative units in Austria. All commuters are assigned to an origin-destination pair of municipalities based on their home address and their workplace address.[7] Since municipalities are generally very small regional units, this allows us to create an intricate description of the commuting patterns in Austria. The average (median) municipality is 13.8 (9.4) square-miles large, has 3373 (1575) inhabitants and 1.19 (1) gasoline stations. For the average (median) municipality strictly positive commuter flows to 51 (32) other municipalities are observed.

In order to assign commuter flows to gas stations we merge the municipality-level data on the spatial distribution of commuters with data on the precise location of each station within the road network using GIS software (WiGeoNetwork Analyst, ArcGIS). This allows us to

[6] Houde (2012) emphasizes the role of commuters on firms' pricing decisions. Commuters also tend to purchase more fuel, than their non-commuting counterparts and therefore gain more from information regarding the price distribution (Marvel (1976), Sorensen (2000)).

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

Figure 1: Commuter flows



We illustrate the commuter flow assignment using two stations in the municipality of Kremsmünster as an example. Commuter flows from and to Kremsmünster are automatically assigned to the two stations located in it (33+38+68+9 commuters are added to the informed share of consumers). The assignment of the 1 commuter from Rohr to Sattledt to one of the stations (e.g. Lagerhaus) is based the distance of the time-minimizing path from Rohr to Sattledt (approx. 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. This is 100 meters more than he would travel otherwise. 100 meters is with-in our critical distance, so we would count the commuter as one of the informed consumers in the market of the Lagerhaus station.

determine how many individuals reside in the municipality where a given station i is located but commute to a different municipality. Let this number be denoted by C_i^{out}, the number of individuals commuting *out* of the municipality where station i is located. Commuters who work in the municipality of station i but live in a different municipality also belong to the station's informed potential consumers. We denote their number by C_i^{in}, the number of consumers commuting *in*to the municipality where station i is located.

For a complete measure of informed consumers, we also need to take into account consumers 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 and denote them by C_i^{tr}. We assume that transit consumers are familiar with the prices of gasoline stations located directly on the commuting path, but not with the entire gasoline market in the municipality. As such, they are likely to be part only of the market of stations who are located directly on their commuting path. In order to obtain a measure C_i^{tr} of transit consumers, we use the shortest path algorithm integrated in ArcGIS. The algorithm computes the optimal route from the origin municipality o to the 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 residence and workplace of commuters with the address of the administrative center of the respective municipalities (usually the town hall) when calculating distances.

Assigning commuter flows to gas stations

We use the shortest path algorithm, to determine whether a commuter flow will pass through a given station i, by comparing the length of the optimal route from the origin municipality to the destination municipality ($dist_{od}$) with the length of the optimal route between the two which passes through the station (see Figure 1). The distance of the optimal route between the origin o and the station i is denoted by $dist_{oi}$ and the distance between the gas station and the destination is given by $dist_{id}$. If the difference in the calculated distances is less than our chosen critical value ($\overline{dist}$),[8] the commuter flow might pass by the station and as such plays a role in the local market. The commuter flow from municipality o (origin) to municipality d (destination) is assigned to station i whenever

$$dist_{oi} + dist_{id} - dist_{od} < \overline{dist}. \tag{3}$$

For our main specification we use a small critical distance ($\overline{dist} = 250$ meters), in order to ensure that the price of the station can be sampled while staying on the road (the station is visible without a deviation from the commuting route). One could also argue that commuters are willing to incur small costs in order to obtain extra information.[9]

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 (3) 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 gas station. To calculate the weights we have to determine the number of potential routes going from o to d satisfying equation (3) a and check if a particular station is included in all of these routes or only a selection of those. The details of the weighting scheme are given in Appendix B.

Using the methodology outlined above, we construct the following measure for the total

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

[9] We have performed robustness checks by employing slack distances ranging from 50 meters to 1 kilometer, yielding similar results. These results are available from the authors upon request.

number of informed consumers on the market of station i (I_i):

$$I_i = C_i^{out} + C_i^{in} + C_i^{tr} \tag{4}$$

We approximate the number of uninformed consumers on the market (U_i) with the number of employed individuals living in the municipality in which the station is located who do not regularly commute over long distances by car.[10]

Having determined the number of uninformed consumers, we calculate a station-specific proxy for the fraction of informed consumers in station i's market μ_i:

$$\mu_i = \frac{I_i}{U_i + I_i} \tag{5}$$

Table 1 shows summary statistics for measure of the fraction of informed consumer. The mean value of our information measure lies close to the 60 percent mark. This skewness towards larger values could indicate that commuter flows account for a significant fraction of the gas 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 variability in our measure of informed consumers allows us to examine the effects of information on the most common measures of price dispersion. Only very low values of μ are not present in 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

3.3 Measuring Price Dispersion

We now describe how we construct measures of dispersion, the main variable we wish to explain. Below we explain how we construct "residual" prices, define local markets, and the various of measures of price dispersion we employ.

