DISCUSSION PAPER SERIES

No. 10771

INFORMATION AND PRICE DISPERSION: THEORY AND EVIDENCE

Dieter Pennerstorfer, Philipp Schmidt-Dengler, Nicolas Schutz, Christoph Weiss and Biliana Yontcheva

INDUSTRIAL ORGANIZATION

Centre for Economic Policy Research

ISSN 0265-8003

INFORMATION AND PRICE DISPERSION: THEORY AND EVIDENCE

Dieter Pennerstorfer, Philipp Schmidt-Dengler, Nicolas Schutz, Christoph Weiss and Biliana Yontcheva

Discussion Paper No. 10771
August 2015
Submitted 06 August 2015

Centre for Economic Policy Research
77 Bastwick Street, London EC1V 3PZ, UK
Tel: (44 20) 7183 8801
www.cepr.org

INFORMATION AND PRICE DISPERSION: THEORY AND EVIDENCE[†]

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. We construct a new measure of information based on precise commuter data from Austria. Regular commuters can freely sample gasoline prices on their commuting route, providing us with spatial variation in the share of informed consumers. We use detailed information on gas station level prices to construct price dispersion measures. Our empirical estimates of the relationship are in line with the theoretical predictions.

JEL Classification: D43, D83 and L13
Keywords: commuter data, price dispersion, retail gasoline and search

Dieter Pennerstorfer Dieter.Pennerstorfer@wifo.ac.at
Austrian Institute of Economic Research and University of Vienna

Philipp Schmidt-Dengler philipp.schmidt-dengler@univie.ac.at
University of Vienna, Austrian Institute for Economic Research, CESifo, ZEW and CEPR

Nicolas Schutz nicolas.schutz@polytechnique.org
University of Mannheim

Christoph Weiss c.weiss@eib.org
Vienna University of Economics and Business

Biliana Yontcheva biliana.yontcheva@wu.ac.at
Vienna University of Economics and Business

[†] We thank Marcus Asplund, Tomaso Duso, Luisa Herbst, Chao Ma, Jose L. Moraga-Gonzalez, Kathleen Nosal, Konrad Stahl, Matthijs Wildenbeest and seminar participants at CREST, DIW Berlin, DICE, Emory, Johns Hopkins, St. Gallen, University of Queensland, Queensland University of Technology, Vienna University of Economics and Business, WIFO, Yale, the 2014 Winter Marketing-Economics Summit, the 2013 Winter Seminar of the Gesellschaft füur Regionalforschung, EARIE 2014, the CEPR Applied IO Workshop 2014, MaCCI Annual Meeting 2014, the MaCCI search workshop, the SFB-TR15 Mannheim meeting and the 61st Annual North American Meeting of the Regional Science Association International for helpful comments.

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 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 if consumers are not fully informed about prices (see Baye et al. (2006)).

We theoretically and empirically examine 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 differ in their respective degree of informedness. For some, obtaining an additional price quote is costly. Others are aware of all prices charged in the relevant market: they have access to the "clearinghouse." 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 as 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 a 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. Sengupta and Wiggins (2014) find no significant relationship between price dispersion and the share of internet usage for airline fares.

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. 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.[1] Third, firms may charge different prices on and offline.

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

[1] Recently it has become possible to compare gasoline prices online. This was not the case during our sample period (1999-2005).

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.

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 regarding different market definitions. We further find evidence in favor of a first order 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 based on 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 a version of 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 willingness to pay $v > c$. A share $\mu \in (0,1)$ of consumers comprises of "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 $s > 0$.[2]

Equilibrium price distribution. It is well known that for any $\mu \in (0,1)$ there is no pure strategy equilibrium, but rather a unique symmetric mixed strategy equilibrium. The equilibrium price distribution $F(.)$ is pinned down by the fact that a firm should be indifferent to setting any price p in support $\left[\underline{p}, \bar{p}\right]$ or setting price $\bar{p}$:

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

which yields:

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

for all $p \in \left[\underline{p}, \bar{p}\right]$. 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: Janssen et al. (2005) and Janssen et al. (2011) show that $\bar{p} = \min(\rho, v)$, where $r = \rho \equiv c + \frac{s}{1-A}$ and $A = \int_0^1 \frac{dz}{1+\frac{\mu}{1-\mu}Nz^{N-1}} \in (0,1)$.

Observe that if $s \geq v - c$, then non-shoppers never find searching profitable and our model is equivalent to Varian's model of sales. In this case, $\rho > v$ and $\bar{p} = v$ for all (μ, N),

[2]Recent extensions and modifications of the Stahl (1989)-model typically address the assumptions imposed on non-shoppers. These alterations include models where the first price quote is costly as well (Janssen et al., 2005), where revisiting a store is costly(Janssen and Parakhonyak, 2014), where uninformed consumers are uncertain about the firms' underlying production costs (Janssen et al., 2011), or where non-shoppers only know the support of the underlying price distribution (Parakhonyak, 2014). In Lach and Moraga-Gonzalez (2012) the consumers' knowledge about prices is described by a more general distribution rather than the strict dichotomy of the Varian (1980)- and the Stahl (1989)-model. Stahl (1996) and Chen and Zhang (2011) allow for heterogeneous search costs.

