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Consumer Information and Price Transmission: Empirical Evidence*

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Abstract

We investigate how consumer information affects price adjustment in the Austrian retail gasoline market. Our measure of consumer information is obtained from detailed census data on commuting behavior, as commuters can freely sample prices on their commuting route and are thus better informed about prices. A threshold error-correction model suggests that prices adjust more quickly if cost shocks exceed certain thresholds. Parametric and semi-parametric regressions show that a larger share of informed consumers increases both transmission speed and pass-through elasticity. Better informed consumers reduce the asymmetry in thresholds, but have no effect on the asymmetry in the speed of adjustment.

JEL Classifications: D43, D83, L13

Key Words: Price Transmission, Consumer Information, Commuters, Gasoline Market, Threshold Error-Correction Model

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1 Introduction

'We must look at the price system as such a mechanism for communicating information if we want to understand its real function – a function which, of course, it fulfils less perfectly as prices grow more rigid' (Hayek, 1945, p. 526).

Following Hayek's early observation, economists regard the adjustment of prices as an important mechanism by which information about changes in demand and costs is communicated to market participants. Accordingly, measures of the extent and speed by which exogenous shocks are transmitted into prices are frequently used as a yardstick for assessing the functioning of markets. The empirical literature on price transmission (and cost pass-through) is enormous and covers many different markets and time periods.[1] This literature clearly suggests that prices adjust (a) infrequently and/or slowly and (b) often asymmetrically to exogenous shocks.

Different arguments have been proposed to account for a slow, incomplete and/or asymmetric price transmission: market power (Borenstein, Cameron, and Gilbert, 1997 and Weyl and Fabinger, 2013), menu costs (Ball and Mankiw, 1994), lags in adjustment of production and inventory management (Borenstein, Cameron, and Gilbert, 1997), habit formation and consumption inertia (Xia and Li, 2010) and product differentiation (Loy and Weiss, 2019).

Recently, explanations related to consumer search behavior have received a lot of formal attention (see Yang and Ye, 2008; Tappata, 2009; Lewis, 2011; Cabral and Fishman, 2012). While the technical details differ, a common feature of all models is that consumers' search behavior and firms' price setting are determined simultaneously. Firms' incentives to adjust prices (upwards or downwards) to exogenous shocks are determined by how well consumers are informed about prices. At the same time, the motivation of consumers to become informed and learn about individual prices depends on firms' price setting behavior (more details will be provided in the following section). In these models cost increases are transmitted more quickly compared to cost decreases, because consumers search more (and are thus better informed) in the first case. These models therefore provide a search-theoretic rationale for the 'rockets and feathers phenomenon'.[2]

[1] Kouyaté and Cramon-Taubadel (2016) uncover 492 recent papers using price transmission as a search term. Excellent reviews of the voluminous empirical literature on price transmission and cost pass-through are provided in Meyer and Cramon-Taubadel (2004), Frey and Manera (2007), Wolman (2007), Bakucs, Falkowsky, and Fertö (2014), Hassouneh et al. (2015) and Lloyd (2017). The existing literature often uses the terms 'price transmission' and 'cost pass-through' interchangeably to characterize the impact of cost changes on retail product prices.

[2] Bacon (1991) introduces the term 'rockets and feathers phenomenon' for situations in which prices respond more quickly to cost increases than to decreases.

Despite the recent wave of theoretical work on the impact of information and consumer search on price setting, empirical evidence is scarce. The reasons for this are two-fold: Firstly, consumers' information endowments or consumers' search costs usually cannot be observed directly and are therefore difficult to quantify. Secondly, as indicated above, consumers' search behavior is likely to be influenced by firms' pricing decisions and is thus endogenous: frequent and substantial price changes reduce consumers' incentives to search because the depreciation rate of (price) information is high (Marvel, 1976). Likewise, consumers' gains from search are small if firms charge similar prices and price dispersion in a market is low (Tappata, 2009). This endogeneity of consumer search makes it difficult to identify the causal effect of information on price setting in general, and on price transmission in particular.

We contribute to this scarce empirical literature in two dimensions: First, we apply a novel measure of consumer information based on precise commuting patterns that is arguably independent of firms' price setting behavior and thus allows identification of causal effects. We investigate price transmission in the retail gasoline market in Austria for a time period when websites reporting comprehensive and up-to-date information on gasoline prices were not yet available. Actually going to a specific gasoline station was in fact the only way for consumers to learn about current gasoline prices at that station.[3] As pointed out by Marvel (1976), information about gasoline prices differs significantly between two consumer groups: commuters and non-commuters. Commuters can freely sample all price quotes for gasoline along their commuting route and are therefore typically better informed than non-commuters. We obtain a measure of consumer information by using detailed data on commuting behavior from the Austrian census to calculate the share of commuters passing by each individual gas station (Pennerstorfer et al., 2019). Note that this measure of consumer information is determined by consumers' long-run decisions to commute (i.e. where to live and work), which is orthogonal to stations' short-run pricing decisions.

Second, we use a flexible empirical approach for measuring the degree of price transmission by estimating threshold error-correction models (TECM). This method determines the optimal threshold values endogenously for each station to classify a

[3] The availability of price comparison websites as well as smart phone applications and automobile global positioning system, which provide the current price of gasoline at nearby retail locations, had a substantial effect on consumer search costs in the gasoline market. At the same time, it also makes it easier for firms to monitor each other's prices and could thus facilitate collusion between firms. In such a setting, identification of the effects of consumer information on price dynamics is impeded. Interesting empirical studies on price search behavior on the basis of these technologies include Lewis and Marvel (2011), De los Santos, Hortacsu, and Wildenbeest (2012) and Byrne and de Roos (2017).

station's price spell into different regimes, and estimates separate price adjustment parameters for each regime. This approach takes into account firms' transmitting cost changes at different speeds, depending on the size and the sign of the cost shock. We can therefore distinguish between an asymmetry in the speed of adjustment and an asymmetry in thresholds (and thus the size of the different regimes). This turns out to be important for interpreting our empirical results in light of theoretical models (see, for instance, Cabral and Fishman, 2012).

Consistent with theoretical predictions, we find empirical evidence that gasoline stations' price transmission is influenced by consumers' information endowments. A larger share of informed commuters leads to a higher speed of price transmission and a higher pass-through elasticity. We further find a significant and negative effect of consumer information on the asymmetry in adjustment thresholds. The 'rockets and feathers phenomenon' becomes less important for gasoline stations with a large share of informed consumers.

The remainder of this article is organized as follows: Section 2 briefly reviews theoretical models of consumer search and price dynamics and discusses measures of consumer information used in the existing empirical literature. Section 3 presents the data and Section 4 reports estimation results. Section 5 describes results from alternative estimation experiments and Section 6 concludes.

2 Literature

2.1 Theory

A number of theoretical models attribute asymmetric price transmission to consumer search behavior. The central feature of these models is that price rigidity or, conversely, the speed of price adjustment is related to consumers' search intensities or consumers' information endowments: If more consumers become informed, markets become more competitive, price-cost margins decline, and cost changes are passed on to consumers more quickly. Although the exact mechanisms differ, asymmetric price adjustment in these models is generated by consumers searching more when costs or prices increase than when costs or prices decrease: In Yang and Ye (2008) consumers do not observe production costs directly, but learn about costs by observing firms' prices. Consumers learn about positive cost shocks more quickly and cost increases are thus passed on faster than cost decreases. In Tappata (2009) consumers search more when costs increase, and a rise in input prices is therefore passed on more quickly. In Lewis (2011) consumers search more when prices (and hence costs) are increasing, with similar consequences on the asymmetry of price dynamics. In Cabral and Fishman (2012) consumers learn about cost shocks by observing price changes, which induces them to search the market. In order to avoid consumer search firms refrain from passing on small cost decreases, leading to slower pass-through of (small) cost decreases relative to cost increases.

To facilitate interpretation of the existing empirical evidence, we briefly revisit Tappata's (2009) model, which is most closely related to our empirical analysis. In this model a finite number of $n > 1$ firms is selling a homogeneous product. They face constant marginal costs 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 $\lambda \in [0, 1]$ of consumers can sample all prices without costs. As common in the literature (see e.g. Baye, Morgan, and Scholten, 2004) we refer to these consumers as 'shoppers'. These consumers buy at the lowest price, provided that it does not exceed their willingness to pay v. In the empirical part we will derive a measure for the share of shoppers based on each consumer's commuting behavior.

The remaining share of consumers $(1 - \lambda)$ have positive search costs and will be referred to as 'non-shoppers' henceforth. We consider two alternative assumptions regarding this consumer group: In one variant the search costs of non-shoppers are prohibitively high and all of them remain uninformed (as in Varian, 1980). In a second variant (as in Tappata, 2009) non-shoppers are heterogeneous regarding the search costs they have to pay to become perfectly informed about all prices in the market. Search costs s_j of these non-shoppers are distributed in the interval $[0, \bar{s}]$ according to the probability function $g(s_j)$. The non-shoppers' decisions to search depend on the size of their search costs relative to the expected gains from search $E[p - p_{min}]$, with p_{min} being the lowest price in the market. The gains from search (also labeled as value of information) are a measure of the price dispersion in the market, which in turn depends on the total share of informed consumers μ. In the Varian (1980) model the fraction of informed consumers $\tilde{\mu}^V$ equals the share of shoppers λ, whereas in the Tappata (2009) model the equilibrium share of informed consumers $\tilde{\mu}^T$ is given by $\lambda + (1 - \lambda)G(\tilde{s})$. $\tilde{s}$ denotes the search costs of the consumer indifferent about searching the market or remaining uninformed, and $G(\tilde{s})$ characterizes the share of non-shoppers searching the market in equilibrium. The non-shoppers remaining uninformed buy one unit of the product at a random store, as long as the price does not exceed their willingness to pay v.

In a static equilibrium[4] firms randomly draw a price from the cumulative distri-

[4]See Tappata (2009) for details.

bution of market prices:

$$F(p, \mu; c) = 1 - \left(\frac{(1-\mu)(v-p)}{\mu n(p-c)} \right)^{\frac{1}{n-1}}$$

for all $p \in \left[p^* = c + \frac{(1-\mu)(v-c)}{1+(n+1)\mu}, v \right]$. This results in an expected price dispersion given by:

$$E[p - p_{min}|\mu] = E\left[\int_{p^*}^{v} p \left[1 - n \left[1 - F(p, \mu; c) \right]^{n-1} \right] dF(p, \mu; c) \right]$$

The expected gains from search are zero if there is no heterogeneity in information endowments (i.e. if $\mu \in \{0, 1\}$) and price dispersion is positive and strictly concave for $\mu \in (0, 1)$. For a given share of informed consumers μ price dispersion depends negatively on production costs c.