[10]Given the localized character of competition and the assumed lack of mobility for uninformed consumers, a more narrow definition of U_i could be preferable for very large municipalities. Since data availability impedes such an approach, we exclude stations located in Vienna throughout the empirical analysis. As a robustness exercise we also exclude stations located in the three largest towns in Austria besides Vienna (Graz, Linz and Salzburg). Regression results excluding stations in these municipalities are reported in Table 12 in Appendix D. Results including Vienna are not reported but available from the authors upon request.

Residual prices. Even though diesel fuel is homogeneous in terms of its physical characteristics, gas stations differ not only in their location, but also in terms of services provided and other characteristics. Thus, a simple explanation for the observed existence of price dispersion relies on heterogeneity. The challenge is to obtain a measure of price dispersion after removing the main sources of heterogeneity. We follow the literature[11] and obtain the residuals of a price equation and interpret these residuals as the price of a homogeneous product. 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}) using seller (ζ_i) and time (χ_t) fixed effects:

$$p^r_{it} = \alpha + \zeta_i + \chi_t + u_{it} \tag{6}$$

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 store specific effects and fluctuations in prices common to all stores. We are aware of the risk of misspecification bias in this regression. As Chandra and Tappata (2011) point out, the results are only valid if the fixed station effects are additively separable from stations' costs. We will therefore present results for our key relationship of interest for both cleaned (p) and raw (p^r) prices.

Local markets. In order to construct measures of price dispersion, we need to define local markets. We do so by connecting each location to the Austrian road network and defining a unique local market for each firm. The local market contains the location itself and all rivals within a critical driving distance. Similar concepts have been applied when studying retail gasoline markets (see for example Hastings (2004) and Chandra and Tappata (2011)). We depart from the existing literature by using driving distance rather than distance as the crow flies. Local markets are thus not characterized by circles, but by a delineated part of the section network. We use a critical driving distance of two miles in our main specification, but apply different ways to delineate local markets in our sensitivity analysis to show the robustness of our results.

Measures of price dispersion. To examine the impact of our measure of informed consumers on price dispersion we need to summarize the price distribution in a (local) market in a single metric. Several measures of price dispersion have been proposed in the literature. We will first focus on the "value of information" (VOI, also known as "gains from search"). This is a commonly used measure and the testable prediction in section 2 is based on this

[11] See e.g. Lach (2002), Barron et al. (2004), Bahadir-Lust et al. (2007), Hosken et al. (2008) or Lewis (2008)

metric. This measure has a very intuitive interpretation: it corresponds to a consumer's expected benefit of being informed. The value of information is defined as the difference between the expected price and the lowest expected price in the market. If we denote the local market around station i by m_i, then the VOI for the market defined by station i is given by $VOI_i = E[p^{m_i}] - E[p^{m_i}_{min}]$.[12] While the estimate of $E[p^{m_i}_{min}]$ is given by $p^{m_i}_{(1)}$ (i.e. the first order statistic of prices sampled in market m_i), there are two possibilities to construct $E[p^{m_i}]$. One is to use station i's price as the expected price: $E[p^{m_i}] = p_i$ and $VOI_i = p_i - p^{m_i}_{min}$. Another possibility is to follow Chandra and Tappata (2011) and use the average local market price $\overline{p}^{m_i}$, and therefore $E[p^{m_i}] = \overline{p}^{m_i}$ and $VOI^{m_i} = \overline{p}^{m_i} - p^{m_i}_{min}$. We denote this measure by VOI^M (M for "market"). In what follows, and apply both definitions to calculate the value of information.

Another common measure of price dispersion is the sample range, defined as $R_i = p^{m_i}_{max} - p^{m_i}_{min}$. As this measure is strongly influenced by outliers, we also use the Trimmed Range $TR_i = p^{m_i}_{(N-1)} - p^{m_i}_{(2)}$, i.e. the difference between $(N-1)$-th and second order statistic, as a measure of price dispersion The obvious disadvantage of the latter measure is that the trimmed range TR_i can only be constructed for local markets with at least four firms.

As the value of information, Range and Trimmed Range are based on extreme values of the local price distribution, 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, as done by the standard deviation. Similar as with the VOI we can compare the price of a particular station i, or the prices of all stations within a local market with the average (local) market price. In the first case this measure equals the absolute difference between the price and of station i and the average market price (and thus $AD_i = |p_i - \overline{p^{m_i}}|$), whereas in the latter case the standard deviation is defined as $SD^{m_i}_i = \sqrt{\sum_{i \in m_i} (p_i - \overline{p}^{m_i})^2 / (N^{m_i} + 1)}$ with N^{m_i} as the number of rivals in station i's market m_i.

