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A Network Model of Price Dispersion

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CTN – Coalition Theory Network

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A Network Model of Price Dispersion

Summary

We analyze a model of price competition *à la* Bertrand in a network environment. Firms only have a limited information on the structure of network: they know the number of potential customers they can attract and the degree distribution of customers. This incomplete information framework stimulates the use of Bayesian-Nash equilibrium. We find that, if there are customers only linked to one firm, but not all of them are, then an equilibrium in randomized strategies fails to exist. Instead, we find a symmetric equilibrium in randomized strategies. Finally, we test our results on US gasoline data. We find empirical evidence consistent with firms playing random strategies.

Keywords: Bertrand Competition, Bayesian- Nash Equilibrium, Mobility Index

JEL Classification: D43, D85, L11

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1 Introduction

What we observe in everyday life is a stark dispersion of prices for otherwise homogeneous products. In addition there are even fluctuations of prices across time for the same product offered by the same seller. The typical explanation of this phenomena is that goods are state contingent: an ice-cream in the desert or in summer is not the same product as an ice-cream in Siberia or in wintertime. This does however only marginally explain much of the variability observed in the data. For instance, gasoline sold across US cities, or chicken sold in different supermarkets in The Netherlands, or plane tickets sold online, display unexplainable price dispersion both along time and across locations.¹

One of the ways by which classical economic theory explains the formation of prices is the Bertrand competition model. Bertrand competition, however, imposes strict restrictions: agents are homogeneous and fully informed while firms compete against each others on prices. In the case of constant marginal costs, firms will undercut each other, thereby gaining all of the demand, and pushing the equilibrium price down to marginal costs.

Previous works (Salop and Stiglitz (1977, 1982), Wilde and Schwartz (1979), Varian (1980)) relaxed the full information assumption, dividing agents into informed and uninformed customers. The informed would compare prices and buy from the firm with the lowest price while the uninformed would just sample one firm. In this setup it can be shown that the equilibrium is such that firms randomize on prices with identical probability distributions. Baye and Morgan (2001) analyze advertising and consider a gatekeeper who charges advertising fees. Interestingly, they obtain similar equilibrium properties as the models mentioned above.

Starting with the seminal work of Stiglitz (1987), a second branch in the literature considers search-theoretical models of price dispersion. In these models agents are heterogenous in preferences and/or search costs. Under non-generic setups, there are only Nash equilibria in mixed strategies. Further, as first shown by Stiglitz (1987), an increase in the number of firms (more competition) may lead to an increase in the average price. Stahl (1996) and Kuksov (2006) identify sufficient conditions such that the previous ‘counter-intuitive’ outcome is excluded.

Finally, a different type of models (e.g. Kranton and Minehart (2001) or Corominas-Bosch (2004)) analyze bargaining situations on exogenously

¹Barron et al. (2004) analyze gasoline price dispersion in a cross-sectional dataset. See below for a description of the gasoline price dataset we analyze. Supermarket prices of homogeneous goods in the Netherlands have been analyzed empirically by Wildenbeest (2007). Clemons et al. (1999) analyze prices of plane tickets, sold by online travel agencies.

given non-regular networks. However, these bargaining situations become soon very complex as the size of the network grows. Hence, these models restrict their analysis to simple networks. On the contrary, we keep the transaction between buyers and sellers simple, which allows to generalize to any topology of relations between buyers and sellers.

We model our market through an exogenous network.² This allows customers to be more heterogeneous in their ability to compare prices: they can be not only either uninformed or fully informed, but also partially informed. Both customers and firms are nodes of this network. A firm can only attract those customers it is linked to and customers can only compare prices of the firms they are linked to.

We assume that firms only have information about the number of potential customers they could attract and on the probability distribution characterizing the number of links each customer has (i.e. the number of firms whose prices she can compare and whose goods she can buy). We are excluding any other knowledge by the firms about the full topology of the network. This assumption seems to be realistic since real world wholesaler normally do not know the shopping habits of each individual consumer, but rely their strategy on survey data representing the shopping habits of average customers. This incomplete information framework motivates the use of the Bayesian-Nash equilibrium concept, as e.g. in Jackson and Yariv (2007) or Galeotti, Goyal, Jackson, Vega-Redondo and Yariv (2007).

Within this setup, if there are completely uninformed customers, an equilibrium in pure strategies fails to exist. Instead, firms will randomize on prices. We identify two interesting properties of this equilibrium price distribution using stochastic dominance criteria. First, if we add links to a customer with more than one link, then the average price will increase. The intuition behind this surprising result is that, since in equilibrium firms randomize on prices between the monopoly and the competitive price, an increase in the number of links will increase competition and firms will shift more probability on higher prices in order to balance the expected payoff. In a sense this result is similar to Stiglitz (1987) who increases the total number of firms to model an increase in competition. Second, if we add a link to a customer with already many links this will have a larger positive effect on the average price than if we add the link to a customer with few links.

However, we provide examples in which an increase in competition will decrease the average prices. This can happen because also the number of

²In this sense we compute the equilibrium price distributions for any network architecture. In principle, this result allows us to define an allocation rule of the network and to endogenize Nash equilibria of the network formation game through backward induction, in the spirit of Bala and Goyal (2000).

uninformed customers decreases and hence also the profits from monopolistic pricing decrease.

Finally, in order to restore the balance between theory and application, we test our theoretical model on a gasoline prices panel dataset, making reasonable assumptions on the shape of the networks under simple characteristics such as town size or population density. We find that much of the variability in prices can be explained by these simple characteristics. We first replicate the result of Barron et al. (2004) and Baye et al. (2004) on a different dataset: more competition lead to lower average price, and price dispersion is persistent along time. We then use transition analysis to test directly firms' randomizing behavior: we find evidence supporting the hypothesis that cross sectional price dispersion is the empirical counterpart of a mixed strategy equilibrium.

Section 2 describes the model and the analytical results. Section 3 analyzes the data, while Section 4 concludes.

2 Model description

Formally, our environment is characterized by an exogenously given bipartite undirected network, that is a network where nodes are of two distinct types (firms and customers) and each link can only be between a firm and a customer.³ We assume that N potential buyers and H firms are located in this bipartite network.

Customers are assumed to need one unit each of a homogeneous good produced by firms. Customers compare all prices of the firms they are linked with and buy from the firm offering the lowest price, provided that this price does not exceed a reservation price r . In case of a tie, demand is assumed to be equally randomly split.

We assume that firms know the probability distribution characterizing the number of links each customer has (i.e. the number of firms whose prices she can compare and whose goods she can buy). So, firms know the probability that a given customer has only one link (call this probability q_1), two links (q_2), three links (q_3), and so forth, yielding a probability distribution \vec{q} , with $\sum_{i=1}^{\infty} q_i = 1$. We call \vec{q} the *degree distribution of customers*. In this incomplete information environment firms consider customers to be a priori homogeneous, even if the number of connections they have will vary across the network. In addition, we assume that each firm i knows the potential number of customers that it can attract, i.e. it knows its own degree d_i .

³We do not model informational links between customers, since this case can be replicated connecting them exactly to the same firms.