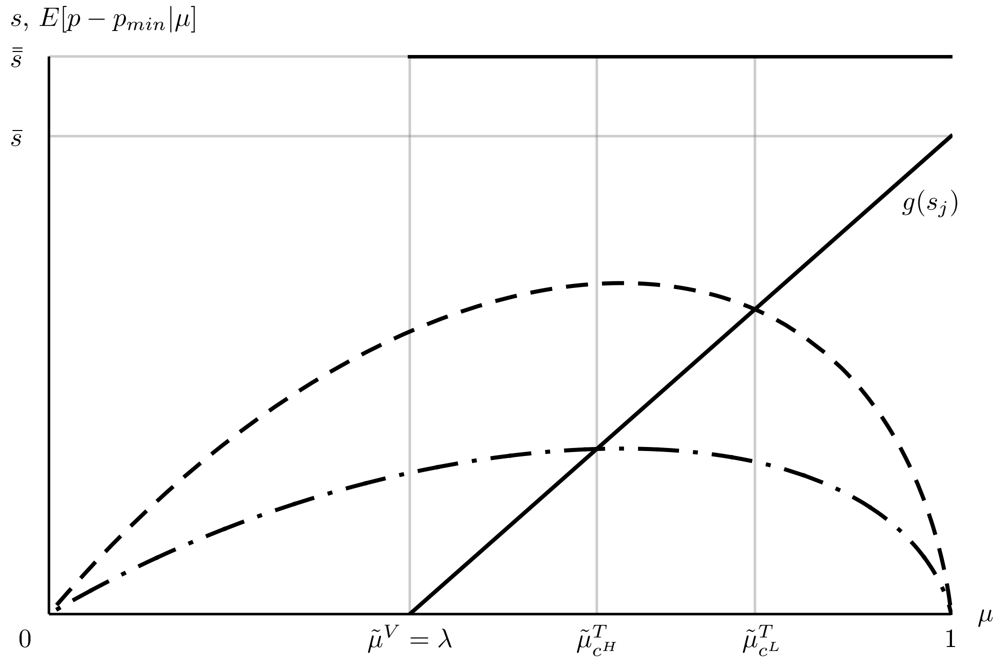
For the interpretation of the results of empirical models it is important to note that Tappata (2009) distinguishes explicitly between 'shoppers' (λ) and 'informed consumers' (μ). While in the Varian (1980) model the equilibrium share of informed consumers equals the fraction of shoppers (thus $\tilde{\mu}^V = \lambda$), in the Tappata (2009) model the share of informed consumers is fully and uniquely characterized by $\tilde{\mu}^T = \lambda + (1-\lambda)G(\tilde{s})$[5] by comparing non-shoppers' search costs s_j with the expected gains from search $E[p - p_{min}|\mu]$. The share of informed consumers is higher in this model variant, because some of the non-shoppers choose to become informed, but the exact share depends on the amount of price dispersion in the market.

The relationship between the share of shoppers λ, the share of informed consumers μ and the gains from search $E[p - p_{min}|\mu]$ is illustrated in Figure 1. In the Varian (1980) model the search costs of non-shoppers are prohibitively high (illustrated by $\bar{\bar{s}}$) and thus $\tilde{\mu}^V = \lambda$. To illustrate the Tappata (2009) model we assume search costs to be distributed uniformly between $[0, \bar{s}]$. In Figure 1 the dashed line denotes the price dispersion if production costs are low ($c = c^L$), while the dash-dotted line indicates the gains from search if production costs are high ($c = c^H > c^L$). Clearly, the share of informed consumers μ decreases with production costs c (see Tappata, 2009, Lemma 2).

The first implication of the model is that consumers' search intensities (con-

[5]We follow Tappata (2009) and assume that $\frac{\partial g^{-1}}{\partial \mu} > \frac{\partial E[p-p_{min}]}{\partial \mu}$ to ensure that the market equilibrium is unique.

Figure 1: Consumer Search in Low Cost and High Cost States



Notes: The dashed line illustrates the expected gains from search $E[p - p_{min}]$ (price dispersion) in a low cost state ($c = c^L$) and the dashed-dotted line depicts price dispersion in a high cost environment ($c = c^H$). The share of shoppers is indicated by λ. The search costs of non-shoppers is illustrated by the probability function $g(s)$ for the Tappata (2009) model, indicating the heterogeneity of consumers' search costs in the interval $[0, \bar{s}]$, and by the (homogeneous) search costs $\bar{\bar{s}}$ for the Varian (1980) model. $\tilde{\mu}^V$ depicts the equilibrium share of informed consumers in the Varian (1980) model, whereas $\tilde{\mu}^T_{c^H}$ and $\tilde{\mu}^T_{c^L}$ indicate the equilibrium share of consumers in the Tappata (2009) model in a high cost (c^H) and a low cost (c^L) environment, respectively.

sumers' information endowments) affect the competition intensity among firms: The higher the share of informed consumers, the more elastic the demand the firms face and the quicker the adjustment of prices to cost changes. Tappata (2009) shows formally that the cost pass-through rate increases with the share of informed consumers, i.e. $\frac{\partial^2 \bar{p}}{\partial c \partial \mu} > 0$, with $\bar{p}$ as the average price in the market. As $\frac{\partial \mu}{\partial \lambda} > 0$ this qualitative result also holds for the share of shoppers, thus $\frac{\partial^2 \bar{p}}{\partial c \partial \lambda} > 0$.

In order to explain asymmetries in price adjustment, Tappata (2009) introduces uncertainty about costs into the model. Firms operate under high cost (c^H) or low cost (c^L) conditions, but consumers do not observe the current cost regime.[6] They form expectations about production costs based on cost realizations in previous periods. As there are just two cost realizations, i.e. H and L, a cost decrease is equivalent to costs declining from c^H to c^L. Consumers do not observe the contemporaneous cost realization c^L and assume that costs are still c^H, as in the previous period. Consumers thus expect price dispersion to be low and consequently the share of informed consumers will be low ($\tilde{\mu}^T = \tilde{\mu}^T_{c^H}$). If, on the other hand, costs increase from c^L to c^H, consumers (misleadingly) expect to be in a low-cost environment, expect price dispersion to be high and thus the share of informed consumers ($\tilde{\mu}^T = \tilde{\mu}^T_{c^L} > \tilde{\mu}^T_{c^H}$) will be larger. As the share of informed consumers is higher in case of cost increases, positive cost shocks are passed on more quickly than negative ones.

A direct empirical test of this prediction is generally difficult, because even if researchers observe consumers' actual search behavior in time periods of both cost increases and decreases, the share of informed consumers $\tilde{\mu}^T_{c^L}$ and $\tilde{\mu}^T_{c^H}$ will nevertheless be endogenous.[7] To avoid endogeneity concerns we use a measure for the (exogenous) share of shoppers λ in the empirical application. Note that Tappata's (2009) analysis does not provide clear predictions regarding this consumer group: The relationship between the difference in the equilibrium share of informed consumers between a low-cost and a high-cost environment $\left(\tilde{\mu}^T_{c^L} - \tilde{\mu}^T_{c^H}\right)$, responsible for the asymmetry in price transmission, and the share of shoppers λ can be either negative over the entire range of $\lambda \in [0, 1]$ or characterized by an inverse-U-shaped

[6] The assumption of only two marginal cost states (high and low) is criticized in Lewis (2011), since this makes it impossible to distinguish predictions about the speed of price response during high and low margin periods and a prediction about response to positive and negative cost changes. Lewis (2011) develops a theoretical model (and also presents empirical evidence) showing that prices respond faster to cost changes during periods when margins are low.

[7] Empirical articles observing consumer search behavior directly at the individual level (De los Santos, Hortacsu, and Wildenbeest, 2012) or at the market level (Lewis and Marvel, 2011; Byrne and de Roos, 2017) are indeed interested in explaining consumer search rather than evaluating the effect of consumer information on prices.

relationship.[8]

Another implication of the theoretical model outlined above is that the speed of cost transmission is independent of the size and the sign of the cost shock if non-shoppers have prohibitively high search costs. Contrariwise, when non-shoppers have heterogeneous search costs firm conduct is characterized by two 'regimes', where cost increases are passed on to consumers more quickly than cost decreases. In a different theoretical setting, Cabral and Fishman (2012) develop a search-theoretic model where prices are sticky as to cost changes within specific ranges. In this model price changes are likely to induce consumer search, which firms want to avoid, because better informed consumers make the market more competitive. If cost shocks are positively correlated across firms (which is most likely in the retail gasoline market), the gains from adjusting prices to moderate cost decreases are small relative to the expected loss due to inducing consumer search. Prices remain constant if costs decrease moderately, while large negative as well as positive cost shocks are passed on to consumers quickly, resulting in three regimes with a higher speed of price transmission in the outer regimes.

On the basis of this short review of theoretical models, we identify two issues that are particularly important for the interpretation of the empirical evidence. First, the extent to which consumers' search in order to obtain information about prices is endogenous. This endogeneity of search calls for an adequate strategy to identify the causal effects of consumer information on price transmission. We account for this by providing a measure for the share of shoppers λ, a variable exogenous in the theoretical models. Second, an adequate measurement of the degree and asymmetry of price transmission needs to differentiate between different dimensions of price adjustment. In Tappata (2009) the asymmetry in price adjustment stems from differences in the speed of transmission of cost increases compared to cost decreases. In Cabral and Fishman (2012), on the other hand, the asymmetry comes from the thresholds confining the 'inner regime' (characterized by sticky prices) being asymmetric (i.e. not centered around zero). In our empirical analysis we thus estimate very flexible threshold error-correction models (TECM) that allow us to differentiate between asymmetries in the speed of price transmission and in threshold levels.

[8] It is obvious from Figure 1 that $\tilde{\mu}^T_{c^L} - \tilde{\mu}^T_{c^H} > 0$ if $\lambda \in (0,1)$, that $\left(\tilde{\mu}^T_{c^L} - \tilde{\mu}^T_{c^H}\right) \to 0$ if $\lambda \to 1$, and thus $\partial \left(\tilde{\mu}^T_{c^L} - \tilde{\mu}^T_{c^H}\right) / \partial\lambda < 0$ if $\lambda \to 1$. However, if the share of shoppers λ is small and the upper bound of non-shoppers' search costs $\bar{s}$ is high, then $\partial \left(\tilde{\mu}^T_{c^L} - \tilde{\mu}^T_{c^H}\right) / \partial\lambda$ may be positive, leading to an inverse-U-shaped relationship.

2.2 Information and Prices: Evidence

An obvious challenge in the empirical literature on the relationship between information and prices is the measurement of individual consumers' information endowments or buyers' search activities. In his seminal work on 'The Economics of Information', Stigler (1961) argues that consumers will search more if the benefits from search increase and/or if search costs decrease. In the absence of a direct measure of consumers' information endowment, the proxy variables typically used can be classified along these lines, i.e. indicators related to the benefits from as well as the costs of search.

In one of the first empirical studies on the impact of consumer information and prices in the gasoline market, Marvel (1976) uses gasoline consumption per car to proxy benefits from search. Gains will be larger if per capita consumption is high. Median family income and schooling are used to measure costs of search. Marvel (1976) argues that an increase in family income raises opportunity costs of time (costs of search)[9] and that better education increases the efficiency of search. Sorensen (2000), investigating the market for prescription drugs, argues that purchase frequency is an important element of the search decision. If prescriptions are purchased repeatedly, price information obtained from searching the markets can be used multiple times before this information 'expires'. These markets should thus be characterized by better informed consumers compared to markets for products purchased less frequently.

A novel approach of measuring the effects of search costs is adopted by Sherman and Weiss (2017). On the basis of hand-collected data from an outdoor market in Jerusalem, the authors use cross-sectional and temporal variation in pedestrian congestion as one proxy of search costs. Indirect evidence on the effects of costs and benefits from search over a long time period are provided in Eckard (2004). Eckard (2004) compares price dispersion for the same commodities in 1901 and 2001 and finds that price dispersion has increased over time, despite the introduction of significant search cost-reducing technologies in transportation and communication. The author argues that the products analyzed constituted substantially smaller shares in the consumers' budgets in 2001 compared to 1901. The decline in search costs

[9]Measures of family income are also used as proxies for search costs in Barron, Taylor, and Umbeck (2000), for example. Similarly, Chandra and Tappata (2011), Remer (2015) and Chesnes (2016) ascribe consumers of alternative products or different types of stores to different income levels, arguing that individuals consuming premium gasoline (Chandra and Tappata, 2011; Remer, 2015) or going to branded gas stations (Chesnes, 2016) earn more, have higher search costs and therefore search less. By estimating a structural model, Nishida and Remer (2018) provide empirical evidence that search costs and household income are indeed closely related.

might thus have been offset by a decline in the benefits from search (associated with the reduction in the budget shares of these products) over time.

Arguably the most frequently used indicator of consumer information endowment is consumer access and use of the Internet. Ellison and Ellison (2005), for instance, argue that 'the Internet has provided researchers with the opportunity to study how markets function in novel and extreme circumstances. A vivid example is that with the growth of the Internet, we suddenly have markets with essentially no search costs' (p. 140). The impact of online search and Internet purchases on prices has been investigated for many different markets, including automobiles (Morton, Zettelmeyer, and Silva-Risso, 2001), life insurances (Brown and Goolsbee, 2002), books (Tang, Smith, and Montgomery, 2010), consumer electronics products (Baye, Morgan, and Scholten, 2004), airline tickets (Orlov, 2011; Sengupta and Wiggins, 2014), electricity (Gugler et al., 2018) and retail gasoline (Luco, 2019) .