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 $\mu \geq \hat{\mu}$.[3] 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

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

where the second line follows by using equation (2) and change of variables $z = 1 - F(p)$. It is immediate that the expected price decreases in the fraction of shoppers μ, as both A and ρ decrease in μ. In order to validate the model, we will first test the following prediction according 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 the expected price and the expected minimum price in the market:

$$E(p - p_{min}) = \int_{\underline{p}}^{\bar{p}} p \left[1 - N \left[1 - F(p)\right]^{N-1}\right] dF(p). \tag{3}$$

Substituting the equilibrium price distribution (2) into equation (3) and applying again

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

change of variables $z = 1 - F(p)$ yields

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

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 $c + \frac{s}{1-A}$ or $\bar{v}$.[4] 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 $A - \frac{1-\mu}{\mu}(1 - A)$ 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 $s\left(\frac{A}{1-A} - \frac{1-\mu}{\mu}\right)$, which is strictly decreasing in μ by Lemma 1, stated and proven in Appendix A. This concludes the proof of Proposition 1.

Lemma 1 is proven as follows. We first notice that $s\left(\frac{A}{1-A} - \frac{1-\mu}{\mu}\right)$ is strictly decreasing in μ on $(0, 1)$ if and only if $g(x) = \frac{B(x)}{1-B(x)} - \frac{1}{x}$ 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 $B(.)$ is

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

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

the solution of a differential equation, and that $\Gamma(.)$ is a subsolution of the same differential equation. From this, we can conclude that $B(x) > \Gamma(x)$ for all $x > 0$. We refer the reader to Appendix A for more details. □

To see the 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 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 $\mu \geq \hat{\mu}$, 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, price 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.

The following remark generalizes Proposition 1 to the case where 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 to pay 0 with complementary probability $1 - \phi$. A non-shopper is willing to pay v (resp. 0) with probability $\psi \in (0, 1]$ (resp. $1 - \psi$). Then, there is still an inverse-U shaped relationship between price dispersion and the proportion of informed consumers.*

Proof. Indifference condition (1) becomes:

$$(p - c) \left(\mu\phi \left(1 - F(p)\right)^{N-1} + (1 - \mu)\psi \frac{1}{N} \right) = (\bar{p} - c)\,(1 - \mu)\psi \frac{1}{N}. \tag{4}$$

Define $\nu(\mu) = \frac{\mu\phi}{\mu\phi + (1-\mu)\psi} \in (0, 1)$ and notice that $d\nu/d\mu > 0$. Then, condition (4) is equivalent to

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

which is equivalent to condition (1) if we replace μ by ν. This implies that the equilibrium mixed strategy in the model with heterogeneous demands and proportion of informed consumers μ is the same as the equilibrium mixed strategy in Stahl (1989)'s model with proportion of consumers $\nu(\mu)$.

Let $h(\mu)$ be the value of information in Stahl (1989)'s model. Then, the value of information in the model with heterogeneous demands is $VOI(\mu) = h\,(\nu(\mu))$. h is strictly quasi-concave (by Proposition 1) and ν is strictly increasing. Therefore, $VOI = h \circ \nu$ is strictly quasi-concave. Moreover, since $\nu(0) = 0$ and $\nu(1) = 1$, $VOI(0) = VOI(1) = 0$. It follows that VOI is inverse-U shaped. □

This is a useful result, because one could argue that shoppers' demand differs systematically from non-shoppers' demand in our empirical application.

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.[5] 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 frequenting a gas station depends on the relative size of

[5]Houde (2012) emphasizes the role of commuters in 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)).

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.[6] Since municipalities are generally very small regional units, this allows us 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 positive commuter flows to 51 (32) other municipalities.

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 determine the number of individuals residing in the municipality where a given station i is located, who commute to a different municipality. We denote this number 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 this 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

[6]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.