We assume that firms produce at constant marginal costs (which we set to 0 without loss of generality). In this sense, our model is a good approximation of the behavior of shops and wholesalers. Under this assumption the private information of firms (i.e. the number of customers each firm can potentially attract) does not affect the optimal strategy of each firm.

So, the private information of firm i is the number d_i of its own links. On the contrary, the public information of firms is given by the reservation price r of buyers, and the vector \vec{q} of probabilities.

The strategy of each firm i is to fix a price p_i , or more generally, as we will see, a distribution $f_i(p)$ of prices.

The number of expected links in the network is $L = N \cdot \sum_{i=1}^H i q_i$. The number of expected links for a single firm is then $\frac{L}{H} = \frac{N}{H} \cdot \sum_{i=1}^H i q_i$.

2.1 Formal analysis

It is easy to show that if $q_1 = 0$ (i.e. all consumers compare at least two prices), then we obtain the same result as in Bertrand competition. Formally:

Lemma 1 (Bertrand competition) *If $q_1 = 0$, then the only equilibrium is such that each firm plays $p = 0$.*

Proof First note that no firm will charge a price above r and below 0. In the former case it will attract no customers at all whereas in the latter it will make losses. So, consider a situation where all firms charge the same price $0 \leq p \leq r$. A given firm i with degree d_i expects profits of

$$\pi_i = d_i \sum_{j=1}^k \frac{q_j}{j} p \quad . \quad (1)$$

A deviant firm could now charge a slightly lower price $p - \epsilon$ and thereby attract all potential customers. This would yield a profit of $d_i(p - \epsilon)$ which is, for small enough $\epsilon > 0$, higher than the profit specified in (1). If $q_1 = 0$ firms keep on undercutting until we reach the point where $p = 0$ and $\pi = 0$.

■

It is also trivial to check that, if $q_1 = 1$, i.e. all customers go to exactly one shop, all firms will act as monopolists. Formally:

Lemma 2 (Monopoly) *If $q_1 = 1$, then the only equilibrium is such that each firm plays $p = r$.*

In what follows we address the remaining interesting case where $q_1 \in (0, 1)$. In particular, we show that if $0 < q_1 < 1$ the only symmetric equilibrium is such that all firms will randomize on price. This result is related to previous results, as Salop and Stiglitz (1977, 1982), Wilde and Schwartz (1979) and Varian (1980).

We stress that, even if the game we consider is a one-shot game, the equilibrium we expect is not in pure strategies, but rather an equilibrium where each firm randomizes strategies. This motivates our search for empirical evidence in the time-series data discussed in Section 3.

We start by noting that under the assumption of constant marginal costs, every potential customer can be considered as an independent game between all the firms connected to her. In this sense, firms are homogeneous and can only be distinguished by the number of games they play (the number of customers they are connected to, which they know). Each game is played by j different players (with probability q_j), but this number is unknown to the players. In the next proposition we will consider the symmetric strategies when there is a positive non-trivial probability that a customer is connected only to one firm ($q_1 \in (0, 1)$).

Proposition 3 *If $q_1 \in (0, 1)$, then there is no symmetric equilibrium in pure strategies, but there exist a symmetric equilibrium in randomized strategies, given by the distribution function $f(p)$. The support of $f(p)$ is $[q_1 r, r]$, on this support its cumulative distribution $F(p) = \int_{q_1 r}^r f(p) dp$ is given by*

$$F_{\vec{q}}(p) = 1 - \Psi_{\vec{q}}^{-1} \left(\frac{q_1 r}{p} \right) , \quad (2)$$

where $\Psi_{\vec{q}}(x)$ is defined as $\Psi_{\vec{q}}(x) \equiv \frac{\sum_{i=1}^{\infty} q_i x^i}{x}$.⁴

Proof If $q_1 \in (0, 1)$ a firm i can charge a price of r and assure itself a profit of $d_i q_1 r$. Note that this implies that no firm will charge a price lower than $q_1 r$.

Suppose that all firm charge the same price $q_1 r$. They will make an expected profit, on each customer, of $\sum_{j=1}^k \frac{q_j}{j} r q_1 < r q_1$, and hence could improve by setting a price of r .

Suppose now that the symmetric equilibrium has a point of mass on a given price $p > q_1 r$. In this case a profitable deviation would be to shift this

⁴It means that $\Psi_{\vec{q}}(x)$ is the generating function of \vec{q} divided by x , this definition works for any $x \in [0, 1]$.

If $q_i = 0$ for any $i > H$, then the definition is still valid, but one can truncate the sum at H . It is easy to check that $\Psi_{\vec{q}}$ is monotonically increasing and hence invertible. Finally, note that since $\sum_{i=1}^{\infty} q_i = 1$, $\Psi_{\vec{q}}$ increases from $\Psi_{\vec{q}}(0) = q_1$ to $\Psi_{\vec{q}}(1) = 1$.

point of mass to $p - \epsilon$, for some low enough $\epsilon > 0$, as discussed in the proof of Lemma 1.

Suppose finally that the support of $f(p)$ is exactly $[q_1 r, r]$ (i.e. $f(p) > 0$ for any $p \in [q_1 r, r]$). If we show that this assumption can be consistent with the well known requirement of a mixed-strategies equilibrium, that every strategy in the support yields the same expected payoff, then this equilibrium exists.

We suppose that each firm plays a random strategy $f(p)$, where the support of $f(p)$ is $[q_1 r, r]$, and there are no points of mass.

Let $F(p) = \int_{q_1 r}^p f(p) dp$ be the symmetric cumulative distribution function of prices. The probability that a customer with j links buys a product from a given firm is $[1 - F(p)]^{j-1}$. This means that the profit to firm i by setting price distribution $f(p)$ is given by

$$\pi_i(p) = d_i \int_{q_1 r}^r \left(\sum_{j=1}^H q_j [1 - F(p)]^{j-1} \right) p f(p) dp . \quad (3)$$

Since firms randomize on prices that guarantee the same expected profit, we define $\pi_i \equiv \pi_i(p)$ for all p with $f(p) > 0$, and then $\pi_i = \pi_i(r) = d_i r q_1$. From the previous point and from (3), we obtain

$$\sum_{j=1}^H q_j [1 - F(p)]^{j-1} = \frac{q_1 r}{p} \quad (4)$$

$$\Psi_{\vec{q}}(1 - F(p)) = \frac{q_1 r}{p} , \quad (5)$$

which is independent from d_i , yielding (2).

Hence, a symmetric equilibrium in mixed strategies exists, which has price-support on $[q_1 r, r]$, and satisfies the property that each price on the support guarantees the same expected payoff. ■

We now provide two examples on how the probability distribution $f(p)$ can be inferred from different degree distributions.