While investigating online markets or drawing on Internet usage to derive measures of consumer information has provided many interesting insights, some problems are also associated with this approach. First, as Baye and Morgan (2001) point out, consumers' decisions to use price comparison websites are endogenous and depend on firms' pricing decisions. The gains from search will be low if price dispersion is low (Tappata, 2009; Chandra and Tappata, 2011) or if price volatility is high (Marvel, 1976; Borenstein, Cameron, and Gilbert, 1997). Lewis and Marvel (2011) and Byrne and de Roos (2017) provide empirical evidence that consumers' search activities are indeed influenced by firms' pricing decisions: Using web traffic data from gasoline price reporting websites Lewis and Marvel (2011) find that consumers search more when prices rise than when prices fall, and Byrne and de Roos (2017) report that consumers' search activities are influenced by both price dispersion and price volatility. Second, the availability of the Internet or of Internet comparison sites may not only provide a reduction in consumers' search costs, but may also have anti-competitive effects. If firms can easily monitor their rivals' actions, better information may facilitate coordination in firms' price setting behavior. Luco (2019) presents a model to show that price transparency can facilitate coordination in a dynamic context. The author also studies the impact of price-disclosure policies in the Chilean retail gasoline industry empirically and finds that anti-competitive effects dominate: price disclosure decreased the intensity of competition on average. Third, 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.

And finally, firms selling products in both online and brick-and-mortar stores may charge different prices online and offline.

Compared to this voluminous empirical literature on the impact of (different proxies for) consumer information on price levels, mark-ups, as well as price dispersion, hardly any empirical evidence of the impact of consumer information on price dynamics and pricing asymmetries is available. Marvel (1976) observes that prices vary more at low-price stations. Assuming that customers of low-price stations choose to obtain more information than consumers of high-price stations, the author interprets this result as evidence that shocks are more widely transmitted in gasoline markets with more well-informed customers. According to our knowledge, the only empirical evidence of the impact of information on adjustment dynamics is provided by Johnson (2002) and Remer (2015). Johnson (2002) compares the adjustment of diesel and gasoline prices and argues that consumers purchase gasoline infrequently and may have relatively little incentive to search for competitive prices. In contrast, purchasers of diesel fuel typically buy larger quantities more frequently and thus have greater incentives to search for lower prices. The market for diesel should thus be characterized by better informed consumers. Empirical evidence indeed indicates a much faster response in the diesel market. Johnson (2002) also investigates asymmetries in price adjustment. The author observes that the adjustment to long-run equilibrium levels is quicker for wholesale price increases than for decreases, which is consistent with the argument that the incentive to search is higher when prices rise than when they fall. An asymmetric response is observed in both, the diesel and gasoline markets; the paper thus does not provide a test of the impact of information on the degree of asymmetry. Similarly, in trying to identify the impact of information on price dynamics, Remer (2015) relies upon the differences in consumers who purchase regular versus premium unleaded gasoline. The author argues that drivers of more expensive cars are more likely than owners of less expensive cars to purchase premium gasoline. Luxury car owners tend to have higher incomes and thus greater search costs. Remer (2015) identifies the existence of 'rockets and feathers' in the U.S. retail gasoline industry and provides evidence in support of consumer search costs as the underlying cause. Premium prices fall more slowly than regular prices following a cost decrease, while premium and regular fuel prices rise at the same speed.

3 Data

3.1 Gasoline Prices

We analyze price transmission between the Brent Crude Oil Index as our cost measure C_t and retail gasoline prices $P_{i,t}$. Retail prices are available for a balanced panel of all $N = 281$ gasoline stations of a leading vertically integrated oil company in Austria. Retail prices are observed daily for the period from January 1st, 2003 to December 5th, 2004 ($T = 705$ days), and are measured in Eurocents per liter.[10] The Brent Crude Oil Index is taken from the commodity futures exchange ICE (Intercontinental Exchange), specialized in trading Brent, the main European type of crude oil. Crude oil prices (net of taxes) are reported on a daily basis in US-Dollars and are converted into Eurocents per liter based on the prevailing exchange rate.

As competition in the retail gasoline market is highly localized (Slade, 1986; Pinkse, Slade, and Brett, 2002), variables indicating the intensity of competition are based on the spatial proximity of rival stations. The 281 stations in the sample are therefore merged with all (2,815) gasoline stations in Austria. The exact geographical location and characteristics of all gasoline stations were collected by the company Experian Catalist in August 2003.[11] The first measure of competition is calculated as the number of rival stations within a 2 km radius around a particular station.[12] In addition, we use the driving distance to the nearest rival station (not belonging to the same oil company). Last, we include a dummy variable indicating whether the station is located along a highway (Autobahn), which is a premium location with reduced competition and highly inelastic demand (since leaving the highway to search for rival stations is very costly).

To account for station heterogeneity we include the number of pumps of the location, a dummy variable indicating whether the station has attendant service (instead of self-service) and whether it is open 24 hours a day. To control for local demand conditions we include the average daily volume of gasoline sold in the period under consideration.

[10] We use gross prices including a fuel tax and VAT. The fuel tax amounts to 40.7 Eurocents in 2003 and 41.7 Eurocents after January 1st 2004. The 20 percent VAT is calculated based on the sum of net prices and fuel tax. There is no variation in fuel tax or VAT across Austrian regions.

[11] See `http://www.catalist.com` for company details.

[12] This approach has been widely used in the empirical literature, see for instance Hastings (2004), Barron, Taylor, and Umbeck (2004), Eckert and West (2005), Hastings and Gilbert (2005), Hosken, McMillan, and Taylor (2008), Lewis (2008) or Pennerstorfer (2009).

3.2 Share of Informed Customers

To derive a measure indicating consumers' information endowments we draw on observed commuting patterns. The main idea behind our measure of information is based on the notion, first mentioned in Marvel (1976), that commuters have access to information on the price distribution along their commuting route at virtually no costs, 'simply because stations can be canvassed along the route taken to work with only slight additional effort and delay' (p. 1043 f.). Commuters also benefit more from such information, because they consume more gasoline.[13] We use data at a very disaggregated regional level, allowing us to identify and link commuter flows with individual gasoline stations, and to calculate the share of commuters per gasoline station. This will constitute our measure of the share of shoppers λ. We thus contribute to the literature on price dynamics by providing an alternative and a more direct measure of consumers' information endowments, novel to the literature on cost transmission. Note that (i) the (long-run) decision to commute is independent of (short-run) price dynamics, allowing a causal interpretation of the results, and that (ii) unlike proxies for search behavior based on Internet use, commuting patterns provide an indicator for an 'information clearinghouse' that cannot be accessed by firms, consistent with most models on consumer search.[14] The identification is thus based on the spatial variation of this information measure.

We have access to very detailed information on long-distance commuters, defined as individuals who daily commute by car beyond the boundaries of their municipality, from the Population Census 2001 of Statistics Austria. The data comprises information on the commuting behavior of all 3,624,116 employed individuals in Austria, including the respective place of residence, place of work and mode of transport.[15] Out of those, 1,396,426 individuals comply with our definition of long-distance commuters. Long-distance commuters are considered shoppers for a given gasoline station i if they belong to one of the following groups: First, individuals who reside in the municipality where the gasoline station is located and commute to another municipality (K_i^{out}). Second, individuals who live in a different municipality, but work in the municipality where the station is located (K_i^{in}). Third, individuals who pass by the specific station, but neither work nor live in the municipality where station i

[13] Houde (2012) emphasizes the role of commuters in determining the competitive pressure in local markets. Theoretical models of Claycombe (1991) and Raith (1996) indicate that markets become more competitive if the share of commuters increases.

[14] The period of investigation comprises the years 2003 and 2004, when online price comparison sites were not yet available.

[15] Municipalities are very small regional units in Austria. The average municipality has a size of 13.8 square-miles and a population of 3,373 inhabitants.

is located. These individuals are described as transit commuters and denoted as K_i^{tr}. They are only included in the number of shoppers if the respective gasoline station is located directly on their commuting path.[16] As an indicator for the number of non-shoppers for each gasoline station i we take the number of employed individuals who live in the municipality where the station is located, but do not regularly commute by car over long distances.[17] The share of shoppers for a station i, λ_i, is calculated by dividing the number of shoppers ($\text{shoppers}_i = K_i^{out} + K_i^{in} + K_i^{tr}$) by the total number of shoppers and non-shoppers:[18]

$$\lambda_i = \frac{\text{shoppers}_i}{\text{non-shoppers}_i + \text{shoppers}_i}$$

Table 1 shows the summary statistics for prices, costs, as well as the gasoline stations' characteristics.

4 Empirical Analysis

We apply a two-step estimation procedure to investigate the effects of consumers' information endowments on the measures of price transmission. In the first step of the empirical analysis, we calculate the speed, cost pass-through elasticity and asymmetry parameters by estimating the price transmission process for each gasoline station separately. In particular, we apply a threshold error-correction model (TECM), introduced by Balke and Fomby (1997), as a feasible way to combine regime switches and cointegration. This model allows for differences in the speed of the price adjustment depending on how far the time series of prices and costs deviate from their long-run relationship. This procedure is thus very flexible and allows for

[16]The assignment of commuters to this group is based on the shortest path algorithm in ArcGIS. We compare the distance of the optimal (i.e. the fastest) route between the individual's place of residence and his/her place of work, with the sum of the distances from the place of residence to station i and from station i to the place of work. If the distance of traveling via the respective station i is equal or only marginally longer than the shortest path distance, then the respective commuter is assumed to pass by station i and is counted as a shopper for this station. If the commuting distance is long there may be multiple routes of similar length as the optimal commuting path. We thus weight transit commuters for a particular station by the fraction of possible routes passing by the respective gasoline station. A more detailed description on the calculation is provided in Pennerstorfer et al. (2019).

[17]We are aware that this measure may underestimate the total number of uninformed consumers, but this definition is a restriction implied by the availability of the data.

[18]In the sensitivity analysis we include the total number of shoppers and non-shoppers instead of the share of informed consumers, but find qualitatively very similar results. The regression results are also robust to alternative ways of calculating the share of shoppers λ. See Section 5 for a discussion.

Table 1: Sample Description

Variables	Mean	Std. Dev.	Min	Max	# Obs.
Panel/Time Series Variables					
Gasoline price ($P_{i,t}$)					
overall	90.64	5.76	71.90	104.90	198,105
between	90.64	2.03	85.00	95.42	281
within	90.64	5.40	72.56	108.03	705
Crude oil price (C_t)					
within	17.51	2.89	13.09	26.08	705
Cross Section Variables					
Share of shoppers (λ_i)	0.54	0.14	0.20	0.91	281
# of shoppers (in 1,000)	16.44	18.11	0.16	71.50	281
# of non-shoppers (in 1,000)	19.91	25.91	0.14	101.28	281
# of rival stations within 2 km	7.17	7.49	0	33	281
Distance to nearest rival station (in km)	1.80	2.56	0	21.74	281
Station is located on the highway	0.06	0.24	0	1	281
# of pumps	3.19	1.23	0	8	281
Open 24 hours	0.26	0.44	0	1	281
Services offered by station	0.09	0.28	0	1	281
Quantity of gasoline sold (in 1,000 liters)	4.87	6.15	0.61	72.45	281

Note: Prices are in Eurocents per liter.

heterogeneity in price adjustment between gasoline stations as well as between cost shocks of different size.