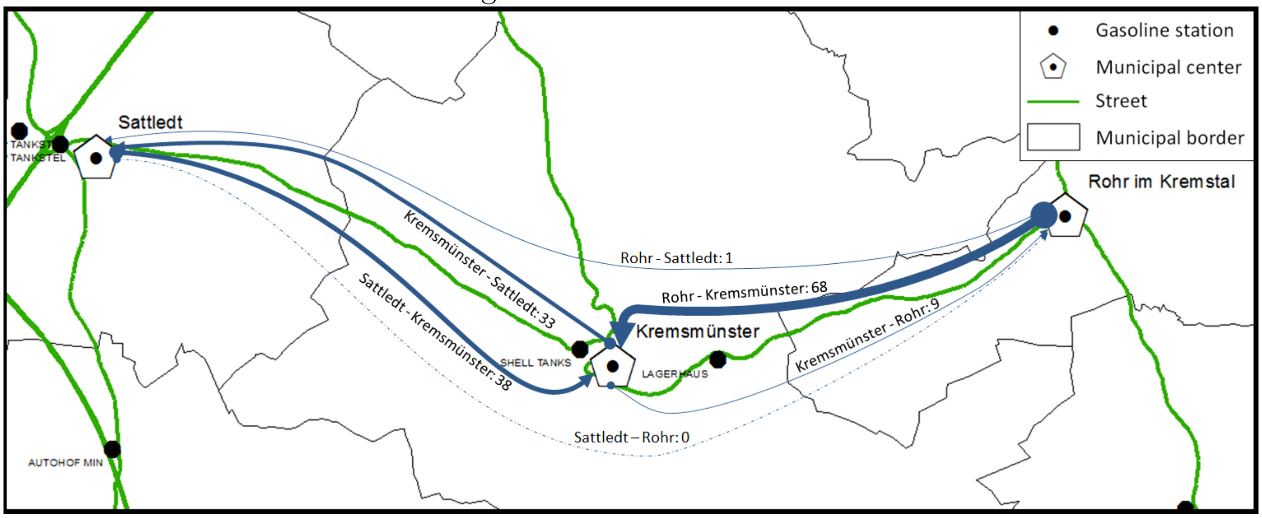
by C_i^{tr}. We assume that transit consumers are familiar with the prices of gasoline stations located directly on the commuting path, but not with the entire gasoline market in the municipality. As such, they are likely to be part only of the market of stations which are located directly on their commuting 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. Given the small size of the municipalities, we can determine quite accurately which road transit commuters take. Our prediction will be less accurate in densely populated municipalities, as high population densities usually go hand in hand with more complex infrastructure. We therefore drop gas stations located in Vienna from the sample in our main specification.

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 ($\overline{dist}$),[7] 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

[7] We allow for this slack variable in distance when passing by station i as the translation of the address data to coordinates as well as 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 defined to be on the commuting path if it is located less than 125 meters off the optimal route.

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 on 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 within our critical distance, so we would count the commuter as one of the informed consumers in the market of the Lagerhaus station.

municipality d (destination) is assigned to station i whenever

$$dist_{oi} + dist_{id} - dist_{od} < \overline{dist}. \tag{5}$$

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 without turning off the road (the station is visible without a deviation 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 (5) 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. This corresponds to the assumption that consumers randomize uniformly over routes. To calculate the weights we thus determine the number of potential routes going from o to d satisfying equation (5), and check if a particular station is included in all of these routes or only a selection of them. The details of the weighting scheme are given in Appendix B. The results from this algorithm show that consumers indeed pass by a substantial number of gas stations: The average (median) commuter passes by 20 (11) gas stations, and 90% of commuters pass by at least two gas stations.

Using the methodology outlined above and imposing the strict separation of shoppers and non-shoppers as suggested by theory, 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 on the market (U_i) with the number of employed individuals who live in the municipality in which the station is located, and who do not regularly commute over long distances by car.[8]

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

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

Table 1 shows summary statistics on the share of informed consumer. The mean value of our information measure lies close to the 60 percent mark. This skewness towards larger values indicates 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

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

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 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

3.2 Diesel Prices and Stations

Our empirical analysis focuses on the retail diesel market in Austria. The retail diesel market is particularly suitable for our purpose: Retail diesel is a fairly homogeneous product with the main source of differentiation being spatial location, which is easily controlled for. Further, consumers primarily frequent gas stations to purchase fuel, 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[9] from October 1999 to March 2005. Prices from each station were collected by the Austrian Chamber of Labor ("Arbeiterkammer") within three days in each time period, on weekdays. We merge the price data with information on the geographical location of all 2,814 gas stations as well as their characteristics: the number of pumps, whether the station has service bays, a convenience store, etc.[10] Retail prices are nominal and measured in Euro cents per litre, 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 each 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

[9]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)

[10]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.

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 gas stations is linked to information on the Austrian road system.[11] This allows us to generate accurate measures of distance as well as the commuting behaviour across the road network.

3.3 Measuring Price Dispersion

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

Residual prices. Even though diesel fuel is homogeneous in terms of its physical characteristics, gas stations differ not only in their locations, 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[12] 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

[11] 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").

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

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 linear distance. 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. In addition to delineating markets by (exogenously) chosen driving distances we also use observed commuting patterns to define local markets: If the the share of common (potential) consumers - which we denote as relative overlap (ROL) - for both stations exceeds a certain threshold, two stations are considered to be in the same local market. A detailed description of this procedure is provided in Appendix B.