Example 1 (Exponential network) *Suppose that probabilities q_i are generated by an exponential law, so that $q_i \propto \alpha^i$, with $\alpha \in (0, 1)$.*

In order to get the normalization $\sum_{i=1}^H q_i = 1$, since $\sum_{i=1}^H \alpha^i = \alpha \frac{1-\alpha^H}{1-\alpha}$ we need

$$q_i = \alpha^{i-1} \frac{1-\alpha}{1-\alpha^H} .$$

Equation (5) reads

$$\begin{aligned} \sum_{i=1}^H \alpha^{i-1} \frac{1-\alpha}{1-\alpha^H} [1-F(p)]^{i-1} &= q_1 \frac{r}{p} \\ \frac{1-(\alpha[1-F(p)])^H}{1-\alpha[1-F(p)]} &= \frac{r}{p} \end{aligned} \quad (6)$$

for $p \in [\frac{1-\alpha}{1-\alpha^H}r, r]$.

If $H \rightarrow \infty$ then (6) becomes

$$\begin{aligned} \frac{1}{1-\alpha[1-F(p)]} &= \frac{r}{p} \\ F(p) &= \frac{p}{\alpha r} - \frac{1-\alpha}{\alpha} \end{aligned} \quad (7)$$

for $p \in [(1-\alpha)r, r]$, so that $f(p) = \frac{1}{\alpha r}$ on this support (uniform probabilities), and is 0 otherwise. The expected price is $E[f(p)] = r - \frac{\alpha}{2}$.

If α increases, also the probabilities that customers have more connections increase, and expected prices decrease. ■

Example 2 (Random Network) Suppose that H and N are fixed, and any link between a customer and a firm has probability λ . In this case, by the binomial distribution,

$$q_i = \binom{H}{i} \lambda^i (1-\lambda)^{H-i} .$$

Note that there is also a positive probability for $q_0 = (1-\lambda)^H$. The expected number of potential customers is actually $(1-(1-\lambda)^H)N < N$.

We can divide every q_i , with $i > 0$ by $(1-q_0)$ to re-normalize things, obtaining

$$q_i = \binom{H}{i} \lambda^i \frac{(1-\lambda)^{H-i}}{1-(1-\lambda)^H} .$$

Noting that $q_1 = H\lambda \frac{(1-\lambda)^{H-1}}{1-(1-\lambda)^H}$ equation (5) becomes now

$$\begin{aligned} \sum_{i=1}^H \binom{H}{i} \lambda^i \frac{(1-\lambda)^{H-i}}{1-(1-\lambda)^H} [1-F(p)]^{i-1} &= \frac{q_1 r}{p} \\ \frac{(1-\lambda)^{H-1}}{1-(1-\lambda)^H} \left[(1+\lambda[1-F(p)])^H - 1 \right] &= H\lambda \frac{(1-\lambda)^{H-1}}{1-(1-\lambda)^H} \frac{r}{p} [1-F(p)] \\ (1+\lambda[1-F(p)])^H &= 1 + H\lambda \frac{r}{p} [1-F(p)] \end{aligned} \quad (8)$$

for $p \in [q_1 r, r]$, $F(p) = 0$ for $p < q_1 r$ and $F(p) = 1$ for $p > r$. It is not possible to compute analytically $F(p)$ and hence $f(p)$.

There are however two things that it is possible to infer from (8). Note first that if we call $\xi(p) \equiv \lambda[1 - F(p)]$, then (8) can be written as

$$(1 + \xi(p))^H = 1 + H \frac{r}{p} \xi(p)$$

1. As H (keeping fixed λ) grows we approximate (by the law of large numbers) a regular network with $H\lambda$ links per customer, moreover $q_1 \rightarrow 0$. (8) tells us that in this case, for any $p > q_1 r \rightarrow 0$: $1 - F(p) \rightarrow 0$. This implies that we approximate Bertrand Competition.
2. As λ grows (keeping fixed H) $\xi(p)$ is fixed, $1 - F(p)$ decreases, and so $F(p)$ increases.

Finally note that an increase in λ implies higher chances for the customers to be connected to more firms, and that an increase in $F(p)$ means that the expected price decreases. ■

The popular case of a scale-free network ($q_i \propto i^{-\gamma}$, with $\gamma > 0$) could also be treated analytically, but the series can not be solved for explicitly and the result would just be a rephrasing of equation (4).⁵

2.2 Comparative statics

Although, we can not always explicitly solve for the equilibrium pricing strategies we can nevertheless perform some comparative statics using equation (2) provided in Proposition 3. In particular, we can show that an increase in the (expected) number of links of the network, leaving the proportion q_1 of uninformed customers unaffected, will increase the average price. Similar results have been obtained in a search-based context with heterogeneous agents by Stiglitz (1987).

In Stiglitz (1987), when the costs of search are non-linear, every firm randomizes in-between the monopoly price and the competitive price. In this setting, an increase in the number of firms will increase competition,

⁵Suppose that $q_i \propto i^{-\gamma}$. Under the additional assumption that $H \rightarrow \infty$, (4) becomes:

$$Li_\gamma[1 - F(p)] = \frac{r}{p}[1 - F(p)] ,$$

for any $p \in [\frac{r}{\zeta(\gamma)}, r]$. Here $Li_\gamma(x) \equiv \sum_{i=1}^{\infty} x^i i^{-\gamma}$ is the *polylogarithm*, and $\zeta(\gamma) \equiv \sum_{i=1}^{\infty} i^{-\gamma}$ is the *Riemann zeta function*.

and hence reduce revenues from competing. In order to counter-balance competition, firms will shift more weight towards the monopoly price. The main difference in the comparative statics between our setup and Stiglitz (1987) is that he increases competition by increasing the number of firms, whereas we increase the density (i.e. the number of links) of the network. The intuition behind our results is similar: increasing the density of the network, each firm will expect an increase in the number of potential competitors.

Formally, if we assume that some degree distribution \vec{q}' first order stochastically dominates (FOSD) another degree distribution \vec{q} , but $q_1 = q'_1$, then also the resulting probability distribution of prices under q' will FOSD the resulting price distribution under q .

Proposition 4 *Consider two customer degree distributions, \vec{q} and \vec{q}' , with $q_1 = q'_1 > 0$. Call $f(p)_{\vec{q}}$ and $f(p)_{\vec{q}'}$ the resulting symmetric equilibria (as defined in (2)). If \vec{q}' FOSD \vec{q} , then $f_{\vec{q}'}(p)$ FOSD $f_{\vec{q}}(p)$.*

Proof Equation (2) holds for $p \in [q_1 r, r]$, $F(p) = 0$ for $p < q_1 r$ and $F(p) = 1$ for $p > r$. Given the definition of Ψ , if q' FOSD q , then

$$\Psi_{\vec{q}'}(x) < \Psi_{\vec{q}}(x)$$

for any $x \in (0, 1)$.

Since $q_1 = q'_1$, $\Psi_{\vec{q}'}(0) = \Psi_{\vec{q}}(0) = q_1$, moreover, for any $p \in (q_1 r, r)$, we have $\frac{q_1 r}{p} > q_1$.