Table 2 reports summary statistics for these measures of price dispersion for different market delineations, namely two miles, 1.5 miles and using administrative boundaries (the municipality where the station is located). For each market delineation the number of observations is reduced sharply when calculating the trimmed range, as the sample is restricted to markets where the number of rival firms $N_o \geq 3$. All measures of price dispersion are slightly

[12] Note that all these measures are calculated for both raw and residual prices.

larger (smaller) when using two miles rather than 1.5 miles (municipality boundaries) to delineate local markets. The standard deviation (SD) is less dependent on different types of market definitions, as expected. While raw prices are more dispersed than cleaned prices, the difference is rather small.

3.4 Descriptive Evidence

In this section we highlight the importance of permanent (spatial) as well as temporal price variation and provide first descriptive evidence on the relationship between consumers' information endowment and price dispersion.

Permanent (spatial) price differences

Table 3 summarizes regression results on the level of prices. The first and second columns report parameters obtained from a model estimated on the entire sample, whereas the third and fourth (fifth and sixth) columns show the estimation results when the sample is restricted to stations where prices are available for at least one (three) rival firm(s) in the local market. All regressions are estimated using either time fixed effects (first, third and fifth columns) or the crude oil price index (second, fourth and sixth columns). The results remain nearly unchanged if the fixed time effects are replaced by the crude oil price-index to capture the effects of cost shocks that are common to all gasoline stations. As expected (and documented in the existing empirical literature (Eckert, 2013)), crude oil prices exert a positive and highly significant impact on the level of retail gasoline prices. Our results suggest that a larger share of informed consumers reduces market prices in line with Remark 1 in Section 2. Going from no informed consumers to all consumers being informed would reduce prices by about 2 cents.

In Table 4 we use stations' average price levels (which correspond to the fixed station-level effects ζ_i from the two-way fixed effects regression model in equation (6)) instead of actual prices to investigate permanent price differences between firms. We again find a negative effect of the share of informed consumers (μ). Note that the size and the statistical significance of the parameter estimates are hardly affected when analyzing stations' average (rather than actual) prices.

Temporal price variations

Chandra and Tappata (2011) observe that price dispersion may come from permanent price differences and suggest to look at changes in price rankings over time. The aim is to establish

Table 2: Descriptive Statistics on Measures of Price Dispersion

Local market delineation	2 Miles		1.5 Miles		Municipality	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Residual Prices						
VOI^M	0.725	(0.781)	0.644	(0.721)	0.847	(0.902)
VOI	0.723	(1.095)	0.643	(1.034)	0.847	(1.204)
Range	1.467	(1.526)	1.306	(1.415)	1.725	(1.770)
SD^M	0.538	(0.546)	0.508	(0.542)	0.571	(0.556)
AD	0.466	(0.608)	0.446	(0.590)	0.486	(0.632)
Raw Prices						
VOI^M	0.747	(0.960)	0.655	(0.874)	0.900	(1.123)
VOI	0.749	(1.355)	0.655	(1.264)	0.900	(1.536)
Range	1.546	(2.028)	1.364	(1.880)	1.951	(2.513)
SD^M	0.538	(0.546)	0.541	(0.724)	0.652	(0.819)
AD	0.498	(0.797)	0.471	(0.760)	0.548	(0.892)
# of rival firms (N)	6.965	(6.415)	5.051	(4.126)	13.781	(19.145)
# of rival firms with prices (N_o)	4.428	(4.351)	3.346	(2.888)	7.919	(10.054)
# of obs.	14,851		13,464		14,037	
Descriptive Statistics for Trimmed Range only:						
Residual Prices						
Trimmed Range	0.881	(0.921)	0.753	(0.827)	1.210	(1.149)
Raw Prices						
Trimmed Range	0.879	(1.226)	0.746	(1.112)	1.255	(1.529)
# of rival firms (N)	10.560	(6.769)	8.069	(4.233)	22.682	(21.662)
# of rival firms with prices (N_o)	7.030	(4.505)	5.660	(2.857)	13.035	(10.943)
# of obs.	7,996		6,141		7,895	

Local markets are restricted to having a minimum of one rival firm with price information ($N_o \geq 1$). For the trimmed range markets are restricted to three rival firms with price information ($N_o \geq 3$).

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)	(0.519)	(0.393)	(0.520)
# of rival firms (N)	-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.	21905	21905	14851	14851	7996	7996
R^2	0.804	0.171	0.805	0.166	0.809	0.166

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and random station effects, as well as dummy variables for missing exogenous variables. Models (1), (3) and (5) include fixed time effects. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 4: Regression results on stations' average price levels (delineation: 2 miles)

Dependent variable: Average price over all periods	Full sample	Markets with at least 2 firms	Markets with at least 4 firms
	(7)	(8)	(9)
μ	-2.264***	-1.814***	-2.005***
	(0.350)	(0.422)	(0.593)
# of rival firms (N)	-0.015*	-0.008	-0.011
	(0.009)	(0.009)	(0.011)
Constant	-1.473***	-1.375***	-1.053*
	(0.390)	(0.492)	(0.610)
# of obs.	1513	1015	570
R^2	0.543	0.572	0.636