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 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 expected minimum 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 $VOI_i = E[p^{m_i}] - E[p^{m_i}_{min}]$.[13] 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, we 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 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 $SD^{m_i}_i = \sqrt{\sum_{i \in m_i}(p_i - \overline{p}^{m_i})^2/(N^{m_i})}$ with N^{m_i} as the number of suppliers in station i's market m_i (including station i).

Table 2 reports summary statistics for these measures of price dispersion for different market delineations, namely two miles, using a 50% relative market overlap and administra-

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

tive 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 $N_o^c \geq 3$. The lowest values of price dispersion are observed with the two-mile delineation. Price variability increases if the market is identified using administrative boundaries and is even higher if a relative overlap approach is used. 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.

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 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 obs.	7,996		7,840		7,895	

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

3.4 Descriptive Evidence

Before testing the key prediction in the next section, we validate our use of the clearinghouse model in this subsection by means of descriptive evidence on how the share of informed consumers affects the price level and evidence on intertemporal price variation.

Information and the price level

Recall that the clearinghouse model predicted that prices charged at a gas-station should decrease with the share of informed consumers (Remark 1). Table 3 presents results of regressing prices on our measure of the share of informed consumers μ. 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 prices of at least one (three) rival firm(s) in the local market are available. All regressions are estimated using either time fixed effects (first, third and fifth column) or the crude oil price index (second, fourth and sixth column). The results remain nearly unchanged if the time fixed 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. In Table 4 we use stations' average price levels (which correspond to the station-level fixed 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. Our results suggest that a larger share of informed consumers reduces market prices in line with Remark 1 in Section 2. Going from zero informed consumers to all consumers being informed would reduce prices by about 2 cents.

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

Standard errors in parentheses
Regressions include station- 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^c)	-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.	1,513	1,015	570
R^2	0.543	0.572	0.636

Standard errors in parentheses
Regressions include station- 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.

Intemporal price variation

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

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

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

4 Testing the Relationship between Information and Price Dispersion

In this section we apply both parametric and non-parametric techniques to investigate whether the 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.

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:

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

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 5, 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

[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.

Table 5: Regression results using residual 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	1.705***	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

Standard errors in parentheses

Regressions include station- 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.

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 intersection-union test as the null hypothesis is that the parameter vector is contained in a union of specified sets. Results are reported in Table 5. 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 for the VOI^M, *Range*, and the *Trimmed Range* measures, at the 5% level for the VOI and AD measures, and at the 10% level for the SD measure.

The regression results explaining price dispersion based on raw rather than residual prices are summarized in Table 6. 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. 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.

The empirical findings using a local market definition based on commuting patterns are even more convincing: 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. These results are summarized in Table 7.

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.

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

Standard errors in parentheses
Regressions include station- 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 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

Standard errors in parentheses
Regressions include station- 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.

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 an intermediate information endowment of consumers, our findings clearly reject the "law of one price". We next examine the sensitivity of our results regarding spatial correlation and parametric restrictions,[15] and provide several robustness checks regarding market definition and construction of our information measure.

Accounting for Spatial Correlation

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 particular gas station with prices charged by other stations in the local market, which challenges 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.[16] The matrix $\boldsymbol{W}$ is

[15] 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. Recently, Kostyshak (2015) suggested a critical bandwidth based approach in non-parametric regression.

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

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
Regressions include station- 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 a variance-covariance matrix of the residuals that accounts for a spatially autoregressive process in the residuals and is based on a robust (heteroscedasticity consistent) estimator of variance of the remaining error (White, 1980). ρ is estimated using GMM based on residuals of OLS regression. Asterisks denote statistical significance in a t-test at 1% (***), 5% (**) or 10% (*) level.

row-normalized with typical element $w_{it,js} = \frac{w^*_{it,js}}{\sum_j w^*_{it,jt}}$.[17] 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 the spatial autocorrelation parameter λ as described in Kelejian and Prucha (1999) and adjust the variance-covariance matrix as described above.[18] The results are reported in Table 8. The parameter estimates are negligibly affected as the sample size is slightly smaller.[19] 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 least) at the 5%-significance level, and the implied critical level lies between 0.70 and 0.76.

Semi-Parametric Evidence

In this section we illustrate that the estimated relationship between information and price dispersion is not driven by 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, but we do not impose any parametric restrictions on the relationship between our measures of price dispersion and information μ. We estimate the following equation semi-parametrically:

$$PD_{it} = \alpha + f(\mu_i) + X_{it}\theta + \eta_{it}, \tag{7}$$

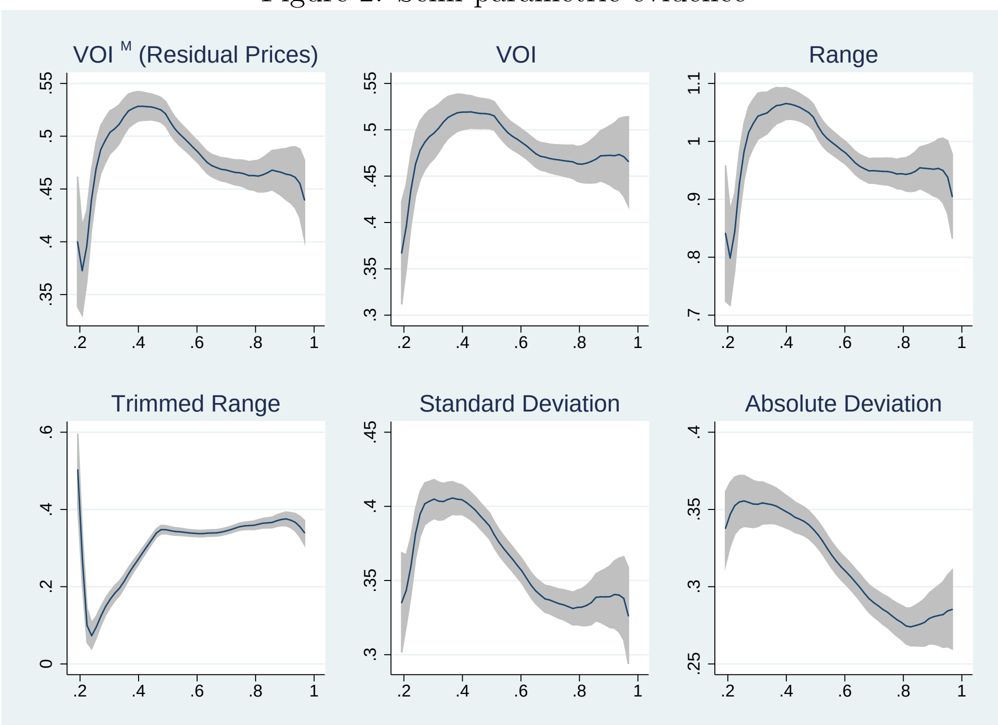
[17]Row-normalization is commonly used when specifying spatially autocorrelated residuals. It facilitates interpretation as $\sum_j w_{it,jt}\eta_{jt}$ is the (spatially weighted) average of residuals of other stations located in the same local market as station i, and it ensures that $\boldsymbol{I}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

[18]We allow for heteroskedasticity of unknown form in the remaining error $\nu_i t$ as suggested by White (1980).

[19]The sample size is slightly reduced when we account for the spatial dependance structure in the residuals as we exclude stations that are located in a market with no other stations in the sample (to enable row-normalization of $\boldsymbol{W}$). This can occur as we exclude stations located in Vienna in the entire analysis. So 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 specifications above) but exclude this observation here.

We use the two-step procedure proposed by Robinson (1988) to obtain an estimate $\hat{f}(\cdot)$. We first obtain non-parametric 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 2 reports results obtained for the non-parametric component of regression equation (7) with a kernel-weighted local polynomial regression.[20] We see that the restriction to a linear quadratic function resulted in a peak further to the right than with a flexible functional form. 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 dispersion, there is strong evidence in favor of an inverted U shape of the relationship of interest.

Figure 2: Semi-parametric 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.

[20]The results of directly regressing price dispersion non-parametrically on μ, i.e. not controlling for X, are actually quite similar. They are available from the authors upon request.

Robustness

In order to confirm that our results are driven neither by the specific product, nor by the way we delineate local markets, nor by particular sub-samples, nor by the approach used to calculate the measure of information endowment μ, we have run regressions using perturbations of these definitions. Results from these estimation experiments are summarized in Appendix C (available online) in Tables 9 to 23 along with a detailed description of the model alterations and a more thorough discussion of the results.

First, we perform the same regressions using regular gasoline instead of diesel. Second, we define local markets using administrative boundaries (municipalities) and a smaller critical distance (1.5 miles instead of 2 miles). When using commuting patterns to define local markets, we use different critical shares of common (potential) consumers (threshold-ROL) to decide whether two stations are in the same local market. Third, 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 information endowment μ: (i) We do not weight commuter flows by the share of possible routes passing by a particular gas stations.[21] (ii) 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. (iii) We account for the fact that long distance commuters (might) pass 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 be attracted, these commuter flows receive lower weights when calculating this alternative measure of information endowment. (iv) The final alteration consists in using 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 consumers'

[21] For each commuter flow from o to d we therefore assign weights $\omega_{i,od} = 1$ if station i complies with equation (5).

information endowment and price dispersion - remains unaffected by these modifications.

5 Conclusions

We have shown that clearinghouse models generate an inverted U relationship between price dispersion and the share of informed consumers. Past studies have relied on internet usage or on a comparison of online and offline markets to examine the effect of consumer information on prices. Using the fact that commuters can freely sample prices at gas stations along their commuting path, we have provided a novel measure of the share of informed consumers in the market for retail gasoline. We have found robust statistical evidence supporting the information mechanism in clearinghouse models. We have also found that an increase in the share of informed consumers lowers market prices. This latter result may be related to the fact that, contrary to measures based on internet usage or adoption, our measure of consumer information is unlikely to be related to how easy it is for firms to monitor each others' prices in a collusive setting.