Since both $\Psi_{\vec{q}'}$ and $\Psi_{\vec{q}}$ are increasing,

$$\Psi_{\vec{q}'}^{-1}\left(\frac{q_1 r}{p}\right) > \Psi_{\vec{q}}^{-1}\left(\frac{q_1 r}{p}\right)$$

for any $p \in (q_1 r, r)$. From (2) we have that $f_{\vec{q}'}(p)$ FOSD $f_{\vec{q}}(p)$. ■

Proposition 4 implies the following: if we increase the number of shops each customer visits, but keep a ratio of customers uninformed, then the equilibrium price distribution will put more weight on higher and less weight on lower prices. Moreover, this implies that the average price may increase if we add links to an existing network. The intuition behind this apparently odd result is that an increase in the number of firms each customer visits decreases each firm's probability to attract the customers with many links. In order to balance this effect and assure themselves the reservation profit $q_1 r$, in equilibrium, firms will charge on average higher prices, to extract more profits from the less informed buyers.

At a first glance the result of Proposition 4 seems not to be in accordance with the final considerations provided in Examples 1 and 2. However in those cases, increasing the density of the network, the probability q_1 decreases and hence Proposition 4 does not apply.

We find that the marginal contribution, in terms of FOSD of price distributions, of adding a new link to a customer is higher the more original links she has.

Proposition 5 *Consider a fixed, not complete network, where every customer has at least one link and there is at least a customer with only one link. We add a link to a customer j , where j stands for the number of links she originally has. If \vec{q}' is the degree distribution obtained by adding it to a customer $k' > 1$, and \vec{q} is the degree distribution obtained by adding it to a customer $k > k'$, then $f_{\vec{q}'}(p)$ FOSD $f_{\vec{q}}(p)$.*

Proof Note that $\vec{q}' - \vec{q} = (0, \dots, -\frac{1}{L+1}, \frac{1}{L+1}, \dots, \frac{1}{L+1}, -\frac{1}{L+1}, \dots, 0)$, where L is the total number of links in the original network, the first $-\frac{1}{L+1}$ is in position k' and the last $-\frac{1}{L+1}$ is in $(k+1)^{th}$ position.

The proof follows the same steps as the proof of Proposition 4. It is clear that $q_1 = q'_1$. Given that Ψ is linear in the elements of \vec{q} and \vec{q}' ,

$$\begin{aligned} \Psi_{\vec{q}'}(x) - \Psi_{\vec{q}}(x) &= \Psi_{\vec{q}' - \vec{q}}(x) = \frac{1}{L+1} \left(-x^k + x^{k+1} + x^{k'} - x^{k'+1} \right) \\ &= \frac{x^{-k}}{L+1} (1-x) \left(x^{k'-k} - 1 \right) < 0 . \end{aligned}$$

This means that

$$\Psi_{\vec{q}'}(x) < \Psi_{\vec{q}}(x)$$

for any $x \in (0, 1)$. ■

Proposition 5 allows us to draw an important conclusion for competition: the return of adding links (in terms of the increase of the average price) is larger for customers with already many links, than for customers with few links.

Finally, we do not perform any global welfare analysis because, in our settings, it would be meaningless. Given that, in equilibrium, every customer will buy one and only one unit of the good, the surplus will be either on the side of firms or on the side of customers, but its aggregate value will remain constant. In this sense, our model is a zero-sum game.

3 Empirical analysis

Price dispersion is a well-known issue in the empirical literature: price dispersion over time is at the basis of time series econometrics, but same goods also have different prices in cross-sectional samples. The empirical implication of our model is that the “law of one price” is not the only equilibrium outcome: given the network structure the model suggests firms will randomize on prices. Thus price dispersion turns out to be an equilibrium. Hence, given a network which is ex-ante heterogeneous, i.e. an environment where the number of potential clients around each firm is not fixed, we expect to find evidence of persistent price dispersion along time. The effect of adding links to an existing network is not straightforward. Examples in Section 2 shows that denser networks exhibit lower average prices. Anyway, we prove in Proposition 4 that there are cases in which an increase in the number of links may lead to a price increase. Wildenbeest (2007) provides empirical evidence of persistent price dispersion in groceries’ goods using data from www.supers.nl, a Dutch website that publishes daily prices once a month for a set of groceries goods sold in 15 different supermarket chains in the Netherlands. The website is freely accessible, thus in principle clients could compare prices every time they need to shop and behave consequently. Nevertheless, price dispersion is present and does not fall over time. Baye et al. (2004) find the same kind of evidence on thousands of consumer goods whose prices are daily compared on a website (Shopper.com).⁶ The idea behind using prices taken from the Internet to provide evidence of price dispersion can be thought to as a “worst case scenario”: the Internet should reduce search costs to zero and thus ex-ante information heterogeneity in the network. Therefore if there is price dispersion in this setting, it can only be worse in a “real world environment”. The drawback is that there may be a potential self selection: customers that compare prices on the Internet are likely to be somewhat more “sophisticated” than the average.

Barron et al. (2004) analyze unleaded gasoline in U.S. They have a cross section of gas-station level data, and using micro-level characteristics of sellers they look for the effect of competition (in terms of spatial proximity of firms) on prices. Their results are in line with the intuitive outcome of our examples: the denser the network, the lower is average price.

We use US gasoline prices as well: our dataset are prices collected monthly by the US bureau of labor statistics representatives across US to compute the Consumer Price Indexes. We have average prices on 5 different types of gasoline, 28 urban areas and 12 region/size class groupings, i.e. average

⁶Further empirical evidence on price dispersion can be found in Baye et al. (2006).

prices in three different city size classes and in the four US macro regions. Depending on the area and gasoline type the time series may vary in length spanning the period between January 1978 and October 2007, thus covering several business cycles (see Tables 4 and 5 in the Appendix for details on regular grade gasoline series). Unlike Barron et al. (2004), we do not have gas station level data, on the other hand our dataset is longitudinal. Using aggregate instead of firm level data could bias our results, thus we first replicate the results of the authors we just cited.

We start with the graphical analysis of the time series of three measures of price dispersion: the first one, standard deviation, is the most straightforward. Since price dispersion is likely to depend on the price level, we computed the coefficient of variation, which is the ratio of standard deviation over the relative mean. The last measure, the interquartile range, is proposed in order to reduce the impact of potential outliers. These measures are computed for each gasoline type and for each month aggregating data at the macro-regional level: North East, Midwest, South and West. While these areas are quite wide, each of them cover both a number of urban areas and suburban ones, thus firms (i.e. gas stations) with higher and lower numbers of potential customers. The time series of each of these measures for leaded and unleaded gasoline are reported graphically in Tables 6 and 7 in the appendix. Results, regardless of the measure chosen, support the presence and persistence of price dispersion: this phenomenon is not going to decline, since there are no clear down sloping trends. For both leaded and unleaded gasoline the mean coefficient of variation lies between 0.02 and 0.05, meaning that the price in different areas within the same region deviates on average between 2% and 5% from the regional mean, with a peak at 13.5% (leaded gasoline in the West). Dispersion is not constant over regions: North East, which is the region characterized by the presence of many urban area, is in general the lower-variability region among the four.