In the second step, the relationships between the estimated measures of price transmission and consumers' information endowments are analysed for the cross-section of gasoline stations.[19]

4.1 Specification Tests

When investigating high frequency data, a careful analysis of the time-series properties of the data is necessary to get adequate estimates of the degree of cost transmission. First, we test the crude oil price spell as well as the retail diesel price time series of each gasoline station for unit roots by applying the Augmented Dickey and Fuller (ADF; Dickey and Fuller, 1979) and the Phillips and Perron (Phillips

[19] Another estimation approach would be to estimate both steps combined in one panel model, as in Deltas (2008). This approach would force the error-correction parameters to be the same for all gasoline stations, thus assuming a common long-run equilibrium for all locations. Alternatively, we estimate a more flexible Mean Group (MG) Panel Model as a robustness exercise that allows the speed parameters to vary across groups (see Pesaran and Smith, 1995; Pesaran, Shin, and Smith, 1999; Blackburne and Frank, 2007). The results using this estimation technique are discussed in Section 5 and reported in Appendix A.

and Perron, 1988) test procedure.[20] Both the ADF and the Phillips and Perron test statistics suggest that retail price and the crude oil price time series follow unit root processes.

Second, we test if the price and cost series are co-integrated by applying the standard two-step Engle and Granger procedure (Engle and Granger, 1987). According to this procedure, the residuals from the following model are tested for stationarity:

$$P_{i,t} = \rho_{0,i} + \rho_{1,i} C_t + \epsilon_{i,t} \tag{1}$$

where $\epsilon_{i,t}$ denotes the error term for gasoline station i at time t. The test results reject the null hypothesis of no co-integration for 269 out of 281 gasoline stations (96 %), indicating a long-run relationship between the diesel retail price $P_{i,t}$ and the Brent crude oil price C_t as given in equation (1) for virtually all stations in our data.

4.2 Measuring Cost Transmission: Time-Series Analysis

Given co-integration between two time series, any deviation from the long-run equilibrium will be temporary and according to the Representation Theorem of Engle and Granger (1987) the co-integrated series can be represented by an error-correction model as follows:

$$\Delta P_{i,t} = \tau_i + \gamma_i ECT_{i,t-1} + \sum_{a=1}^{A} \delta_{1,i,a} \Delta P_{i,t-a} + \sum_{b=0}^{B} \delta_{2,i,b} \Delta C_{i,t-b} + \zeta_{i,t} \tag{2}$$

We will refer to this equation as the standard error-correction model (ECM); more details on empirical applications of this model in the gasoline market are provided in Eckert (2013). The error-correction term ECT in the above equation represents the deviation of the retail price from its long-run relationship with the crude oil price for each gasoline station, as described in equation (1). Thus, $ECT_{i,t} \equiv \hat{\epsilon}_{i,t} = P_{i,t} - \hat{\rho}_{0,i} - \hat{\rho}_{1,i} C_t$. The coefficient γ_i indicates the speed of adjustment of prices towards the long-run equilibrium (the rate at which the errors are corrected) for gasoline station i. Given co-integration, the speed parameter γ_i is expected to be negative and different from zero. In order to restore the equilibrium, prices decrease in periods when they are above their long-run relationship with costs, and are expected to increase in periods when prices are below this long-run relationship. The coefficients δ_1 indicate the short-run response of the retail price to own changes

[20] When testing for unit root and co-integration we use the optimal lag length of two, determined by Akaike information criteria (AIC).

in the past two days ($A = 2$), and the coefficients δ_2 measure the short-run response of the retail price to changes in the crude oil price within the last two days ($B = 2$). The parameter τ_i indicates the constant and $\zeta_{i,t}$ denotes the error term. Equation (2) is estimated by ordinary least-squares (OLS) for each gasoline station using a lag order of two.[21]

The standard error-correction model (ECM) in equation (2) allows for different price dynamics across stations. However, the adjustment process for a particular gas station is restricted to be the same, irrespective of the sign or the size of the cost shock. This implicit assumption is challenged in search-theoretic models. Cabral and Fishman (2012), for example, conclude that large cost changes are passed on more quickly than small ones (suggesting three different regimes), while cost increases are passed on more quickly than cost decreases in Tappata (2009) (suggesting two regimes). In our empirical analysis, we thus apply a flexible threshold error-correction model in which price adjustments to the long-term equilibrium can be regime-dependent.

Testing for threshold non-linearity is a non-standard inference problem since the nuisance parameter (the threshold) is not identified under the null hypothesis. Consequently the asymptotic distributions of the tests are non-standard. This test problem is known as the Davies Problem (Davies, 1987) in non-linear time series models and has been discussed later by Andrews and Ploberger (1994) and Hansen (1996) in the context of co-integration. Several approaches are available to solve this problem based on the nature of the time series process.[22] We apply the approach proposed by Strikholm and Teräsvirta (2015) based on a smooth transition auto-regression to determine the number of regimes. Results from applying this approach to our data suggest that the price transmission process is characterized by three regimes (two thresholds). The estimation of the thresholds is achieved using a grid search procedure proposed by Enders and Siklos (2001). The grid search procedure follows the idea of Chan (1993), who showed that the value of the threshold minimizing the sum of squared errors from the long-run equilibrium is a super-consistent estimate. For the estimation of the thresholds we proceed as follows: We first estimate the long-run

[21]We use the Akaike information criteria (AIC) test statistics to select the optimal lag order for each gasoline station. Luetkepohl (1985) and Toda and Yamamoto (1995) show that these test statistics will have the standard asymptotic properties even if the variables are integrated of order 1 ($I(1)$). Paulsen (1984) and Nielsen (2001) also show that AIC can be used for both $I(0)$ and $I(1)$ variables.

[22]Tsay (1989) proposed the use of residuals from an arranged auto-regression to test for non-linear behavior. Hansen (1996) and Hansen (1997) propose an alternative method for univariate processes which allows estimating (only) one threshold and the model parameters simultaneously. For the multivariate case see Hansen and Seo (2002).

relationship stated in equation (1) for each gasoline station separately. The largest and smallest 15 % of the estimated residuals of each regression are dropped. The remaining ones are the possible candidates for constituting the threshold. For each of the remaining residuals we estimate a Threshold Autoregressive Model (TAR) on the residuals using 20 %, 45 %, 55 %, and 80 % of the residual values as thresholds to separate the regimes. The estimated thresholds that minimize the residual sum of squares in each regime are the final threshold values that we use to estimate the TECM.

Based on the test results and the estimated thresholds, the following threshold error-correction model (TECM) with three regimes is estimated for each gasoline station by means of ordinary least-squares (OLS):

$$\Delta P_{i,t} = \begin{cases} \tau_i^+ + \gamma_i^+ ECT_{i,t-1} + \sum_{a=1}^{A} \delta_{1,i,a}^+ \Delta P_{i,t-a} + \sum_{b=0}^{B} \delta_{2,i,b}^+ \Delta C_{i,t-b} + \eta_{i,t}^+, & \text{if } ECT_{t-1} > \theta^+ \\ \tau_i^0 + \gamma_i^0 ECT_{i,t-1} + \sum_{a=1}^{A} \delta_{1,i,a}^0 \Delta P_{i,t-a} + \sum_{b=0}^{B} \delta_{2,i,b}^0 \Delta C_{i,t-b} + \eta_{i,t}^0, & \text{if } \theta^+ \geq ECT_{t-1} \geq \theta^- \\ \tau_i^- + \gamma_i^- ECT_{i,t-1} + \sum_{a=1}^{A} \delta_{1,i,a}^- \Delta P_{i,t-a} + \sum_{b=0}^{B} \delta_{2,i,b}^- \Delta C_{i,t-b} + \eta_{i,t}^-, & \text{if } \theta^- > ECT_{t-1} \end{cases} \quad (3)$$

The parameters θ^+ and θ^- indicate the upper and lower threshold values used to identify the three regimes. Note that the error correction term is positive (negative)—and stations are thus in the upper (lower) regime—if they are exposed to a large enough negative (positive) cost shock. The parameters γ^+, γ^0 and γ^- refer to the speed of adjustment in the upper, middle and lower regimes, while τ_i^+, τ_i^0 and τ_i^- indicate the respective constants. The parameters δ_1 (δ_2) denote the short-run adjustment rates to changes in own prices (costs) and are estimated up to a lag order of two. The respective error terms are indicated by η^+, η^0 and η^-. Cost increases will be passed on more quickly to prices than cost decreases if (a) the speed of price adjustment to cost increases exceeds the speed of adjustment to cost decreases (i.e. $|\hat{\gamma}_i^-| > |\hat{\gamma}_i^+|$) and/or (b) the adjustment threshold for price increases is smaller than for price decreases (i.e. $|\hat{\theta}^-| < |\hat{\theta}^+|$). Summary statistics of estimating equations (1) and (3) for each individual gasoline station are provided in Table 2.

An average parameter value for the long-run pass-through elasticity (obtained from estimating equation (1) in a log-log specification) is $\hat{\rho}_{1,i} = 0.317$, which suggests that a 1 % change in crude oil prices leads to an about 0.3 % change in retail prices.[23]

[23] This corresponds well with the fact that crude oil prices (including VAT) account for about one fourth of the total costs of gasoline at the retail level, while some cost elements influencing retail prices (like transport costs) are also affected by changes in crude oil prices. Other cost components (hardly affected by oil price volatility) include the refining margin, overhead expenses and finally taxes. In Austria, fuel taxes and VAT amount to about 55 % of the total costs and are thus the largest part of fuel costs at the filling pumps.

Table 2: Descriptive Statistics of Estimated Parameters

	Mean	Std. Dev.	Min	Max
Estimated Parameters from TECM				
Pass-through elasticity (ρ)	0.317	0.040	0.133	0.435
Positive threshold (θ^+)	1.667	0.898	0.325	4.977
Negative threshold (θ^-)	−1.609	0.834	−5.139	0.065
Speed upper regime (γ^+)	−0.042	0.033	−0.189	0.038
Speed middle regime (γ^0)	−0.034	0.222	−1.191	0.514
Speed lower regime (γ^-)	−0.076	0.040	−0.247	−0.009
Speed and Asymmetry in Cost Transmission				
Average speed outer regimes ($\frac{\lvert\gamma^+\rvert+\lvert\gamma^-\rvert}{2}$)	0.060	0.029	0.017	0.170
Asymmetry in speed ($\lvert\gamma^-\rvert - \lvert\gamma^+\rvert$)	0.033	0.045	−0.088	0.215
Asymmetry in thresholds ($\lvert\theta^+\rvert - \lvert\theta^-\rvert$)	0.058	0.984	−2.654	2.603

Note: The number of observations is 281.

Averaging parameter estimates over all gasoline stations, we find that the lower and upper threshold values ($\theta^- = -1.609$ and $\theta^+ = +1.667$) are nearly identical in absolute terms. The estimated adjustment speed for the inner regime in absolute terms ($|\hat{\gamma}^0| = 0.034$) is smaller than the corresponding parameter for the outer regimes, which corresponds to Cabral and Fishman (2012). The average speed of price increases (i.e. the parameter value in the lower regime $|\hat{\gamma}^-| = 0.076$) exceeds the speed of price decreases (the parameter value estimated for the upper regime $|\hat{\gamma}^+| = 0.042$).

Based on the parameter estimates from the TECM we calculate three variables measuring the speed and the asymmetry of cost pass-through: (i) The speed of price transmission is defined as the mean of the estimated speed parameters in the outer regimes $\left(\frac{|\hat{\gamma}_i^+|+|\hat{\gamma}_i^-|}{2}\right)$; (ii) The asymmetry in the speed of price transmission is defined by the difference between the lower and the upper speed parameters ($|\hat{\gamma}_i^-| - |\hat{\gamma}_i^+|$). (iii) Finally, the asymmetry in the thresholds is defined as $|\hat{\theta}^+| - |\hat{\theta}^-|$.