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state effects as well as dummy variables for missing exogenous variables. Average price level of station i is the station fixed effect ζ_i from equation (6). Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

whether firms indeed employ mixing strategies and hence uninformed consumers are indeed unaware of the identity of the station charging the lowest price. We follow Chandra and Tappata (2011) and calculate a measure of rank reversals 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 prices of both stations at least for two time periods). Let T_{ij} denote the number of periods where price information of both firms are available. Subscripts i and j are assigned to the two stations such that $p_{it} \geq p_{jt}$ for most time periods. The measure of rank reversals is defined as the proportion of observations with $p_{jt} > p_{it}$:

$$r_{ij} = \frac{1}{T_{ij}} \sum_{t=1}^{T_{ij}} \mathbf{I}_{\{p_{jt} > p_{it}\}}, \tag{7}$$

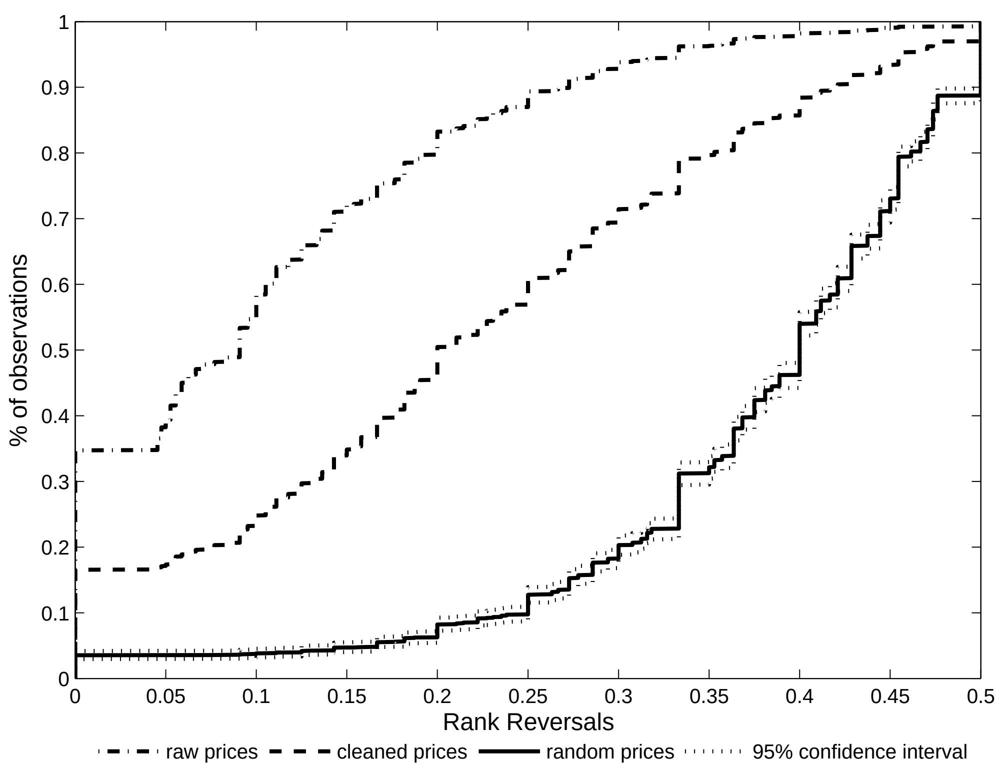
Table 5 shows summary statistics on the measure of rank reversals. When using raw prices, the station that is cheaper most of the time charges higher prices in 10.5% of all time periods. Our measure of rank reversals increases to 21.5% when analyzing cleaned prices instead of actual prices. As a benchmark we calculate this measure of rank reversals based on prices drawn randomly from the observed distribution of prices (conditional upon the number of pairs and the number of time periods where price information on both stations are available). In this benchmark scenario the measure of rank reversals equals 37.4%. Figure 2 shows the cumulative distribution function (CDF) of raw, cleaned and "random" prices. For a large number of station pairs (about 35%) one station charges higher raw prices in all periods where price information on both stations is available. When using cleaned prices instead, this figure reduces to less than 15%. Cleaning prices from permanent differences increases price dynamics between firms in a local market, i.e. firms change their position in the price distribution more often and the cumulative distribution function for cleaned prices thus is always below the respective function for actual (raw) prices. We interpret this as evidence in favor of mixed strategies generated by our model with costly consumer search. However, prices are not purely random, as the cumulative distribution function of rank reversals based on randomly drawn prices is significantly below both raw and residual prices.[13]

[13]Confidence intervals of the CDF of random prices are based on 1000 replications.

Table 5: Summary Statistics of Rank Reversals (Delineation: 2 miles)

	Raw Prices	Cleaned Prices	Random Prices
Average Rank Reversals	0.105	0.215	0.374
# of obs.	2410	2410	2410

Figure 2: CDF of Rank Reversals for Raw, Cleaned and Random Prices



4 Testing the Relationship between Information and Price Dispersion

In this section we apply both parametric and non-parametric techniques to investigate whether inverted-U relationship between information and price dispersion that we derived in Section 2 for the clearinghouse model is supported by the data for the gasoline market.