The second part of our analysis is based on regression results. As in Barron et al. (2004), the aim is to test the implication that big cities - which are networks with a high number of potential links - have a lower average price than non urban areas. To do so we compute differences of (log)prices between a urban area and a sub-urban one. Then, we use it as the dependent variable Δp_t in a regression over a intercept and its autoregressive lag:

$$\Delta p_t = \alpha_0 + \alpha_1 \Delta p_{t-1} + u_t \quad (9)$$

Where u_t has zero mean and σ_t^2 unknown variance. The two original time series are likely to be integrated, i.e. they are likely to be correlated to an underlying oil prices' data generating process. We look at the differences

time series instead in order to control for this common factor and for any other common exogenous shock. The autoregressive term accounts for inertia in price adjustment and persistent shocks. Regression (9) provides a test of our hypothesis: under the null that prices in urban areas are on average lower than in non-urban areas, the intercept term should be significantly different from zero and negative, since it represents Δp_t short-term mean after controlling for its lag.

Results are reported in Table 1 for 6 Δp_t s: we consider two metropolitan areas in Southern U.S. (Houston–Galveston–Brazoria, and Dallas-Fort Worth, both in Texas and both with more than two million inhabitants) and B,C,D area/size average prices for Southern US as well.⁷ Standard errors are robust both to autocorrelation (which is not ruled out given that we assumed σ_t^2 to be time dependent) and to heteroskedasticity. t -tests on α_0 confirm that short time average is significant and negative. The results do not vary significantly across size, while if the difference is taken between the two metropolitan areas, the test is rejected at the 99% level. We chose to report estimates for southern states because metropolitan areas (and town in general) are far away one from the other and thus the underlying assumption that networks with different densities are separated is more realistic. Nevertheless we ran the same regressions on the other regions and gasoline specification, with no significant differences.⁸

Such an evidence, which is in line with Barron et al. (2004), is still not conclusive: if the regression model (9) is correctly specified and it is stationary the process is mean-reverting and thus we can test the long-term mean μ to be negative. Being more specific, (9) is the reduced form for

$$\Delta p_t = \mu + \alpha_1(\Delta p_{t-1} - \mu) + u_t \quad (10)$$

Since from Table 1 α_1 lies always within the unit circle the differences' series are stationary (again, assuming the model is correctly specified). Moreover α_0 is negative throughout the different specifications, accepting $H_0 : \mu < 0$ in (10) is equivalent to reject $H'_0 : \frac{\alpha_0}{1-\alpha_1} = 0$ in (9). Table 2 reports μ estimates, standard errors and test statistics for H'_0 (which are distributed as $\chi^2_{(1)}$). The long term average is always significantly different from zero and negative.

In the same table we report also residuals' skewness estimates, standard errors and t -test for significance: if residuals are normal, there must be no

⁷The Bureau of Labor statistics define four area/size aggregations: A is the average over census metropolitan areas with more than two million inhabitants per county, D is the average over areas with less than 50.000 inhabitants, B and C are intermediate classes, being the benchmark half a million.

⁸The data are not reported but are available upon request.

Table 1: Regression results

	Coefficient	Estimate	Std. dev.	t-stat
Δp : Houston–Galveston–Brazoria	α_0	-0.048	0.009	-5.122
minus B-size average	α_1	0.896	0.039	22.768
Δp : Houston–Galveston–Brazoria	α_0	-0.041	0.0137	-2.982
minus C-size average	α_1	0.926	0.0286	32.411
Δp : Houston–Galveston–Brazoria	α_0	-0.038	0.007	-5.244
minus D-size average	α_1	0.865	0.028	31.332
Δp : Houston–Galveston–Brazoria	α_0	-0.008	0.004	-2.200
minus Dallas–Fort Worth	α_1	0.806	0.038	21.339
Δp : Dallas–Fort Worth	α_0	-0.038	0.008	-4.844
minus B-size average	α_1	0.882	0.034	26.216
Δp : Dallas–Fort Worth	α_0	-0.031	0.014	-2.163
minus C-size average	α_1	0.923	0.027	34.269
Δp : Dallas–Fort Worth	α_0	-0.029	0.010	-4.929
minus D-size average	α_1	0.868	0.059	14.729

Notes: This table reports results from the estimation of 6 versions of Equation (9). The dependent variable, Δp is the period-by-period differences series based on the original prices described on the leftmost column. Prices are all in logs. Standard deviations are Heteroskedasticity and Autocorrelation consistent (Newey–West HAC covariance matrix estimates). The rightmost column report t -tests for the Null that each coefficient is equal to 0. Tests are all strongly rejected.

evidence of skewness on the residuals distribution. On the contrary, excessive left skewness would suggest that not only mean prices are lower on big cities, but that even after controlling for the autoregressive term the whole distribution of big cities prices lies on the left of non-urban areas prices. The results confirm that residuals are significantly left skewed throughout the specifications.

Up to now we replicated the results known in the empirical literature on price dispersion with a new dataset. We can go further and exploit the long time series nature of gasoline prices: we can test directly the randomizing behavior of firms. Being specific, our model implies that firms randomize on the $[q_1 r, r]$ support, and q_1 depends on the particular network structure of a region.⁹ Thus, if the reservation cost is the same for all clients then all firms

⁹The empirical equivalent of this support should include costs we set to 0. Nevertheless a fixed cost c would simply shift the upper and the lower bound of the support for the same amount.

Table 2: Long term average and skewness

		Estimate	std err	test stat
Δp : Houston–Galveston–Brazoria	μ	-0.463	0.219	4.473
minus B–size average	Skewness	-0.319	0.158	-2.007
Δp : Houston–Galveston–Brazoria	μ	-0.549	0.293	3.508
minus C–size average	Skewness	-0.331	0.158	-2.089
Δp : Houston–Galveston–Brazoria	μ	-0.283	0.084	11.329
minus D–size average	Skewness	-0.509	0.130	-3.909
Δp : Houston–Galveston–Brazoria	μ	-0.042	0.022	3.835
minus Dallas–Fort Worth	Skewness	-0.307	0.130	-2.368
Δp : Dallas–Fort Worth	μ	-0.322	0.121	7.079
minus B–size average	Skewness	-0.330	0.158	-2.083
Δp : Dallas–Fort Worth	μ	-0.387	0.203	3.792
minus C–size average	Skewness	-0.579	0.158	-3.654
Δp : Dallas–Fort Worth	μ	-0.371	0.149	6.205
minus D–size average	Skewness	-0.855	0.213	-4.010

Notes: For each specification, the first line report estimate, standard error and F -test of significance of the composite parameter $\mu = \alpha_0/(1 - \alpha_1)$. The F test is distributed as a $\chi^2_{(1)}$, and the null $H'_0 : \mu = 0$ is rejected at 90% level if the test statistic is bigger than 2.71, at 95% if bigger than 3.84 and at 99% if bigger than 6.63. The second line reports estimate, standard error and t -test of significance for skewness. Skewness standard error is approximated with $\sqrt{6/n}$, where n is the number of observations as suggested by Tabachnick and Fidell (1996). n is 239 but for the third and fourth specification where it is 354 and for the last one (132 observations). The t -test is distributed as a standard normal and the null of no skewness is rejected at least at 95% level for all the specifications

share the same upper bound, which means there is a price range $[\max\{q_1\}r, r]$ over which all firms randomize. While we found that on average prices in urban areas are lower than in less dense networks, the empirical equivalent of the fact that firms randomize (partly) over the same support is that such an ordering should not be systematic, i.e. there must be periods in which prices in cities are above those in the other areas. Moreover, the fact that mean prices of firms with denser network are lower is consistent with the fact that all firms share the same upper bound but the higher the number of potential clients, the lower is q_1 and thus the lower bound.