The average speed of adjustment in the outer regimes is $\left(\frac{|\hat{\gamma}_i^+|+|\hat{\gamma}_i^-|}{2}\right) = 0.060$, which corresponds well with estimates obtained from a standard error-correction model in equation (2).[24] Regarding the asymmetry in price adjustment, Table 2 provides some support for the 'rockets and feathers phenomenon' in the speed of adjustment. The calculated absolute difference in the speed of price adjustment in the two outer regimes is $|\hat{\gamma}_i^-| - |\hat{\gamma}_i^+| = 0.034$, which indicates that prices adjust

[24] These results are not reported for brevity reasons, but are available from the authors upon request.

more quickly upwards than downwards in response to cost shocks. Averaging over all gasoline stations, Table 2 suggests hardly any asymmetry in the adjustment thresholds ($|\hat{\theta}^{+}| - |\hat{\theta}^{-}| = 0.058$).

Table 3: Test Results for the Significance of Price Adjustment

Hypothesis	# of observations	Percent
Speed Estimate in the Upper Regime		
Reject H_0: $\gamma^{+} = 0$ at 1% significance level	85	30
Reject H_0: $\gamma^{+} = 0$ at 5% significance level	144	51
Reject H_0: $\gamma^{+} = 0$ at 10% significance level	179	64
Speed Estimate in the Middle Regime		
Reject H_0: $\gamma^{0} = 0$ at 1% significance level	49	17
Reject H_0: $\gamma^{0} = 0$ at 5% significance level	124	44
Reject H_0: $\gamma^{0} = 0$ at 10% significance level	157	56
Speed Estimate in the Lower Regime		
Reject H_0: $\gamma^{-} = 0$ at 1% significance level	180	64
Reject H_0: $\gamma^{-} = 0$ at 5% significance level	237	84
Reject H_0: $\gamma^{-} = 0$ at 10% significance level	252	90

Note: The number of observations is 281.

Note, however, that the parameter estimates for the individual gasoline stations vary considerably (see Tables 3 and 4). Table 3 suggests that the null hypothesis of no price adjustment ($\gamma^0 = 0$) is rejected for about half the gasoline stations (56 %) in the inner regime at the 10 % significance level. The same null hypothesis is rejected for 64 % in the upper regime (for price decreases) and for 90 % of all stations in the lower regime (for price increases).

Table 4 focuses on the difference between parameter estimates obtained from the different regimes for each gasoline station. The null hypothesis of no difference in the speed of price adjustment between the middle regime and the upper regime (between the middle regime and the lower regime) is rejected at the 10 % significance level for 71 % (74 %) of all gasoline stations. A statistical test for an asymmetry in the speed of price adjustment between the upper and lower regime rejects the null hypothesis (of no significant difference) for 22 % of all gasoline stations. The following section aims at investigating these differences between stations more systematically.

Table 4: Test Results for Asymmetric Price Adjustment

Hypothesis	# of observations	Percent
$H_0 : \gamma^+ = \gamma^0$		
Reject H_0 at 1% significant level	46	16
Reject H_0 at 5% significance level	142	50
Reject H_0 at 10% significance level	201	71
$H_0 : \gamma^- = \gamma^0$		
Reject H_0 at 1% significance level	95	34
Reject H_0 at 5% significance level	164	58
Reject H_0 at 10% significance level	208	74
H_0: $\gamma^- = \gamma^+$		
Reject H_0 at 1% significance level	24	9
Reject H_0 at 5% significance level	42	15
Reject H_0 at 10% significance level	62	22

Note: The number of observations is 281.

4.3 Cost Transmission and Consumer Search: Cross-Section Analysis

In the second stage we estimate cross-sectional regressions, relating the estimated speed of price transmission, the estimated long-run price transmission elasticity and the estimated parameters on asymmetry to the consumers' information endowments:

$$\hat{Y}_i = \alpha_0 + \alpha_1 \lambda_i + \boldsymbol{X}_i \boldsymbol{\alpha}_2 + \xi_i \tag{4}$$

The dependent variable $\hat{Y}_i$ represents our estimates from the first stage for the speed, the elasticity and the asymmetry of cost pass-through. The variable λ_i denotes the share of shoppers for each gasoline station. The vector $\boldsymbol{X}_i$ includes measures of local competition and gasoline station characteristics. α_0, α_1 and $\boldsymbol{\alpha}_2$ are parameters to be estimated and ξ_i denotes the error term.

The four specifications of the regression equation (4) are estimated using different estimation techniques. First, we estimate the regressions by OLS. In a second approach, we follow the suggestion of Lewis and Linzer (2005) and provide weighted least square (WLS) estimates of these models by weighting the observations by the inverse of the standard errors of the dependent variable estimates. This accounts for the fact that the dependent variables in equation (4) are estimated parameters rather than observed variables and ensures that equation (4) is estimated efficiently. Third, we estimate the regression semi-parametrically in order to avoid parametric restrictions to a linear function for the relationship between our measures of cost transmission and the share of shoppers λ_i. The modified equation for the semi-parametric cross-section model is:

$$\hat{Y}_i = \alpha_0 + f(\lambda_i) + \boldsymbol{X}_i \boldsymbol{\alpha}_2 + \nu_i, \tag{5}$$

To obtain an estimate $\hat{f}(.)$, we apply the difference estimator outlined in Yatchew (1998). We first sort the data according to the variable λ_i and estimate the first derivative of equation (5):

$$\Delta\hat{Y}_i = \Delta f(\lambda_i) + \Delta \boldsymbol{X}_i \boldsymbol{\alpha}_2 + \Delta\nu_i, \tag{6}$$

As λ_i is a smooth variable, $\Delta f(\lambda_i)$ cancels out in equation (6). We are thus able to obtain a consistent estimate of the parameter vector $\boldsymbol{\alpha}_2$ without explicitly modeling $f(\lambda_i)$. Finally, we regress $\hat{Y}_i - \boldsymbol{X}_i \hat{\boldsymbol{\alpha}}_2$ against λ_i non-parametrically to obtain our estimate $\hat{f}(.)$.

Following the discussion in Section 2.1 we expect that gasoline stations with a large share of shoppers exhibit higher pass-through rates and higher long-run transmission elasticities than gasoline stations with a low share of shoppers. The effect of the share of shoppers on our measures of asymmetry is theoretically ambiguous.

4.3.1 Parametric Evidence

The parametric results on the effects of consumers' information endowments on the speed, the long-run pass-through elasticity and the asymmetry of cost transmission are reported in Table 5. The first four columns report OLS and WLS regression results for the speed of price transmission (columns [1] and [2]) and the pass-through elasticity (columns [3] and [4]). The estimates show that a larger share of informed consumers is associated with a higher speed of price transmission and a higher pass-through elasticity. The parameter estimates are significantly different from zero at the 5 % significance level for the speed of adjustment and at the 1 % level for the pass-through elasticity. The effect of the share of shoppers on the asymmetry in speed (columns [5] and [6]) and in thresholds (columns [7] and [8]) is less clear-cut. All parameter estimates are negative, indicating that asymmetry in cost transmission is smaller if the share of informed consumers is large. However, the parameter estimates are significantly different from zero at the 5 % and 10 % significance level (depending on the estimation method) for the asymmetry in thresholds only.

The estimated effects of consumer information on price transmission are not only statistically robust, but also sizable: If the share of shoppers increases from zero (all consumers are ax-ante uninformed) to one (perfect information), the speed of price transmission increases by about 0.9 standard deviations of the respective endogenous variable. Furthermore, the increase in consumer information of the same amount causes the pass-through elasticity to increase by 1.4 standard deviations and the asymmetry in thresholds to decrease by 1.0 standard deviations (referring to the results of the WLS regressions).

With regards to the control variables, Table 5 suggests that the speed of cost transmission as well as the pass-through elasticity increases with the degree of competition (i.e. increases with the number of competitors within the local market and decreases with the distance to the nearest rival). Regarding the asymmetry in thresholds, we find that more competition is associated with less pass-through asymmetry. In particular, gasoline stations facing a large number of nearby competitors as well as those located closer to the next rival are characterized by less asymmetry in thresholds. All parameter estimates are significantly different from zero at the 1 % significance level. The regression results on the asymmetry in the speed of cost transmission are less clear. While the negative coefficients on the number of rival stations again suggest that more competition in the local market reduces the asymmetry in cost transmission, the negative parameter estimates on the distance to the next rival suggest the opposite. According to Table 5, gasoline stations located on the highway adjust prices more slowly (columns [1] and [2]) and tend to have a smaller long-run pass-through elasticity (column [3]). Regarding differences in pricing asymmetries between highway stations and other gasoline stations, our results are ambiguous. Focusing on the speed of adjustment, gasoline stations on the highway tend to adjust prices more symmetrically while they tend to adjust prices more asymmetrically with respect to adjustment thresholds.

4.3.2 Semi-Parametric Evidence

In this section we show that our results on the relationship between information and price transmission are not driven by the parametric restrictions to a linear function. The results obtained for the non-parametric components of our estimation equations are illustrated in Figure 2. The figures are based on a kernel-weighted local polynomial regression.[25] The graphs indicate a positive relationship between the share of shoppers and both the speed of cost transmission (Figure 2 (a)) and

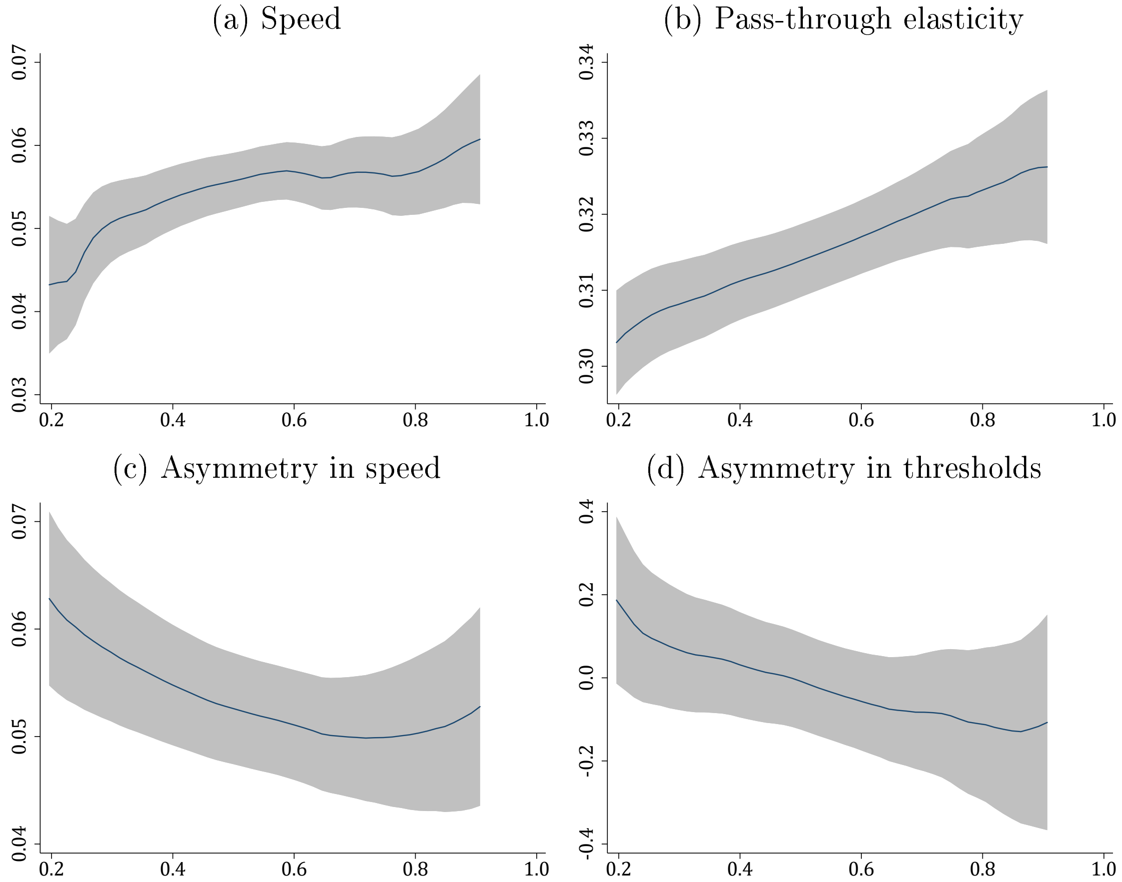
[25] The parametric results on the control variables are similar to the non-parametric regressions reported in Table 5. The results are reported in Table 6 in Appendix A.