4.1 Parametric Evidence

A straightforward approach to test for an inverse-U relationship between price dispersion PD_{it} and the share of informed consumers (μ_i) in station i's market is to estimate the following linear regression model:

$$PD_{it} = \alpha + \beta\mu_i + \gamma\mu_i^2 + X_{it}\theta + \eta_{it}, \tag{8}$$

where X_{it} represents possible confounding factors at the station level as well as over time. More specifically, we control for station-specific characteristics (such as brand name, availability of service bay and/or convenience store, car wash facility, location) and region-specific characteristics (such as population density, traffic exposure of the station), as well as measures characterizing the competitive environment (number of rivals in the market). Further, period fixed effects are included to remove price fluctuations that are common to all gasoline stations.

The main parameters of interest are β and γ. An inverted U-shaped relationship between price dispersion and information, as predicted in *Proposition 1*, would imply that $\beta > 0$ and $\gamma < 0$. According to the parameter estimates reported in Table 6, this proposition is supported by the data in all specifications. While the size of the estimated coefficients varies between the models, the parameter estimates for β (γ) are positive (negative) and statistically significant at the 1%-significance level in all specifications based on the residual prices after controlling for other confounding factors. As the share of informed consumers increases, price dispersion first increases and then starts decreasing once the share of informed consumers exceeds a critical level. The critical level implied by the parameter estimates lies between between 0.70 and 0.76. As the share of informed consumers exceeds this level, the majority of the stations attempts to capture the informed portion of the market which reduces price dispersion.

To formally test 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).[14] 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 between information and price dispersion. The test is an intersectionunion test as the null hypothesis is that the parameter vector is contained in a union of specified sets. Results are reported in Table 8. 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 used. At the upper bound the slope is negative in all specifications. The slope is significantly different from zero at the 1% level (5% level) for the VOI^M and the *Trimmed Range* measures (for the VOI, *Range*, and AD measures) but is not significantly different from zero for the SD^M measure.

The regression results explaining price dispersion based on raw rather than residual prices are summarized in Table 7. The qualitative results hardly change when using raw instead of cleaned prices: The estimates of μ are positive and statistically significant in all model 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.

When comparing the magnitude of our estimates of 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) will be 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 are confronted mainly with either informed or uninformed consumers. For markets with an intermediate information endowment of consumers, our findings clearly reject the "law of one price".

In order to confirm that our results are not driven by the specific definition of market boundaries, by particular sub-samples or by the chosen approach to calculate the measure of information endowment μ, regressions were run using perturbations of these definitions: First, in the sensitivity analysis the market delineation is based on smaller distances, on

[14] 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.

administrative boundaries (municipalities) and on the consumers' commuting behavior. Second, we analyze sub-samples by excluding larger communities and by analyzing local markets with at least three gasoline stations only. Last, we use the commuter flows to calculate μ without weighting the transit commuters by the fraction of possible routes passing by particular gas stations.[15] The main result of our analysis - an inverted-U shaped relationship between consumers' information endowment and price dispersion - remains unaffected by these modifications. Results from these estimation experiments are summarized in Appendix C.

4.2 Semi-Parametric Evidence

In this section we illustrate that the estimated relationship between information and price dispersion is not entirely due to the parametric restriction to a linear quadratic function. Given the large number of controls, we follow a semi-parametric approach: We still restrict attention to a linear specification for the vector of controls, therefore do not pose any parametric restrictions on the relationship between our measures of price disperion and information μ. We estimate the following equation semi-parametrically:

$$PD_{it} = \alpha + f(\mu_i) + X_{it}\theta + \eta_{it}, \tag{9}$$

We use the two-step procedure proposed by Robinson (1988), to obtain an estimate $\hat{f}(\cdot)$. We first obtain nonparametric estimates of $E(PD|\mu)$ and $E(X|\mu)$ and then regress $PD - E(PD|\mu)$ on $X - E(X|\mu)$ to obtain a consistent estimate of θ. We then regress $E(PD|\mu) - E(X|\mu)\hat{\theta}$ on μ non-parametrically to obtain an estimate of $f()$. Figure 3 reports results obtained for the nonparametric component of regression equation (9) with a kernel-weighted local polynomial regression. Although the specific form of the relationship between price dispersion (shown on the vertical axis) and different measures of consumers' information (on the horizontal axis) differ across the measure of price disperion, there is strong evidence in favor of an inverted U shape of the relationship of interest.

5 Conclusions

We have shown that a sequential search model where some consumers have access to the realized prize distribution yields an inverted U relationship between price dispersion and the

[15]For each commuter flow from o to d we therefore assign weights $\omega_{i,od} = 1$ if station i complies with equation (3).