In order to formally test the implications we just described we build transition matrices on the rankings of prices in each macro area. We refer and report the matrix for the South area, but results are qualitatively the same for the other three macro regions. We have 8 price series in the South (5

metropolitan areas and the usual B,C,D sub-urban aggregations). In every period t we rank prices in descending order from 1st to 8th, and then we build an 8×8 transition matrix \mathbf{X} where each entry x_{ij} represent the number of observations that were ranked i^{th} in period t and j^{th} on period $t + 1$. Such a matrix is reported in Table 3.

Table 3: Transition matrix for South macro area

	1st	2nd	3rd	4th	5th	6th	7th	8th
1st	181	42	12	2	1	1	0	0
2nd	45	158	26	7	2	1	0	0
3rd	10	28	145	38	9	5	2	2
4th	3	8	35	137	42	10	3	1
5th	0	3	14	43	129	36	11	3
6th	0	0	5	9	38	147	29	11
7th	0	0	2	3	12	30	173	19
8th	0	0	0	0	6	9	21	203

If ordering were systematic, \mathbf{X} would have been a diagonal matrix. On the other hand if ranking were completely random (i.e. all firms randomize exactly on the same support) then $x_{ij} = x_{ij'} \forall i, j, j'$. Shorrocks (1978) proposed a mobility index based on \mathbf{X} which takes value 0 for the identity matrix and 1 for the completely random one (using the author’s terminology, a ‘perfect mobility matrix’):

$$M(\mathbf{X}) = \frac{n - \text{trace}(\mathbf{P})}{n - 1}$$

where n is the number of rows (and columns) and \mathbf{P} is the row-standardized transition matrix (i.e. $p_{i,j} = x_{i,j}/n_i$ where $n_i = \sum_{j=1}^n x_{i,j}$). We use $M(\mathbf{X})$ as a test statistic: in order to be consistent with the theory model and with the evidence found in the regression analysis, $M(\mathbf{X})$ must be statistically different both from 0 and from 1. $M(\mathbf{X})$ is asymptotically normal¹⁰ and thus we can run two simple t -tests. We obtain a maximum likelihood estimator of $M(\mathbf{X})$, \hat{M} which is equal to 0,382 with a standard deviation equal to 0,012. Thus, both the null hypothesis $H_0^a : M(\mathbf{X}) = 0$ and $H_0^b : M(\mathbf{X}) = 1$ are strongly rejected. \hat{M} for other regions takes values between 0,368 and 0,515 and both hypothesis are always strongly rejected.

¹⁰See Schluter (1998) for a derivation of asymptotic properties of $M(\mathbf{X})$ and other mobility indeces.

4 Conclusion

Our work aims at explaining some of the price dispersion observed in real data both along time and across locations, using combined tools from network theory and standard consumer theory. The network models the heterogeneity in information and purchasing possibility of the consumers at one side, and the variability in the number of potential customers on the side of firms. We maintain the assumption that firms have constant marginal costs, which is reasonable when considering shops or gas stations. We show that there is no symmetric equilibrium in pure strategies, but there is one in randomized strategies. Empirical evidence supports our model: we analyzed twenty years of monthly prices on five different types of gasoline sold in United States. Whatever the time series or the area is chosen, prices exhibit substantial and persistent dispersion, confirming the fact that such an empirical evidence is an equilibrium feature and not a temporary state of the market. Moreover, regression analysis ran on the same data confirm the empirical evidence of previous works: metropolitan areas - i.e. networks with a high number of potential links - have lower average prices and price distribution tilted to the left with respect to sub-urban and rural areas. Last, we find direct empirical evidence of the randomizing behavior of firms: we used a statistic based on a transition matrix between price orderings to test the implication of the model that firms with a higher degree randomize on a wider support than firms with a lower degree, but they all share the same upper bound.

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Appendix: Data description and figures

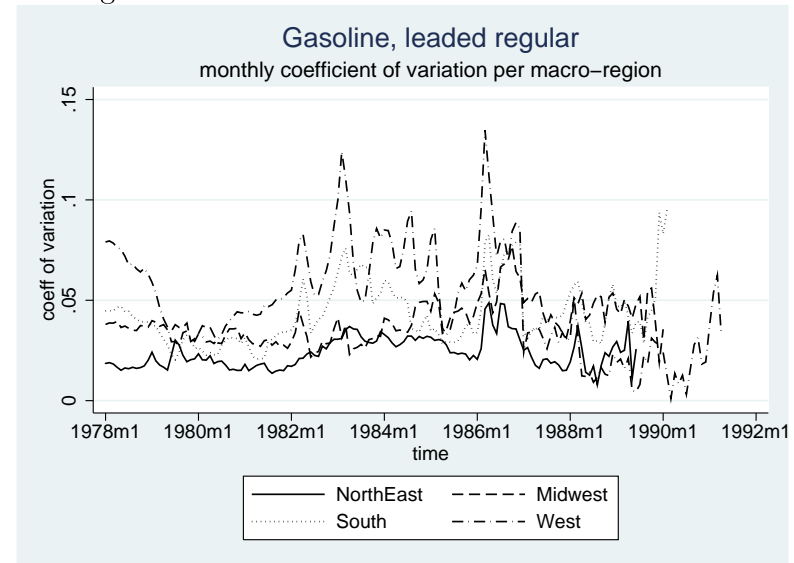
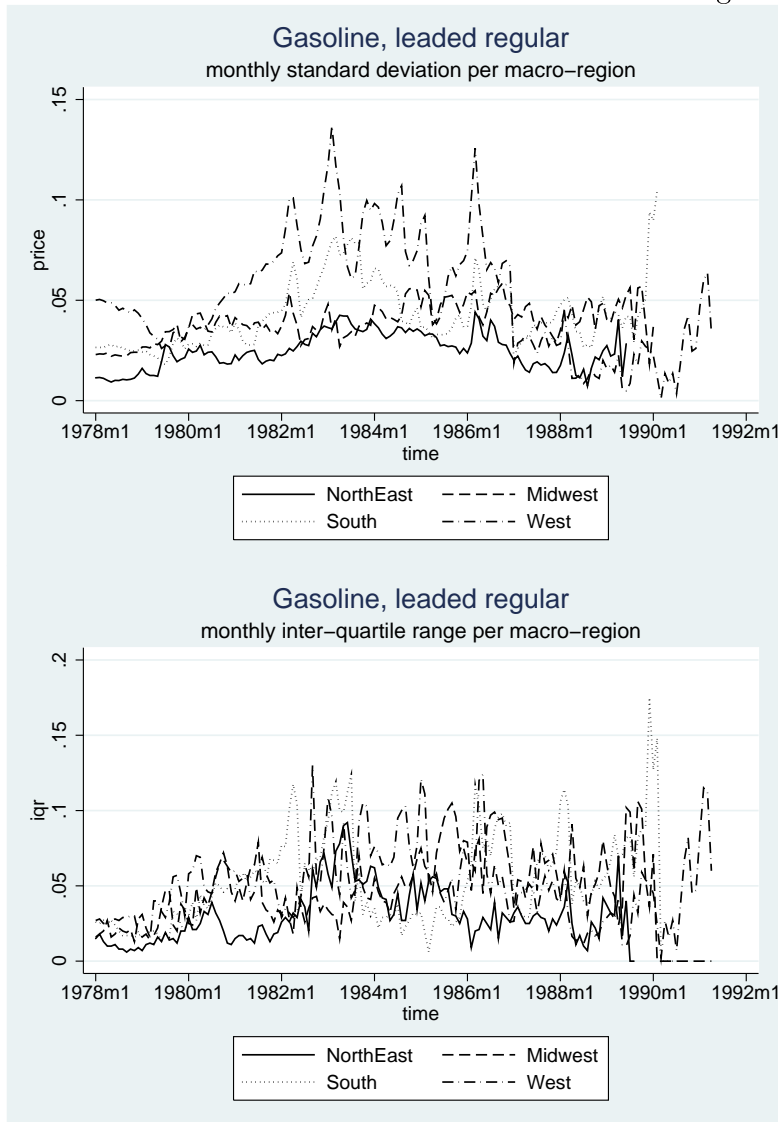
Table 4: Gasoline, leaded regular