Table 5: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS [1]	WLS [2]	OLS [3]	WLS [4]	OLS [5]	WLS [6]	OLS [7]	WLS [8]
Share of shoppers (λ)	0.025**	0.025**	0.059***	0.057***	−0.028	−0.022	−0.876*	−1.015**
	(0.011)	(0.011)	(0.017)	(0.017)	(0.020)	(0.019)	(0.464)	(0.451)
# of stations within 2 km	0.148***	0.152***	0.041	0.054	−0.177***	−0.115***	−2.372***	−3.320***
(in 100)	(0.027)	(0.023)	(0.030)	(0.034)	(0.042)	(0.040)	(0.887)	(0.951)
Distance to nearest rival station	−0.126**	−0.105*	−0.213**	−0.202**	−0.259***	−0.209**	6.263***	6.362***
(in 100 km)	(0.055)	(0.055)	(0.094)	(0.092)	(0.080)	(0.093)	(2.183)	(2.261)
Station is located on highway	−0.028***	−0.026***	−0.014***	−0.010	−0.046***	−0.046***	0.830***	0.642***
	(0.004)	(0.005)	(0.005)	(0.009)	(0.007)	(0.008)	(0.129)	(0.200)
Constant	0.039***	0.034***	0.288***	0.284***	0.068***	0.057***	0.533*	0.753**
	(0.008)	(0.007)	(0.011)	(0.011)	(0.014)	(0.012)	(0.317)	(0.295)
# of observations	281	281	281	281	281	281	281	281
R^2	0.265	0.309	0.076	0.082	0.122	0.145	0.142	0.169

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Figure 2: Semi-Parametric Evidence



Notes: The horizontal axes denote the share of shoppers λ and the vertical axes the respective endogenous variable, namely (a) the speed, (b) the elasticity, (c) the asymmetry in speed and (d) the asymmetry in thresholds. The image is based on an Epanechnikov kernel with a polynomial smooth degree of 0 and a bandwidth suggested by the rule-of-thumb bandwidth estimator provided in Stata, which equals 0.9 for the speed, 0.14 for the elasticity and the asymmetry in speed, and 0.12 for the asymmetry in thresholds. The pilot bandwidth for the standard error calculation is 1.5 times the respective rule-of-thumb bandwidth.

the pass-through elasticity (b). The effects of consumers' information endowments on the asymmetry in speed (c) and the asymmetry in thresholds (d) are negative. When investigating the speed and the elasticity of cost transmission, the confidence bands are rather small relative to the steepness of the curves, suggesting that this relationship is statistically more robust than the effect of information on the asymmetry of cost transmission. These results are very similar to the findings of the parametric specifications reported and discussed above.

5 Sensitivity Analysis

In order to confirm that our results are not driven by the particular model specifications or by a small sub-sample in our data, we provide a number of robustness exercises. As the results confirm the main findings provided above, they are only briefly discussed in the main part of the article, and are reported in Appendix A.

First, we use a rather parsimonious model in the main specifications. Table 7 reports regression results including a larger number of control variables to account for product and station heterogeneity. The point estimates and the significance levels of the parameter estimates on the share of shoppers λ are hardly affected by this modification, indicating that there is no omitted variable bias. Second, we estimate the same regression as reported in Table 5, but exclude highway locations. Stations located on highways are often considered to constitute a separate market,[26] differ considerably from stations off the highway regarding competition, demand and regulations, and may therefore exhibit very different price dynamics. Excluding highway stations ensures that our results are not driven by this small group of stations. The regressions without these stations, reported in Table 8, however, indicate that the results are hardly affected by this modification.

Third, we include the number of commuters and the number of non-commuters (in logarithmic terms) instead of the share of informed consumers. The results are provided in Table 9 in Appendix A. The number of commuters has a significantly positive effect on the speed and the pass-through elasticity, and a significantly negative impact on the asymmetry in thresholds. We find the opposite effects for non-shoppers, who are found to influence the speed of cost transmission and the pass-through elasticity negatively and the threshold asymmetry positively. This is an interesting result, because it seems unimportant whether e.g. an increase in the share of informed consumers λ originates from an increase in the number of shoppers or from a decrease in the number of non-shoppers. Both consumer groups are not significantly related to the asymmetry in speed, in line with the results of the main specifications reported in Table 5.

Fourth, we apply two alternative ways to construct the share of informed consumers λ by weighting one or both consumer groups differently: (i) In the main specification transit commuters are weighted by the share of possible routes passing by a particular gasoline station (see footnote 16). In this sensitivity analysis

[26]The Austrian competition authority finds that stations located on highways usually charge higher prices, and that there is little competition between stations on the highway and off-highway stations (Gruber and Puglisi, 2010).

we refrain from weighting commuter flows by the number of potential routes when calculating the share of informed consumers λ. (ii) Long-distance commuters (may) pass by a large number of gasoline stations and are thus unlikely to refuel at a particular one. Similarly, the probability of a specific station to attract a non-commuter declines with the number of rival stations located in the same municipality. In this specification we account for this by weighting commuters (non-commuters) by the number of gas stations along their commuting route (in their municipality of residence). The regression results for the model specifications (i) and (ii) are reported in Table 10 and Table 11, respectively. In both specifications the share of shoppers influences the speed and the pass-through elasticity positively and the threshold asymmetry negatively, while the parameter estimates on the asymmetry in speed are negative, but not significantly different from zero in both model variants.

Finally, we estimate the speed parameters using two alternative estimation techniques: (i) We estimate an asymmetric ECM with one threshold exogenously defined at zero; (ii) we apply an error-correction model by using a panel mean group (MG) estimator outlined in Pesaran and Smith (1995) to account for the heterogeneity in the parameters. The latter approach relies on the time period being long enough to estimate separate time series for each group in the panel. The MG estimator is the mean of the individual coefficients. It thus allows the intercepts, the slope coefficients and the error variances to differ for each group in the panel. We employ the procedure discussed by Blackburne and Frank (2007), who implement the MG estimator for the error-correction specification in Stata. Cross-section results using the parameter estimates of the asymmetric ECM (two regimes) are depicted in Table 12, and results on the MG regression are reported in Table 13 in Appendix A. Both the asymmetric ECM and the MG estimates are consistent with the main results: The share of informed consumers significantly increases the speed of price transmission.

6 Discussion and Conclusions

This paper investigates the relationship between consumer information and price dynamics. We utilize high-frequency price data for individual retail gasoline stations of a leading vertically integrated company to obtain estimates on the various dimensions of price transmission (i.e., the elasticity as well as the speed and asymmetry of price adjustment) of cost shocks (changes in the crude oil price). Our measure of consumer information is constructed using detailed data on commuting patterns.

Commuters can freely sample prices at gasoline stations along their commuting path and thus tend to be better informed than non-commuters. We use data for a time period when websites providing comprehensive information on gasoline prices were not yet available and going to a specific gasoline station was the only way for consumers to learn about current gasoline prices at that station. The identification strategy of the causal effect of consumer information on price adjustment relies on the fact that our measure of consumer information is determined by consumers' long-run decisions to commute, which are arguably independent of short-run price dynamics.

The results show that gasoline stations with a higher share of informed consumers have a larger cost pass-through elasticity and adjust prices more quickly to exogenous cost shocks. This finding is consistent with the implications of search-theoretic models (see Tappata, 2009; Yang and Ye, 2008; Lewis, 2011) and relates to the literature on price transparency and its effects on competition by showing that the presence of better informed consumers makes a market more competitive. Recent empirical evidence on information disclosure in the retail gasoline market provided by Dewenter, Heimeshoff, and Lüth (2017) and Luco (2019) suggests that the anticompetitive effect of price transparency, due to facilitating collusion among firms, outweighs the competitive effect due to lower consumer search costs. Note that the present study provides an indicator of an 'information clearinghouse' that cannot be accessed by firms and thus isolates and identifies the effect of better informed consumers (instead of firms).[27]

Our analysis further contributes to the large empirical literature on asymmetries in prices (the 'rockets and feathers phenomenon'). While a common strategy of existing studies to examine possible asymmetries is to pre-specify two regimes in an ad-hoc manner, the present analysis endogeneously identifies multiple regimes by applying a sequential model selection approach. This procedure reveals that the price adjustment process is best characterized by three regimes (two thresholds). Estimating multiple threshold error-correction models allows us to differentiate between an asymmetry in the speed of price transmission and an asymmetry in thresholds. We find substantial heterogeneity between gasoline stations with respect to both measures of adjustment asymmetries. While a large share of informed consumers significantly reduces asymmetries in thresholds, no effect of consumer information

[27] It is worth emphasizing that we measure information about prices on the consumers' side. Access to price comparison apps and websites, in contrast, would not only improve consumer information but would also make it easier for firms to monitor each other's prices. In such settings, increased transparency may thus facilitate collusion between firms which would impede the identification of the effects of consumer information on price dynamics.

is observed for asymmetries in the speed of adjustment.

Finally, our study complements the empirical literature on the effects of commuting as an indicator of consumers' information endowments on firms' pricing behavior in the retail gasoline market. Pennerstorfer et al. (2019) find that price levels are lower in regions with a larger share of commuters, while the relationship between information and price dispersion is characterized by an inverse-U. We conclude that consumer information not only influences the level of prices and price dispersion, but also the dynamics of price adjustment and thus the functioning of markets.

References

Andrews, Donald W. K. and Werner Ploberger (1994). "Optimal Tests when a Nuisance Parameter is Present Only Under the Alternative". In: *Econometrica* 62.6, pp. 1383–1414.

Bacon, Robert W. (1991). "Rockets and Feathers: The Asymmetric Speed of Adjustment of UK Retail Gasoline Prices to Cost Changes". In: *Energy Economics* 13.3, pp. 211–218.

Bakucs, Zoltán, Jan Falkowsky, and Imre Fertö (2014). "Does Market Structure Influence Price Transmission in the Agro-food Sector? A Meta-analysis Perspective". In: *Journal of Agricultural Economics* 65.1, pp. 1–25.

Balke, Nathan and Thomas Fomby (1997). "Threshold Cointegration". In: *International Economic Review* 38.3, pp. 627–45.

Ball, Laurence and N Gregory Mankiw (1994). "Asymmetric Price Adjustment and Economic Fluctuations". In: *Economic Journal* 104.423, pp. 247–61.

Barron, John, Beck Taylor, and John R. Umbeck (2004). "Number of Sellers, Average Prices, and Price Dispersion". In: *International Journal of Industrial Organization* 22.8-9, pp. 1041–1066.

Barron, John M, Beck A Taylor, and John R Umbeck (2000). "A Theory of Quality-Related Differences in Retail Margins: Why There Is a 'Premium' on Premium Gasoline". In: *Economic Inquiry* 38.4, pp. 550–569.

Baye, Michael R. and John Morgan (2001). "Information Gatekeepers on the Internet and the Competitiveness of Homogeneous Product Markets". In: *American Economic Review* 91.3, pp. 454–474.

Baye, Michael R., John Morgan, and Patrick Scholten (2004). "Price Dispersion in the Small and in the Large: Evidence from an Internet Price Comparison Site". In: *Journal of Industrial Economics* 52.4, pp. 463–496.

Blackburne, Edward F. III and Mark W. Frank (2007). “Estimation of Nonstationary Heterogeneous Panels”. In: *Stata Journal* 7.2, pp. 197–212.

Borenstein, Severin, A. Colin Cameron, and Richard Gilbert (1997). “Do Gasoline Prices Respond Asymmetrically to Crude Oil Price Changes?” In: *The Quarterly Journal of Economics* 112.1, pp. 305–339.

Brown, Jeffrey R. and Austan Goolsbee (2002). “Does the Internet Make Markets More Competitive? Evidence from the Life Insurance Industry”. In: *Journal of Political Economy* 110.3, pp. 481–507.