References

Anselin, L. (1988). *Spatial econometrics. Methods and models*. Kluwer Academic Publishers, Dordrecht, NL. 1. Edition.

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. Elsevier Science Ltd.

Bell, K. P. and Bockstael, N. E. (2000). Applying the generalized-moments estimation approach to spatial problems involving microlevel data. *The Review of Economics and Statistics*, 82(1):72-82.

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.

Chen, Y. and Zhang, T. (2011). Equilibrium price dispersion with heterogeneous searchers. *International Journal of Industrial Organization*, 29(6):645-654.

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. and Parakhonyak, A. (2014). Consumer search markets with costly revisits. *Economic Theory*, 55(2):481-514.

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.

Janssen, M. C. W., Moraga-Gonzalez, J.-L., and Wildenbeest, M. R. (2005). Truly costly sequential search and oligopolistic pricing. *International Journal of Industrial Organization*, 23(4):451-466.

Kelejian, H. H. and Prucha, I. R. (1999). A generalized moments estimator for the autoregressive parameter in a spatial model. *International Economic Review*, 40(2):509-533.

Kostyshak, S. (2015). Non-parametric testing of u-shaped relationships. unpublished manuscript.

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

Lach, S. and Moraga-Gonzalez, J.-L. (2012). Heterogeneous price information and the effect of competition. unpublished manuscript.

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.

Parakhonyak, A. (2014). Oligopolistic competition and search without priors. *The Economic Journal*, 124(576):594-606.

Robinson, P. M. (1988). Root-n-consistent semiparametric regression. *Econometrica*, 56(4):931-954.

Sengupta, A. and Wiggins, S. N. (2014). Airline pricing, price dispersion, and ticket characteristics on and off the internet. *American Economic Journal: Economic Policy*, 6(1):272-307.

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.

Stahl, D. O. (1996). Oligopolistic pricing with heterogeneous consumer search. *International Journal of Industrial Organization*, 14(2):243–268.

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.

Wildenbeest, M. R. (2011). An empirical model of search with vertically differentiated products. *The RAND Journal of Economics*, 42(4):729–757.

Appendix A. Proofs

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

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

Notice that for all $x > 0$,

$$\begin{aligned} B'(x) &= -\int_0^1 \frac{Nz^{N-1}}{(1+xNz^{N-1})^2} dz, \\ &= \frac{1}{x(N-1)} \left(\frac{1}{1+xN} - B(x) \right), \end{aligned} \tag{8}$$

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

For all $x > 0$, $g'(x) = \frac{B'(x)}{(1-B(x))^2} + \frac{1}{x^2}$. Using equation (8), we see that $g'(x)$ is strictly negative if and only if $P_x(B(x)) < 0$, where

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

$P_x(.)$ 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 $B(x) \in \left(\frac{1}{1+xN}, 1\right)$, it follows that $g'(x) < 0$ if and only if $B(x) > \Gamma(x)$.

Next, let us show that $B(x) > \Gamma(x)$ 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 B three times under the integral sign and applying Taylor's theorem for $x \to 0^+$, we get:

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

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

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

The above expression is strictly negative if and only if

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

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 subsolution of the same differential equation, and $B(x^0) > \Gamma(x^0)$; by Lemma 1.2 in Teschl (2012), $B(x) > \Gamma(x)$ for all $x > x^0$. $\square$

Appendix 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 (5) 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. 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

$$dist_{oi} + dist_{ij} + dist_{jd} - min\left(dist_{oi} + dist_{id}, dist_{oj} + dist_{jd}\right) < \overline{dist} \tag{9}$$

with $dist_{ij}$ as the optimal route between these two stations. Multiple stations are on the same route if all pairs of stations comply with equation (9). If, for a particular commuter flow at least one station complies with equation (5) then each potential route contains at least one station.[22] 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 (5)). More formally, let $\mathcal{R}_{od}$ be the set of potential routes for a commuter flow from o to d. A potential route for this commuter flow $R_{od} \in \mathcal{R}_{od}$, can be fully described by enumerating all the gas stations that this commuter flow will pass along this route. The respective weight of the commuter flow from o to d for station i, $\omega_{i,od}$, can be characterized as:

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

Note that this shortest path algorithm is applied to transit commuters only, therefore

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

$\omega_{i,od} = 1$ if station i is located in either municipality o or d. The aggregated weighted number of commuters for station i is given by $I_i = \sum_o \sum_{d \neq o} \omega_{i,od} C_{od}$, with C_{od} as the commuter flow from o to d.

Market definition based on commuting patterns. 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 means of 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 two 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 (5). The relative overlap between two stations i and j is defined as:

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

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.