series id	area	begin	end
APUA10174712	New York-Northern New Jersey Long Island, NY-NJ-CT-PA	1978, Jan	1989, Dec
APUA10274712	Philadelphia-Wilmington-Atlantic City PA-NJ-DE-MD	1978, Jan	1989, Dec
APUA10374712	Boston-Brockton-Nashua, MA-NH-ME-CT	1978, Jan	1989, Dec
APUA10474712	Pittsburgh, PA	1978, Jan	1989, Dec
APUA10574712		1978, Jan	1986, Dec
APUA10674712		1978, Jan	1986, Dec
APUA20774712	Chicago-Gary-Kenosha, IL-IN-WI	1978, Jan	1989, Dec
APUA20874712	Detroit-Ann Arbor-Flint, MI	1978, Jan	1989, Dec
APUA20974712	St. Louis, MO-IL	1978, Jan	1990, Dec
APUA21074712	Cleveland-Akron, OH	1978, Jan	1988, Dec
APUA21174712	Minneapolis-St. Paul, MN-WI	1978, Jan	1986, Dec
APUA21274712	Milwaukee-Racine, WI	1978, Jan	1986, Dec
APUA21374712	Cincinnati-Hamilton, OH-KY-IN	1978, Jan	1986, Dec
APUA21474712	Kansas City, MO-KS	1978, Jan	1986, Dec
APUA31574712		1978, Jan	1988, Dec
APUA31674712	Dallas-Fort Worth, TX	1978, Jan	1989, Dec
APUA31774712		1978, Jan	1988, Dec
APUA31874712	Houston-Galveston-Brazoria, TX	1978, Jan	1989, Dec
APUA31974712	Atlanta, GA	1978, Jan	1986, Dec
APUA32074712	Miami-Fort Lauderdale, FL	1978, Jan	1987, Dec
APUA42174712	Los Angeles-Riverside-Orange County, CA	1978, Jan	1991, Dec
APUA42274712	San Francisco-Oakland-San Jose, CA	1978, Jan	1991, Dec
APUA42374712	Seattle-Tacoma-Bremerton, WA	1978, Jan	1986, Dec
APUA42474712	San Diego, CA	1978, Jan	1986, Dec
APUA42574712	Portland-Salem, OR-WA	1978, Jan	1986, Dec
APUA42674712	Honolulu, HI	1978, Jan	1986, Dec
APUA42774712	Anchorage, AK	1978, Jan	1986, Dec
APUA43374712	Denver-Boulder-Greeley, CO	1978, Jan	1986, Dec
APUB10074712	Northeast Size B	1978, Jan	1989, Dec
APUB20074712	Midwest Size B	1978, Jan	1989, Dec
APUB30074712	South Size B	1978, Jan	1990, Dec
APUB40074712	West Size B	1978, Jan	1988, Dec
APUC10074712	Northeast Size C	1978, Jan	1989, Dec
APUC20074712	Midwest Size C	1978, Jan	1991, Dec
APUC30074712	South Size C	1978, Jan	1990, Dec
APUC40074712	West Size C	1978, Jan	1991, Dec
APUD10074712	Northeast Size D	1978, Jan	1986, Dec
APUD20074712	Midwest Size D	1978, Jan	1990, Dec
APUD30074712	South Size D	1978, Jan	1989, Dec
APUD40074712	West Size D	1978, Jan	1986, Dec