Byrne, David P. and Nicolas de Roos (2017). “Consumer Search in Retail Gasoline Markets”. In: *The Journal of Industrial Economics* 65.1, pp. 183–193.

Cabral, Luis and Arthur Fishman (2012). “Business as Usual: A Consumer Search Theory of Sticky Prices and Asymmetric Price Adjustment”. In: *International Journal of Industrial Organization* 30.4, pp. 371–376.

Chan, K. S. (1993). “Consistency and Limiting Distribution of the Least Squares Estimator of a Threshold Autoregressive Model”. In: *The Annals of Statistics* 21.1, pp. 520–533.

Chandra, Ambarish and Mariano Tappata (2011). “Consumer Search and Dynamic Price Dispersion: An Application to Gasoline Markets”. In: *The RAND Journal of Economics* 42.4, pp. 681–704.

Chesnes, Matthew (2016). “Asymmetric Pass-Through in U.S. Gasoline Prices”. In: *The Energy Journal* Volume 37.Number 1.

Claycombe, Richard J. (1991). “Spatial Retail Markets”. In: *International Journal of Industrial Organization* 9.2, pp. 303 –313.

Davies, Robert B. (1987). “Hypothesis Testing when a Nuisance Parameter is Present Only Under the Alternatives”. In: *Biometrika* 74.1, pp. 33–43.

De los Santos, Babur, Ali Hortacsu, and Matthijs R. Wildenbeest (2012). “Testing Models of Consumer Search Behavior Using Data on Web Browsing and Consumer Purchases”. In: *The American Economic Review* 102.6, pp. 2955–2980.

Deltas, George (2008). “Retail Gasoline Price Dynamics and Local Market Power”. In: *The Journal of Industrial Economics* 56.3, pp. 613–628.

Dewenter, Ralf, Ulrich Heimeshoff, and Hendrik Lüth (2017). “The Impact of the Market Transparency Unit for Fuels on Gasoline Prices in Germany”. In: *Applied Economics Letters* 24.5, pp. 302–305.

Dickey, David A. and Wayne A. Fuller (1979). “Distribution of the Estimators for Autoregressive Time Series With a Unit Root”. In: *Journal of the American Statistical Association* 74.366, pp. 427–431.

Eckard, E. Woodrow (2004). “The ‘Law of One Price’ in 1901”. In: *Economic Inquiry* 42.1, pp. 101–110.

Eckert, Andrew (2013). “Empirical Studies of Gasoline Retailing: A Guide to the Literature”. In: *Journal of Economic Surveys* 27.1, pp. 140–166.

Eckert, Andrew and Douglas S. West (2005). “Price Uniformity and Competition in a Retail Gasoline Market”. In: *Journal of Economic Behavior & Organization* 56.2, pp. 219 –237.

Ellison, Glenn and Sara Fisher Ellison (2005). “Lessons about Markets from the Internet”. In: *Journal of Economic Perspectives* 19.2, pp. 139–158.

— (2009). “Search, Obfuscation, and Price Elasticities on the Internet”. In: *Econometrica* 77.2, pp. 427–452.

Enders, Walter and Pierre L. Siklos (2001). “Cointegration and Threshold Adjustment”. In: *Journal of Business & Economic Statistics* 19.2, pp. 166–176.

Engle, Robert F. and C. W. J. Granger (1987). “Co-Integration and Error Correction: Representation, Estimation, and Testing”. In: *Econometrica* 55.2, pp. 251–276.

Frey, Giliola and Matteo Manera (2007). “Econometric Models Of Asymmetric Price Transmission”. In: *Journal of Economic Surveys* 21.2, pp. 349–415.

Gruber, Johannes and Laura Puglisi (2010). *Entwicklung der Verkaufsmargen für Diesel und Superbenzin an Autobahn- und Nicht-Autobahntankstellen in Österreich.* Tech. rep. Bundeswettbewerbsbehörde (Federal Competition Authority).

Gugler, Klaus, Sven Heim, Maarten Janssen, and Mario Liebensteiner (2018). *Market Liberalization: Price Dispersion, Price Discrimination and Consumer Search in the German Electricity Markets.* ZEW Discussion Papers. Mannheim.

Hansen, Bruce (1996). “Inference When a Nuisance Parameter Is Not Identified under the Null Hypothesis”. In: *Econometrica* 64.2, pp. 413–30.

— (1997). “Inference in TAR Models”. In: *Studies in Nonlinear Dynamics & Econometrics* 2.1, pp. 1–16.

Hansen, Bruce E. and Byeongseon Seo (2002). “Testing for Two-Regime Threshold Cointegration in Vector Error-Correction Models”. In: *Journal of Econometrics* 110.2. Long memory and nonlinear time series, pp. 293 –318.

Hassouneh, Islam, Carsten Holst, Teresa Serra, Stephan vonCramon-Taubadel, and Jose Maria Gil (2015). “Overview of Price Transmission and Reasons for Different Adjustment Patterns Across EU Member States”. In: *Food Price Dynamics and Price Adjustment in the EU.* Ed. by Steve McCorriston. Oxford University Press: Oxford, England.

Hastings, Justine S. (2004). "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California". In: *American Economic Review* 94.1, pp. 317–328.

Hastings, Justine S. and Richard J. Gilbert (2005). "Market Power, Vertical Integration and the Wholesale Price of Gasoline". In: *The Journal of Industrial Economics* 53.4, pp. 469–492.

Hayek, F. (1945). "The Use of Knowledge in Society". In: *The American Economic Review* 35.4, pp. 519–530.

Hosken, Daniel S., Robert S. McMillan, and Christopher T. Taylor (2008). "Retail Gasoline Pricing: What do we know?" In: *International Journal of Industrial Organization* 26.6, pp. 1425–1436.

Houde, Jean-François (2012). "Spatial Differentiation and Vertical Mergers in Retail Markets for Gasoline". In: *American Economic Review* 102.5, pp. 2147–2182.

Johnson, Ronald N. (2002). "Search Costs, Lags and Prices at the Pump". In: *Review of Industrial Organization* 20.1, pp. 33–50.

Kouyaté, Carolin and Stephan von Cramon-Taubadel (2016). "Distance and Border Effects of Price Transmission: A Meta-Analysis". In: *Journal of Agricultural Economics* 67.2, pp. 255–271.

Lewis, Jeffrey B. and Drew A. Linzer (2005). "Estimating Regression Models in which the Dependent Variable is based on Estimates". In: *Political Analysis* 13.04, pp. 345–364.

Lewis, Matthew S. (2008). "Price Dispersion and Competition with Differentiated Sellers". In: *Journal of Industrial Economics* 56.

— (2011). "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market". In: *Journal of Economics & Management Strategy* 20.2, pp. 409–449.

Lewis, Matthew S. and Howard P. Marvel (2011). "When Do Consumers Search?" In: *The Journal of Industrial Economics* 59.3, pp. 457–483.

Lloyd, Tim (2017). "Fourty Years of Price Transmission Research in the Food Industry: Insights, Challanges and Prospects". In: *Journal of Agricultural Economics* 68.1, pp. 3–21.

Loy, Jens-Peter and Christoph R. Weiss (2019). "Product Differentiation and Cost Pass-Through". In: *Journal of Agricultural Economics* 70.3, pp. 840–858.

Luco, Fernando (2019). "Who Benefits from Information Disclosure? The Case of Retail Gasoline". In: *American Economic Journal: Microeconomics* 11.2, pp. 277–305.

Luetkepohl, Helmut (1985). "Comparison of Criteria for Estimating the Order of a Vector Autoregressive Process". In: *Journal of Time Series Analysis* 6.1, pp. 35–52.

Marvel, Howard P (1976). "The Economics of Information and Retail Gasoline Price Behavior: An Empirical Analysis". In: *Journal of Political Economy* 84.5, pp. 1033–60.

Meyer, Jochen and Stephan von Cramon-Taubadel (2004). "Asymmetric Price Transmission: A Survey". In: *Journal of Agricultural Economics* 55.3, pp. 581–611.

Morton, Fiona Scott, Florian Zettelmeyer, and Jorge Silva-Risso (2001). "Internet Car Retailing". In: *The Journal of Industrial Economics* 49.4, pp. 501–519.

Nielsen, Bent (July 2001). *Order Determination in General Vector Autoregressions.* Economics Papers 2001-W10. Economics Group, Nuffield College, University of Oxford.

Nishida, Mitsukuni and Marc Remer (2018). "The Determinants and Consequences of Search Cost Heterogeneity: Evidence from Local Gasoline Markets". In: *Journal of Marketing Research* 55.3, pp. 305–320.

Orlov, Eugene (2011). "How does the Internet influence Price Dispersion? Evidence from the Airline Industry". In: *Journal of Industrial Economics* 59.1, pp. 21–37.

Paulsen, Jostein (1984). "Order Determination of Multivariate Autoregressive Time Series with Unit Roots". In: *Journal of Time Series Analysis* 5.2, pp. 115–127.

Pennerstorfer, Dieter (2009). "Spatial Price Competition in Retail Gasoline Markets: Evidence from Austria". In: *The Annals of Regional Science* 43.1, pp. 133–158.

Pennerstorfer, Dieter, Philipp Schmidt-Dengler, Nicolas Schutz, Christoph Weiss, and Biliana Yontcheva (2019). "Information and Price Dispersion: Theory and Evidence". In: *International Economic Review* forthcoming.

Pesaran, M. Hashem, Yongcheol Shin, and Ron P. Smith (1999). "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels". In: *Journal of the American Statistical Association* 94.446, pp. 621–634.

Pesaran, M. Hashem and Ron Smith (1995). "Estimating long-run Relationships from Dynamic Heterogeneous Panels". In: *Journal of Econometrics* 68.1, pp. 79–113.

Phillips, Peter C. B. and Pierre Perron (1988). "Testing for a Unit Root in Time Series Regression". In: *Biometrika* 75.2, pp. 335–346.

Pinkse, Joris, Margaret E. Slade, and Craig Brett (2002). "Spatial Price Competition: A Semiparametric Approach". In: *Econometrica* 70.3, pp. 1111–1153.

Raith, Michael (1996). "Spatial Retail Markets with Commuting Consumers." In: *International Journal of Industrial Organization* 14.4, pp. 447 –463.

Remer, Marc (2015). “An Empirical Investigation of the Determinants of Asymmetric Pricing”. In: *International Journal of Industrial Organization* 42.C, pp. 46–56.

Sengupta, Anirban and Steven N. Wiggins (2014). “Airline Pricing, Price Dispersion, and Ticket Characteristics on and off the Internet”. In: *American Economic Journal: Economic Policy* 6.1, pp. 272–307.

Sherman, Joshua and Avi Weiss (2017). “On Fruitful and Futile Tests of the Relationship between Search and Price Dispersion”. In: *Economic Inquiry* 55.4, pp. 1898–1918.

Slade, Margaret E. (1986). “Exogeneity Tests of Market Boundaries Applied to Petroleum Products”. In: *The Journal of Industrial Economics* 34.3, pp. 291–303.

Sorensen, Alan T. (2000). “Equilibrium Price Dispersion in Retail Markets for Prescription Drugs”. In: *Journal of Political Economy* 108.4, pp. 833–850.

Stigler, George (1961). “The Economics of Information”. In: *Journal of Political Economy* 69.

Strikholm, Birgit and Timo Teräsvirta (2015). “Determining the number of regimes in a threshold autoregressive model using smooth transition autoregressions”. SSE/EFI Working Papers in Economics and Finance 578.

Tang, Zhulei, Michael D. Smith, and Alan Montgomery (2010). “The Impact of Shopbot Use on Prices and Price Dispersion: Evidence from Online Book Retailing”. In: *International Journal of Industrial Organization* 28.6, pp. 579–590.

Tappata, Mariano (2009). “Rockets and Feathers: Understanding Asymmetric Pricing”. In: *The RAND Journal of Economics* 40.4, pp. 673–687.