Figure 3: Semiparametric Evidence

The image is based on an Epanechnikov kernel with a polynomial smooth degree of 0 and 0.8 bandwidth. The pilot bandwidth for the standard error calculation is 0.12.

fraction of informed consumers. Past studies have relied on internet usage or a comparison of online and offline markets to examine the effect of informed consumers on prices. We provide a novel measure of the fraction of informed consumers in the market for retail gasoline: Commuters who can freely sample prices at gas stations along their commuting path. We found robust statistical evidence supporting the information mechanism in clearinghouse models. We also found that more informed consumers lower market prices. This may also be related to our measure of information which - contrary to measures related to the internet - is less relevant for how difficult monitoring is in a collusive setting.

References

Bahadir-Lust, S., Loy, J.-P., and Weiss, C. R. (2007). Are they always offering the lowest price? an empirical analysis of the persistence of price dispersion in a low inflation environment. *Managerial and Decision Economics*, 28(7):777-788.

Barron, J. M., Taylor, B. A., and Umbeck, J. R. (2004). Number of sellers, average prices, and price dispersion. *International Journal of Industrial Organization*, 22:1041-1066.

Baye, M. R. and Morgan, J. (2001). Information gatekeepers on the internet and the competitiveness of homogeneous product markets. *American Economic Review*, 91(3):454-474.

Baye, M. R., Morgan, J., and Scholten, P. (2006). Information, search and price dispersion. In Hendershott, T., editor, *Economics and Information Systems*, pages 323-377.

Brown, J. R. and Goolsbee, A. (2002). Does the internet make markets more competitive? Evidence from the life insurance industry. *Journal of Political Economy*, 110(3):481-507.

Chandra, A. and Tappata, M. (2011). Consumer search and dynamic price dispersion: An application to gasoline markets. *The RAND Journal of Economics*, 42(4):681-704.

Eckert, A. (2013). Empirical studies of gasoline retailing: A guide to the literature. *Journal of Economic Surveys*, 27(1):140-166.

Ellison, G. and Ellison, S. F. (2005). Lessons about markets from the internet. *Journal of Economic Perspectives*, 19(2):139-158.

Ellison, G. and Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica*, 77(2):427-452.

Hastings, J. S. (2004). Vertical relationships and competition in retail gasoline markets: Empirical evidence from contract changes in Southern California. *American Economic Review*, 94(1):317-328.

Hosken, D. S., McMillan, R. S., and T.Taylor, C. (2008). Retail gasoline pricing: What do we know? *International Journal of Industrial Organization*, 26(6):1425-1436.

Houde, J.-F. (2012). Spatial differentiation and vertical mergers in retail markets for gasoline. *American Economic Review*, 102(5):2147-2182.

Janssen, M., Pichler, P., and Weidenholzer, S. (2011). Oligopolistic markets with sequential search and production cost uncertainty. *The RAND Journal of Economics*, 42(3):444–470.

Lach, S. (2002). Existence and persistence of price dispersion: An empirical analysis. *Review of Economics and Statistics*, 84(3):433-444.

Lewis, M. (2008). Price dispersion and competition with spatially differentiated sellers. *Journal of Industrial Economics*, 56(3):654-678.

Lind, J. T. and Mehlum, H. (2010). With or without u? an appropriate test for a u-shaped relationship. *Oxford Bulletin of Economics and Statistics*, 72(1):109-119.

Marvel, H. P. (1976). The economics of information and retail gasoline price behavior: An empirical analysis. *Journal of Political Economy*, 84(5):1033-1060.

Robinson, P. M. (1988). Root-n-consistent semiparametric regression. *Econometrica*, pages 931-954.

Sorensen, A. T. (2000). Equilibrium price dispersion in retail markets for prescription drugs. *Journal of Political Economy*, 108(4):833-850.

Stahl, D. O. (1989). Oligopolistic pricing with sequential consumer search. *American Economic Review*, 79(4):700-712.

Statistik Austria (2006). Kfz-bestand 2005. available online at http://www.statistik.at/web_de/static/kfz-bestand_2005_021489.pdf, last accessed 19/07/2013.

Stigler, G. J. (1961). The economics of information. *Journal of Political Economy*, 69(3):213-225.

Tang, Z., Smith, M. D., and Montgomery, A. (2010). The impact of shopbot use on prices and price dispersion: Evidence from online book retailing. *International Journal of Industrial Organization*, 28:579-590.

Tappata, M. (2009). Rockets and feathers: Understanding asymmetric pricing. *The RAND Journal of Economics*, 40(4):673-687.

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

Varian, H. R. (1980). A model of sales. *American Economic Review*, 70:651-659.

White, H. (1980). A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48:817-838.