Table 5: Gasoline, unleaded regular

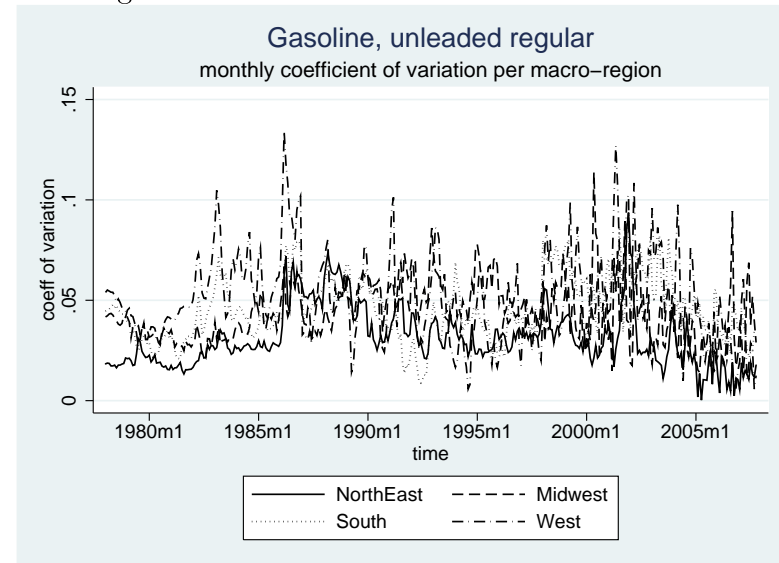
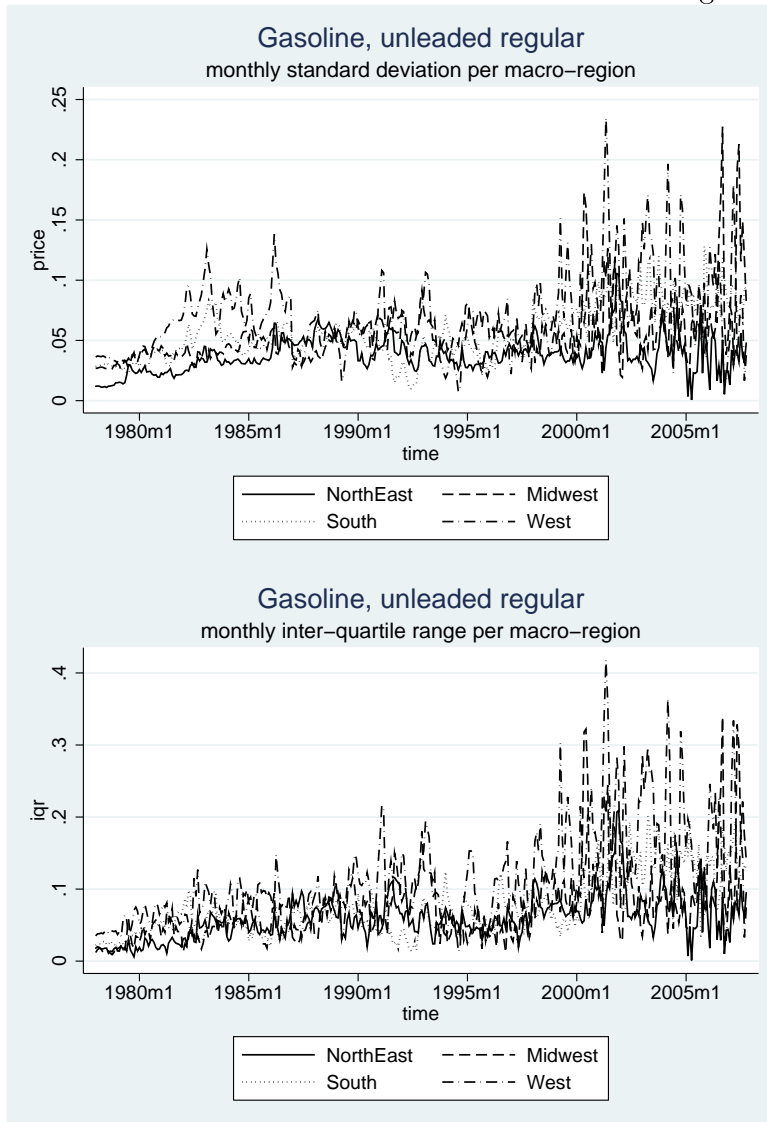
series id	area	begin	end
APUA10174714	New York-Northern New Jersey Long Island, NY-NJ-CT-PA	1978, Jan	2007, Oct
APUA10274714	Philadelphia-Wilmington-Atlantic City PA-NJ-DE-MD	1978, Jan	2007, Oct
APUA10374714	Boston-Brockton-Nashua, MA-NH-ME-CT	1978, Jan	2007, Oct
APUA10474714	Pittsburgh, PA	1978, Jan	1997, Dec
APUA10574714		1978, Jan	1986, Dec
APUA10674714		1978, Jan	1986, Dec
APUA20774714	Chicago-Gary-Kenosha, IL-IN-WI	1978, Jan	2007, Oct
APUA20874714	Detroit-Ann Arbor-Flint, MI	1978, Jan	2007, Oct
APUA20974714	St. Louis, MO-IL	1978, Jan	1997, Dec
APUA21074714	Cleveland-Akron, OH	1978, Jan	2007, Oct
APUA21174714	Minneapolis-St. Paul, MN-WI	1978, Jan	1986, Dec
APUA21274714	Milwaukee-Racine, WI	1978, Jan	1986, Dec
APUA21374714	Cincinnati-Hamilton, OH-KY-IN	1978, Jan	1986, Dec
APUA21474714	Kansas City, MO-KS	1978, Jan	1986, Dec
APUA31174714	Washington-Baltimore, DC-MD-VA-WV	1998, Jan	2007, Oct
APUA31574714		1978, Jan	1997, Dec
APUA31674714	Dallas-Fort Worth, TX	1978, Jan	2007, Oct
APUA31774714		1978, Jan	1997, Dec
APUA31874714	Houston-Galveston-Brazoria, TX	1978, Jan	2007, Oct
APUA31974714	Atlanta, GA	1978, Jan	2007, Oct
APUA32074714	Miami-Fort Lauderdale, FL	1978, Jan	2007, Oct
APUA42174714	Los Angeles-Riverside-Orange County, CA	1978, Jan	2007, Oct
APUA42274714	San Francisco-Oakland-San Jose, CA	1978, Jan	2007, Oct
APUA42374714	Seattle-Tacoma-Bremerton, WA	1978, Jan	2007, Oct
APUA42474714	San Diego, CA	1978, Jan	1986, Dec
APUA42574714	Portland-Salem, OR-WA	1978, Jan	1986, Dec
APUA42674714	Honolulu, HI	1978, Jan	1986, Dec
APUA42774714	Anchorage, AK	1978, Jan	1986, Dec
APUA43374714	Denver-Boulder-Greeley, CO	1978, Jan	1986, Dec
APUB10074714	Northeast Size B	1978, Jan	1997, Dec
APUB20074714	Midwest Size B	1978, Jan	1997, Dec
APUB30074714	South Size B	1978, Jan	1997, Dec
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APUC10074714	Northeast Size C	1978, Jan	1997, Dec
APUC20074714	Midwest Size C	1978, Jan	1997, Dec
APUC30074714	South Size C	1978, Jan	1997, Dec
APUC40074714	West Size C	1978, Jan	1997, Dec
APUD10074714	Northeast Size D	1978, Jan	1986, Dec
APUD20074714	Midwest Size D	1978, Jan	2007, Oct
APUD30074714	South Size D	1978, Jan	2007, Oct
APUD40074714	West Size D	1978, Jan	1986, Dec

Table 6: Regular leaded gasoline



Variable	Mean	Std. Dev.	Min.	Max.	N
North East					
standard deviation	0.025	0.009	0.007	0.044	138
coeff. variation	0.024	0.008	0.008	0.049	138
interquartile range	0.03	0.018	0	0.092	140
Midwest					
standard deviation	0.04	0.009	0.018	0.058	145
coeff. variation	0.04	0.01	0.019	0.077	145
interquartile range	0.047	0.026	0	0.106	156
South					
standard deviation	0.043	0.017	0.018	0.105	146
coeff. variation	0.043	0.016	0.02	0.095	146
interquartile range	0.053	0.033	0	0.175	151
West					
standard deviation	0.052	0.029	0.001	0.137	160
coeff. variation	0.049	0.027	0.001	0.135	160
interquartile range	0.051	0.026	0.002	0.13	160

Table 7: Regular unleaded gasoline



Variable	Mean	Std. Dev.	Min.	Max.	N
North East					
standard deviation	0.038	0.015	0.001	0.105	358
coeff. variation	0.031	0.015	0	0.094	358
interquartile range	0.059	0.03	0.001	0.209	358
Midwest					
standard deviation	0.056	0.026	0.019	0.227	358
coeff. variation	0.044	0.015	0.014	0.114	358
interquartile range	0.075	0.051	0.009	0.339	358
South					
standard deviation	0.057	0.022	0.01	0.128	358
coeff. variation	0.046	0.016	0.009	0.088	358
interquartile range	0.075	0.042	0.015	0.23	358
West					
standard deviation	0.068	0.034	0.007	0.235	358
coeff. variation	0.05	0.022	0.006	0.134	358
interquartile range	0.11	0.068	0.013	0.418	358

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