Toda, Hiro Y. and Taku Yamamoto (1995). “Statistical Inference in Vector Autoregressions with Possibly Integrated Processes”. In: *Journal of Econometrics* 66.1, pp. 225 –250.

Tsay, Ruey S. (1989). “Testing and Modeling Threshold Autoregressive Processes”. In: *Journal of the American Statistical Association* 84.405, pp. 231–240.

Varian, Hal R (1980). “A Model of Sales”. In: *American Economic Review* 70.4, pp. 651–59.

Weyl, E. Glen and Michal Fabinger (2013). “Pass-Through as an Economic Tool: Principles of Incidence under Imperfect Competition”. In: *Journal of Political Economy* 121.3, pp. 528–583.

Wolman, Alexander L. (2007). “The Frequency and Costs of Individual Price Adjustment”. In: *Managerial and Decision Economics* 28.6, pp. 531–552.

Xia, Tian and Xianghong Li (2010). "Consumption Inertia and Asymmetric Price Transmission". In: *Journal of Agricultural and Resource Economics* 35.2.

Yang, Huanxing and Lixin Ye (2008). "Search with Learning: Understanding Asymmetric Price Adjustments". In: *The RAND Journal of Economics* 39.2, pp. 547–564.

Yatchew, Adonis (1998). "Nonparametric Regression Techniques in Economics". In: *Journal of Economic Literature* 36.2, pp. 669–721.

Appendix A. Additional Regression Tables

Table 6: Parametric Results of Semi-Parametric Regressions

	Speed	Pass-through elasticity	Asymmetry in speed	Asymmetry in threshold
# of stations within 2 km	0.129***	0.045	−0.187***	−1.351
(in 100)	(0.029)	(0.044)	(0.055)	(1.111)
Distance to nearest rival station	−0.177**	−0.004	−0.275*	6.808**
(in 100 km)	(0.086)	(0.129)	(0.161)	(3.261)
Station is located on highway	−0.025***	−0.013	−0.042***	0.782***
	(0.008)	(0.012)	(0.015)	(0.298)
# of observations	280	280	280	280
R^2	0.196	0.014	0.105	0.089

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 7: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission, controlling for Station Characteristics

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.025**	0.026**	0.060***	0.059***	−0.022	−0.016	−0.911*	−1.043**
	(0.011)	(0.011)	(0.017)	(0.018)	(0.020)	(0.019)	(0.466)	(0.452)
# of stations within 2 km	0.159***	0.161***	0.058*	0.069*	−0.133***	−0.078*	−2.388**	−3.270***
(in 100)	(0.028)	(0.024)	(0.033)	(0.036)	(0.046)	(0.041)	(0.925)	(0.991)
Distance to nearest rival station	−0.113**	−0.094*	−0.204**	−0.196**	−0.235***	−0.185**	6.296***	6.331***
(in 100 km)	(0.055)	(0.055)	(0.093)	(0.093)	(0.077)	(0.092)	(2.148)	(2.257)
Station is located on highway	−0.017**	−0.013*	−0.003	0.002	−0.008	−0.010	0.528	0.276
	(0.008)	(0.008)	(0.011)	(0.013)	(0.013)	(0.013)	(0.322)	(0.319)
# of pumps	0.001	0.001	−0.001	−0.001	−0.001	0.000	0.039	0.028
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.044)	(0.047)
Open 24 hours	−0.004	−0.003	−0.005	−0.004	−0.016***	−0.014**	−0.234*	−0.251
	(0.004)	(0.004)	(0.007)	(0.006)	(0.006)	(0.006)	(0.134)	(0.156)
Attendant service	−0.016**	−0.016**	−0.013*	−0.011	−0.029**	−0.029***	0.543*	0.627**
	(0.008)	(0.007)	(0.007)	(0.010)	(0.012)	(0.011)	(0.298)	(0.270)
Quantity of gasoline sold	0.000	0.000	0.000	0.000	0.000	0.000	−0.001	−0.001
(in 1,000 liters per day)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.008)	(0.010)
Constant	0.036***	0.031***	0.289***	0.286***	0.071***	0.057***	0.466	0.708**
	(0.008)	(0.008)	(0.012)	(0.012)	(0.014)	(0.013)	(0.324)	(0.315)
# of observations	281	281	281	281	281	281	281	281
R^2	0.294	0.334	0.087	0.090	0.168	0.191	0.165	0.195

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 8: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission, excluding Stations located on the Highway

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.025**	0.025**	0.059***	0.058***	−0.029	−0.024	−0.892*	−1.023**
	(0.011)	(0.011)	(0.018)	(0.018)	(0.021)	(0.020)	(0.486)	(0.482)
# of stations within 2 km	0.147***	0.152***	0.039	0.052	−0.179***	−0.119***	−2.330**	−3.235***
(in 100)	(0.027)	(0.023)	(0.031)	(0.035)	(0.043)	(0.041)	(0.905)	(0.991)
Distance to nearest rival station	−0.136**	−0.114*	−0.233**	−0.222**	−0.276***	−0.231**	6.652***	7.008***
(in 100 km)	(0.061)	(0.059)	(0.105)	(0.100)	(0.088)	(0.101)	(2.407)	(2.474)
Constant	0.040***	0.034***	0.288***	0.284***	0.069***	0.059***	0.532	0.739**
	(0.008)	(0.008)	(0.011)	(0.012)	(0.015)	(0.013)	(0.332)	(0.317)
# of observations	264	264	264	264	264	264	264	264
R^2	0.185	0.204	0.068	0.076	0.072	0.037	0.083	0.116

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 9: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission, Absolute # of Shoppers and non-Shoppers

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
# of shoppers (in logs)	0.010***	0.010***	0.023***	0.023***	0.000	0.002	−0.377***	−0.431***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.005)	(0.140)	(0.121)
# of non-shoppers (in logs)	−0.006***	−0.006***	−0.015***	−0.015***	0.004	0.003	0.225**	0.252**
	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.004)	(0.107)	(0.100)
# of stations within 2 km	0.113***	0.107***	−0.045	−0.032	−0.214***	−0.167***	−0.862	−1.246
(in 100)	(0.034)	(0.027)	(0.034)	(0.039)	(0.047)	(0.048)	(0.899)	(1.143)
Distance to nearest rival station	−0.065	−0.037	−0.060	−0.036	−0.173*	−0.117	3.559	3.274
(in 100 km)	(0.062)	(0.060)	(0.093)	(0.100)	(0.094)	(0.102)	(2.523)	(2.460)
Station is located on highway	−0.025***	−0.023***	−0.006	−0.002	−0.043***	−0.042***	0.685***	0.487**
	(0.004)	(0.005)	(0.006)	(0.009)	(0.008)	(0.008)	(0.145)	(0.203)
Constant	0.022*	0.013	0.243***	0.237***	0.016	0.003	1.405**	1.758***
	(0.014)	(0.012)	(0.021)	(0.020)	(0.023)	(0.021)	(0.561)	(0.515)
# of observations	281	281	281	281	281	281	281	281
R^2	0.277	0.327	0.115	0.128	0.128	0.157	0.162	0.195

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 10: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission, no route weights

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers ($\lambda^{no\ weights}$)	0.034***	0.032***	0.054***	0.053***	−0.027	−0.022	−0.941***	−1.040***
	(0.009)	(0.009)	(0.013)	(0.014)	(0.017)	(0.016)	(0.340)	(0.374)
# of stations within 2 km	0.142***	0.147***	0.017	0.029	−0.166***	−0.108***	−2.073***	−2.994***
(in 100)	(0.025)	(0.021)	(0.028)	(0.031)	(0.038)	(0.037)	(0.764)	(0.885)
Distance to nearest rival station	−0.116**	−0.095*	−0.219**	−0.207**	−0.258***	−0.211**	6.188***	6.293***
(in 100 km)	(0.055)	(0.053)	(0.092)	(0.091)	(0.079)	(0.092)	(2.125)	(2.228)
Station is located on highway	−0.029***	−0.027***	−0.014***	−0.010	−0.046***	−0.046***	0.839***	0.654***
	(0.004)	(0.005)	(0.005)	(0.009)	(0.008)	(0.008)	(0.129)	(0.199)
Constant	0.034***	0.029***	0.289***	0.286***	0.068***	0.058***	0.593**	0.790***
	(0.006)	(0.006)	(0.009)	(0.010)	(0.012)	(0.011)	(0.250)	(0.258)
# of observations	281	281	281	281	281	281	281	281
R^2	0.284	0.328	0.084	0.091	0.124	0.147	0.150	0.177

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 11: Estimation Results for Speed, Pass-Through Elasticity and Asymmetry of Price Transmission, using alternative weights

	Speed		Pass-through elasticity		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers ($\lambda^{alternative\ weights}$)	0.031***	0.031***	0.063***	0.060***	−0.023	−0.017	−1.072***	−1.230***
	(0.008)	(0.009)	(0.014)	(0.015)	(0.018)	(0.016)	(0.390)	(0.389)
# of stations within 2 km	0.114***	0.118***	−0.032	−0.018	−0.144***	−0.089**	−1.223*	−1.969**
(in 100)	(0.024)	(0.021)	(0.028)	(0.031)	(0.038)	(0.037)	(0.705)	(0.871)
Distance to nearest rival station	−0.117**	−0.097*	−0.204**	−0.197**	−0.255***	−0.203**	5.965***	6.048***
(in 100 km)	(0.049)	(0.054)	(0.088)	(0.091)	(0.084)	(0.092)	(2.083)	(2.223)
Station is located on highway	−0.030***	−0.028***	−0.016***	−0.012	−0.046***	−0.046***	0.865***	0.699***
	(0.005)	(0.005)	(0.006)	(0.009)	(0.008)	(0.008)	(0.138)	(0.200)
Constant	0.047***	0.042***	0.308***	0.304***	0.057***	0.048***	0.263*	0.428***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.145)	(0.138)
# of observations	281	281	205	281	281	281	281	281
R^2	0.278	0.323	0.095	0.098	0.121	0.144	0.154	0.183

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 12: Estimation Results for Speed and Asymmetry of Price Transmission based on an asymmetric ECM Model (one threshold)

	Speed		Asymmetry in speed	
	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.026^{**}	0.028^{**}	-0.040^{*}	-0.052^{**}
	(0.012)	(0.013)	(0.023)	(0.025)
# of stations within 2 km	0.149^{***}	0.157^{***}	-0.147^{***}	-0.126^{**}
(in 100)	(0.025)	(0.027)	(0.049)	(0.052)
Distance to nearest rival station	-0.166^{**}	-0.141^{**}	-0.271^{***}	-0.187^{*}
(in 100 km)	(0.071)	(0.068)	(0.094)	(0.109)
Station is located on highway	-0.020^{***}	-0.018^{***}	-0.040^{***}	0.030
	(0.005)	(0.006)	(0.008)	(0.028)
Constant	0.048^{***}	0.042^{***}	0.084^{***}	0.088^{***}
	(0.009)	(0.009)	(0.016)	(0.017)
# of observations	281	281	281	235
R^2	0.203	0.213	0.073	0.034

Notes: Standard errors are reported in parentheses. In OLS specifications standard errors are based on a robust variance estimator. In WLS specifications each observation is weighted by the inverse of the standard errors of the dependent variable estimates. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.

Table 13: Panel Mean Group Estimates

Long-Run Relationship	
C_{t-1}	1.116^{***}
	(0.047)
Short-Run Relationship	
ECT_{t-1}	-0.034^{***}
	(0.002)
ECT_{t-1} × share of shoppers (λ)	-0.021^{***}
	(0.002)
ΔP_{t-1}	-0.108^{***}
	(0.004)
ΔP_{t-2}	-0.025^{***}
	(0.003)
ΔC_{t}	0.129^{***}
	(0.004)
ΔC_{t-1}	0.089^{***}
	(0.005)
ΔC_{t-2}	0.058^{***}
	(0.004)
Constant	0.030^{***}
	(0.001)
# of observations	197,262

Notes: Standard errors are reported in parentheses. *** significant at 1 %, ** significant at 5 %, * significant at 10 % level.