Appendix C. Further Sensitivity Analysis

For Online Publication Only

In this Online-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 using regular gasoline instead of diesel, (ii) by the way we delineate local markets, (iii) by analyzing alternative samples and (iv) by applying different definitions to calculate the share of informed consumers μ.

Regular Gasoline (Table 9)

In the main text we focused on diesel as this is the most important fuel for cars in Austria. The regression results using regular (unleaded) gasoline instead of diesel are reported in Table 9. The parameter estimates of μ (μ^2) are positive (negative) in all model specifications and statistically significant at the 5%-significance level in all model 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 information endowment at low levels of μ, the downward-sloping relationship at high levels of μ is not significantly negative in all specifications.

Local Market Delineation (Table 10 – 13)

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 10 and 11. 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 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 not being 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.

When using a market definition based on commuting patterns in the main part of this article we take a critical relative overlap (ROL) of potential consumers of 50% to define whether two stations belong to the same local market. As a robustness exercise we use different threshold levels of 10% (summarized in Table 12) and 90% (reported in Table 13). As in the main part of this article (see Table 7) the parameter estimates of μ (μ^2) are positive (negative) and statistically different from zero at the 1%-significance level for each measure of price dispersion. Additionally, the intersection-union test is rejected at the 1%-significance level in any specification, endorsing the interpretation of an inverse-U relationship between information endowment and price dispersion.

Alternative Samples (Table 14 – 17)

For the model specifications summarized in Table 14 we exclude all stations located in the three largest towns (besides Vienna) of Austria, 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. Alternatively, 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.[23] Evaluating these subsamples hardly affects the

[23] Note that this problem is mitigated as we use driving distance. Even if the linear distance between one station on and one station off the highway is small, they are not considered to be in the same local market if there is no exit close-by.

results, as reported in Table 14 and Table 15: the parameter estimates of 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 each specification.

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 only a rough guess. 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. The intersection-union test, however, is rejected only once (twice) at the 1%- (10%-) significance level. These results are reported in Table 16.

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 17: 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, i.e. that the relationship between price dispersion and the share of informed consumers is characterized by an inverse-U.

Alternative Ways to Calculate μ (Table 18 – 23)

In the last class of sensitivity analysis we provide alternative ways of constructing μ. In the first alteration we refrain from weighting the commuter flows by the number of potential routes when calculating the share of informed consumers μ. Technically, all transit commuters are weighted by $\omega_{i,od} = 1$ if station i complies with equation (5). Again, as summarized in Table 18, 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.

The second alteration in calculating μ deviates from the notion of all commuters being perfectly informed about all prices and assigns 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 respective measure of information endowment μ_i^{degree} is calculated as

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

with $I_i = \sum_o \sum_{d \neq o} \omega_{i,od} C_{od}$ as the weighted number of commuters for station i. $\omega_{i,od}$ denotes the probability of the commuter flow traveling from o to d to pass by station i, as described in section Appendix B. Additionally, each commuter flow is weighted by the degree of informedness for the respective station i, $\tau_{i,od}^I$, depending on the average number of stations the commuters drive past on their way to work and on the total number of stations in the local market. Let $\delta_{i,od} = \min(\text{average \# of stations observed by the commuter flow } C_{od}, N^{m_i})$, then the degree of informedness of a particular commuter flow $\tau_{i,od}^I$ is defined as $\tau_{i,od}^I = \frac{\delta_{i,od}}{N^{m_i}} \in [\frac{1}{N^{m_i}}, 1]$, allowing for the information endowment of commuters to be "less than perfect" (i.e. $\tau_{i,od}^I < 1$). Following Varian (1980)'s and Stahl (1989)'s search models claiming that the non-shoppers U_i are completely uninformed, we assign $\tau_i^U = 0$.

The regression results using the variable μ^{degree}, based on different degrees of informedness, are summarized in Table 19. For all measures of price dispersion the parameter estimates on the linear and the quadratic term of 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 each measure of price dispersion, suggesting an inverted-U shaped relationship between price dispersion and information endowment.

In an alternative model specification reported in Table 20, we assume that non-commuters have information on one price quote (i.e. $\tau_i^U = \frac{1}{N^{m_i}}$). Again, the parameter estimates for μ^{degree} and $(\mu^{degree})^2$ take the expected signs, are significantly different from zero at the 1%-significance level, whereby 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 main specification, see Table 5) and a higher degree of informedness to non-commuters the dispersion of the measure of information endowment gets smaller, causing the parameter estimates to increase in absolute value.