Appendix A. Proofs

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

Proof. For all $x > 0$ and $N \geq 2$, let $\beta(x) = \int_0^1 \frac{dz}{1+xNz^{N-1}}$, and notice that $\beta(x) \in \left(\frac{1}{1+xN}, 1\right)$. Then, $\alpha(\mu) = \beta\left(\frac{\mu}{1-\mu}\right)$ for all $\mu \in (0,1)$. Since $\frac{\mu}{1-\mu}$ is strictly increasing in μ, it follows that $\frac{\alpha(\mu)}{1-\alpha(\mu)} - \frac{1-\mu}{\mu}$ is strictly decreasing in μ on $(0,1)$ if and only if $g(x) = \frac{\beta(x)}{1-\beta(x)} - \frac{1}{x}$ is strictly decreasing in x on $(0,\infty)$.

Notice that for all $x > 0$,

$$\begin{aligned} \beta'(x) &= -\int_0^1 \frac{Nz^{N-1}}{(1+xNz^{N-1})^2}dz, \\ &= \frac{1}{x(N-1)}\left(\frac{1}{1+xN} - \beta(x)\right), \end{aligned} \tag{10}$$

where the second line is obtained by integrating by part. Therefore, if we define

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

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

For all $x > 0$, $g'(x) = \frac{\beta'(x)}{(1-\beta(x))^2} + \frac{1}{x^2}$. Using equation (10), we obtain that $g'(x)$ is strictly negative if and only if $P_x(\beta(x)) < 0$, where

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

$P_x(.)$ is strictly convex, and $P_x(1) < 0 < P_x\left(\frac{1}{1+xN}\right)$. Therefore, there exists a unique $\gamma(x) \in \left(\frac{1}{1+xN}, 1\right)$ such that $P_x(.)$ is strictly positive on $\left(\frac{1}{1+xN}, \gamma(x)\right)$ 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 $\beta(x) \in \left(\frac{1}{1+xN}, 1\right)$, it follows that $g'(x) < 0$ if and only if $\beta(x) > \gamma(x)$.

Next, let us show that $\beta(x) > \gamma(x)$ when x is in the neighborhood of 0, $x > 0$. Applying Taylor's theorem to $\gamma(x)$ for $x \to 0^+$, we get:

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

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

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

It follows that

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

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 $\beta(x) - \gamma(x) > 0$ for all $x \in (0, x^0]$.

Next, we show that $\beta(x) - \gamma(x) > 0$ for all $x > x^0$. We will 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

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

The above expression is strictly negative if and only if

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

The left-hand side is in fact equal to $-4N^2(N-1)^4x^2$, which is indeed strictly negative.

We can conclude: β 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 $\beta(x^0) > \gamma(x^0)$; by Lemma 1.2 in Teschl (2012), $\beta(x) > \gamma(x)$ for all $x > x^0$. $\square$

Appendix B. 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 (3) are on one route from o to d if the optimal route between the two municipalities which passes through both stations is not "too much" longer than the optimal route from o to d passing through one station only. The stations are ordered based on their distance from the origin. This implies that in the equation below, the indexes i and j are assigned to these stations so that $d_{oi} \leq d_{oj}$. Both stations are on the same route if

$$dist_{oi} + dist_{ij} + dist_{jd} - min\left(dist_{oi} + dist_{id}, dist_{oj} + dist_{jd}\right) < \overline{dist} \tag{11}$$

with d_{ij} as the optimal route between these two stations. Multiple stations are on the same route if all pairs of stations comply with equation (11). If at least one station for a particular commuter flow complies with equation (3) than each potential route contains at least one station.[16] 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 for 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 (3)). The aggregated weighted number of transit commuters for station i is given by $C_i^{tr} = \sum_o \sum_{d \neq o} \omega_{i,od} C_{od}$, with C_{od} as the commuter flow from o to d.

Appendix C. Robustness

In this section of the Appendix we show the robustness of the findings reported in the main part of the article by altering the model specification in various dimensions, namely (i) by the way we delineate local markets, (ii) by analyzing sub-samples and (iii) by using a different method to calculate the fraction of informed consumers μ.

Local market delineation. As using a particular distance to delineate markets is rather arbitrary we use administrative boundaries (municipalities) and a different critical distance (1.5 instead of 2 miles) to define local markets. The results on these alterations are reported in Table 9 and 10. In all (all but one) model specifications the parameter estimates of 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

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

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 the model specifications when 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), leaving the downward-sloping part at high levels of μ to be not statistically significant anymore. Nevertheless, the concave relationship between information endowment and price dispersion is supported by virtually all model specifications, while the inverse-U relationship is endorsed by 9 out of 12 specifications.

In addition to delineating local markets by (exogenously) chosen driving distances or by administrative boundaries, we determine whether two stations are considered to be in the same market by the share of common (potential) consumers, which we denote as relative overlap (ROL). Two stations are considered to be within one local market if the share of common (potential) consumers for both stations exceeds a certain threshold. Non-commuters are considered to be potential consumers for both stations if both firms are located in the same municipality. A commuter flow between o and d is considered to indicate potential consumers for both firms if the commuter flow passes by both stations, i.e. both firms comply with equation (3). The relative overlap between two stations i and j is defined as:

$$ROL_{ij} = \frac{Cons_i \wedge Cons_j}{Cons_i \vee Cons_j} \tag{12}$$

with $Cons_i$ ($Cons_j$) as the number of potential consumers - including both commuters and non-commuters - of station i (j). We again construct a local market for each station: Station i's market contains station i itself and all other stations $j \neq i$ as long as ROL_{ij} exceeds a particular critical value.