In the fourth alternative specification we account for the fact that the number of stations passed by differs between various commuter flows as well as between commuters and non-commuters. This specification therefore considers that commuters passing by a particularly large number of gasoline stations (compared to non-commuters and commuters passing by a smaller number of stations) are less likely to be attracted, and that the probability that a non-commuter refuels at a particular gasoline station declines the more stations are 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 gas 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 the following equation:

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

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

The regression results using the variable $\mu^{alternative\ weights}$ are reported in Table 21. Again, for all measures of price dispersion the parameter estimates on the linear term of this measure of information endowment take positive signs, whereas the estimated coefficients on the quadratic term take negative signs. All parameter estimates on $\mu^{alternative\ weights}$ and $(\mu^{alternative\ weights})^2$ are significantly different from zero at the 1%-significance level. The intersection-union test is rejected at the 5%-significance level for each measure of price dispersion, indicating an inverted-U shaped relationship between price dispersion and information endowment.

In the main specification we choose a critical distance $\overline{dist} = 250$ meters, i.e. 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. In this final set of sensitivity analyses we use alternative critical distances in defining the measure of information endowment μ, namely $\overline{dist} = 50$ meters (see Table 22) and $\overline{dist} = 500$ meters (see Table 23). Using a very narrow critical distance of 50 meters results in the parameter estimates of μ and μ^2 taking the expected sign, whereby the absolute size of the parameter estimates gets somewhat smaller. The estimated coefficients of the linear term are significantly different at the 1%- (5%-) significance level for five (all) measures of price dispersion and the parameter estimates on the quadratic term are significantly different at the 1%- (10%-) significance level in four (all) model specifications. The intersection-union test, however, is rejected only twice (four times) at the 5%- (10%-) significance level. Probably the mapping of gasoline stations is not accurate enough to assign transit commuters correctly to gasoline stations if a very small value for $\overline{dist}$ is chosen. On the other hand, 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 23, 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, namely that the relationship between price dispersion and the share of informed consumers is characterized by an inverse-U.

Table 9: 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

Standard errors in parentheses
Regressions include station- 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 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

Standard errors in parentheses
Regressions include station- 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 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^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

Standard errors in parentheses
Regressions include station- 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 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

Standard errors in parentheses

Regressions include station- 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: 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

Standard errors in parentheses
Regressions include station- 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, excluding 3 largest towns (apart from Vienna)

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*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

Standard errors in parentheses
Regressions include station- 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 15: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, excl. highway stations

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *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

Standard errors in parentheses

Regressions include station- 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 16: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, including Vienna

	(1) VOI^M	(2) VOI	(3) $Range$	(4) $Trimmed\ range$	(5) SD	(6) 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

Standard errors in parentheses
Regressions include station- 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 17: Regression 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^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	0.01	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.	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

Standard errors in parentheses
Regressions include station- 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 18: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, no route-weights

	(1) VOI^M	(2) VOI	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *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

Standard errors in parentheses
Regressions include station- 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 19: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, using different degrees of informedness

	(1) VOI^M	(2) VOI	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *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

Standard errors in parentheses
Regressions include station- 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 20: 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) *VOI*^{M}	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *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

Standard errors in parentheses

Regressions include station- 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 21: 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*
$\mu^{alternative\ weights}$	0.588***	0.632***	1.312***	1.395***	0.512***	0.551***
	(0.145)	(0.220)	(0.295)	(0.267)	(0.118)	(0.126)
$(\mu^{alternative\ weights})^2$	-0.673***	-0.684***	-1.274***	-1.493***	-0.507***	-0.633***
	(0.184)	(0.282)	(0.381)	(0.359)	(0.154)	(0.161)
# of rival firms with prices (N_o^c)	0.062***	0.064***	0.120***	0.059***	0.017***	0.007***
	(0.004)	(0.005)	(0.006)	(0.004)	(0.002)	(0.003)
# of rival firms (N^c)	-0.000	0.000	0.007*	0.014***	0.002	0.002
	(0.002)	(0.004)	(0.004)	(0.003)	(0.001)	(0.002)
Constant	-0.063	-0.088	-0.179*	-0.383***	0.035	0.134**
	(0.054)	(0.090)	(0.108)	(0.118)	(0.044)	(0.053)
Overall inverse-U test						
t	3.19	2.00	2.45	3.28	2.46	3.42
p	0.001	0.023	0.007	0.001	0.007	0.000
Extreme ($\hat{\mu} = -\hat{\beta}/2\hat{\gamma}$)	0.437	0.462	0.515	0.467	0.505	0.436
# of obs.	14,851	14,851	14,851	7,996	14,851	14,851
R^2	0.259	0.136	0.280	0.366	0.171	0.104

Standard errors in parentheses

Regressions include station- 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 22: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 50m$

	(1) *VOI^M*	(2) *VOI*	(3) *Range*	(4) *Trimmed range*	(5) *SD*	(6) *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

Standard errors in parentheses
Regressions include station- 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 23: Regression results, using residual prices to calculate dispersion and a market delineation of 2 miles, $\overline{dist} = 500m$

	(1)	(2)	(3)	(4)	(5)	(6)
	VOI^M	*VOI*	*Range*	*Trimmed range*	*SD*	*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

Standard errors in parentheses
Regressions include station- 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.