Table 11 summarizes the regression results when using a threshold-ROL of 50% to delineate local markets. The parameter estimates of 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. The main results remain unchanged if we use low (high) threshold levels for the ROL of 10% (90%). These results are not reported but are available from the authors upon request.

Sub-samples. For the model specifications summarized in Table 12 we exclude all stations located in the three largest towns (besides Vienna), namely Graz, Linz and Salzburg, leaving only firms located in municipalities with less than 120,000 inhabitants in the sample. We do so as our measure of information is based on commuter flows at a municipality level, which is less precise in very large towns. Evaluating this sub-sample hardly affects the results, as reported in Table 12: All parameter estimates of μ and μ^2 take the expected sign and are significantly different from zero at the 1%-significance level. Additionally, the intersection union test is rejected at the 1%-level in each specification.[17]

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 13: Both the sign and the statistical significance of the parameter estimates of μ and μ^2 as well as the intersection union test support our main findings, that the relationship between price dispersion and the share of informed consumers is characterized by an inverse-U. Additionally, we exclude all stations located at highways, as competition between firms on and off highways might be lower than suggested by the distance between these locations. As the point estimates and the confidence intervals of the parameters of interest are hardly affected by this variation, the regression results are not reported but available from the authors upon request.

Alternative ways to calculate μ. In the last sensitivity analysis we refrain from weighting the commuter flows by the number of potential routes when calculating the share of informed consumers μ. Technically, transit commuters are weighted by $\omega_{i,od} = 1$ if station i complies with equation (3). Again, as summarized in Table 14, the parameter estimates of μ and μ^2 take the expected signs and are statistically significant at the 1%-significance level for each measure of price dispersion. The intersection union test again supports the main finding of this article, namely that consumers' information endowment and price dispersion are characterized by an inverted-U shaped relationship.

Appendix D. Tables

[17] We exclude stations located in Vienna throughout the analysis, 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 rather crude. However, including Vienna does not change the main findings: The parameter estimates of μ and μ^2 always take the expected sign and for all measures of dispersion (except the absolute distance (AD)) the parameter estimates of these variables are also significantly different from zero. These results are not reported, but are available from the authors upon request.

Table 6: 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)	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)	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)
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	0.722	0.732	0.706	0.761	0.716
# of obs.	14851	14851	14851	7996	14851	14851
R^2	0.260	0.136	0.280	0.370	0.172	0.104

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 7: Regression results using raw 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	1.325***	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)	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)	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.	14851	14851	14851	7996	14851	14851
R^2	0.238	0.160	0.270	0.373	0.178	0.131

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 8: 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)	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)	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	-0.636	-0.578	-0.964	-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	0.722	0.732	0.706	0.761	0.716
# of obs.	14851	14851	14851	7996	14851	14851
R^2	0.260	0.136	0.280	0.370	0.172	0.104

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

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)	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)	-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.	14037	14037	14037	7895	14037	14037
R^2	0.340	0.194	0.376	0.543	0.182	0.104

Standard errors in parentheses

Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

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

	(1) VOI^M	(2) VOI	(3) $Range$	(4) $Trimmed\ range$	(5) SD	(6) 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)	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)	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	0.13
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.707	0.742	0.733	0.659	0.765	0.717
# of obs.	13464	13464	13464	6141	13464	13464
R^2	0.237	0.119	0.256	0.330	0.172	0.110

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 11: Regression results using residual prices to calculate dispersion and a market delineation of 50% relative overlap

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*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)	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)	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.	13980	13980	13980	7840	13980	13980
R^2	0.335	0.194	0.378	0.543	0.169	0.097

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 12: Regression results using residual prices to calculate dispersion and a market delineation of 2 miles, excluding 3 largest towns

	(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)	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)	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.	13116	13116	13116	6366	13116	13116
R^2	0.216	0.108	0.233	0.342	0.161	0.106

Standard errors in parentheses

Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 13: Results using residual prices and a market delineation of 2 miles, 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)	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)	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	0.01	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.	10685	10685	10685	7996	10685	10685
R^2	0.244	0.125	0.262	0.370	0.189	0.112

Standard errors in parentheses
Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

Table 14: 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*
μ (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)
μ^2 (no weights)	-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)	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)	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.	14851	14851	14851	7996	14851	14851
R^2	0.260	0.136	0.280	0.369	0.172	0.105

Standard errors in parentheses

Regressions include stations- and region-specific characteristics, fixed state and fixed time effects as well as dummy variables for missing exogenous variables. Inference of the parameter estimates is based on robust (heteroscedasticity consistent) standard errors (White, 1980). Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.