

CONSUMER INFORMATION AND PRICE TRANSMISSION: EMPIRICAL EVIDENCE*

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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 rate, but has no effect on the asymmetry of cost transmission.

I. 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).

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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) 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 *et al.* [1997]; Weyl and Fabinger [2013]), menu costs (Ball and Mankiw [1994]), lags in adjustment of production and inventory management (Borenstein *et al.* [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

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]).

¹ Kouyaté and von 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 von Cramon-Taubadel [2004], Frey and Manera [2007], Wolman [2007], Bakucs *et al.* [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.

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.* [2020]). 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 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]).

³ The availability of price comparison websites as well as smart phone applications and automobile global positioning systems, 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 *et al.* [2012] and Byrne and Roos [2017].

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 rate. We do not observe a significant effect of consumer information on the asymmetry of price adjustment, neither in the speed of adjustment nor in adjustment thresholds.

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

II. LITERATURE

II(i). *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' information endowment and search intensity: If more consumers become informed, the intensity of competition increases, 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.⁴ In this model, a finite number of $n > 1$ firms sell a homogeneous product. They face constant marginal costs c and compete in prices. There is

⁴ A more detailed review of Tappata's [2009] model is presented in Online Appendix B, which is available at the Journal's editorial web site.

a unit mass of consumers with unit demand for the product and willingness to pay $v > c$.

Tappata [2009] distinguishes between different groups of consumers. A share $\lambda \in [0, 1]$ of consumers observes all prices at no cost; these ‘shoppers’ obtain price information unintentionally (in the case of gasoline, for example, commuters observe prices from gasoline stations on their commuter route). The remaining share of consumers $(1 - \lambda)$ have positive, but heterogeneous search costs and will be referred to as ‘non-shoppers.’ Non-shoppers decide whether or not to search by comparing their search costs with the expected gains from search $E[p - p_{\min}]$, with p_{\min} being the lowest price in the market. If non-shoppers choose to search, they observe all prices in the market (all-or-nothing nonsequential search) and thus become fully informed. Together, shoppers as well as those non-shoppers, who decide to search, constitute the group of informed consumers; their share among all consumers is μ . Informed consumers buy from the cheapest store, provided that its price does not exceed their willingness to pay v . The $1 - \mu$ uninformed consumers (the non-shoppers, who choose not to search) buy from a randomly selected store, as long as the price at this store does not exceed v .

In this model, consumers’ search intensities (consumers’ information endowments) affect the degree of competition among firms: a higher share of informed consumers implies a more elastic firm demand, which translates into higher cost pass-through rates. Tappata [2009] shows formally that the cost pass-through rate increases with the share of informed consumers, i.e., $\frac{\partial^2 \bar{p}}{\partial c \partial \mu} > 0$, where \bar{p} denotes the average market price. Since $\frac{\partial \mu}{\partial \lambda} > 0$, this result also holds for the share of shoppers ($\frac{\partial^2 \bar{p}}{\partial c \partial \lambda} > 0$).

In order to explain asymmetries in price adjustment, Tappata [2009] introduces a simple dynamic model in which consumers do not know the actual production cost. Their search decisions are based upon past cost realizations and the elasticity of demand differs between periods of marginal cost increases or decreases. More specifically, Tappata [2009] assumes that marginal production costs can be high (c^H) or low (c^L), and a cost decrease (increase) is thus equivalent to costs changing from c^H to c^L (from c^L to c^H).⁵ Consumers do not observe the contemporaneous cost realization, but form expectations about production costs based on cost realizations in the previous period. If marginal costs were high (c^H) in the previous period, consumers still expect high costs today. In this case, price dispersion is expected to be low, which reduces the incentives to search. Consequently the share of

⁵ The assumption of only two marginal cost states (high and low) is criticized in Lewis [2011], since this makes it difficult to identify whether potential effects originate from high vs. low margin periods or from positive vs. 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.

informed consumers will be low, which reduces the elasticity of demand faced by each firm. The market gets less competitive and the link between costs and prices becomes weaker. 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 search more intensively. The increasing mass of informed consumers increases the demand elasticity and makes the market more competitive. Tappata [2009] thus concludes that positive cost shocks are passed on to prices more quickly than negative ones.

A direct empirical test of Tappata's [2009] model prediction regarding asymmetries in price adjustment is difficult, because even if researchers observe consumers' actual search behavior in time periods of both cost increases and decreases, the share of informed consumers will nevertheless be endogenous.⁶ To avoid endogeneity concerns we use a measure for the (exogenous) share of shoppers λ in the empirical application. Note, however, that Tappata's [2009] analysis does not provide clear predictions regarding the effect of this consumer group on the asymmetry of price transmission: the relationship between the difference in the equilibrium share of informed consumers between a low-cost and a high-cost environment, 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 relationship.⁷

Another implication of Tappata's [2009] model is that the speed of cost transmission depends on the sign, but not on the size of the cost shock. In a different theoretical setting, Cabral and Fishman [2012] develop a search-theoretic model where prices are sticky for 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 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

⁶ Empirical articles observing consumer search behavior directly at the individual level (De los Santos *et al.* [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.

⁷ See Online Appendix B for a more detailed discussion of this point.

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.

II(ii). *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)⁸ 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.

⁸ Measures of family income are also used as proxies for search costs in Barron *et al.* [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.

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 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 *et al.* [2001]), life insurance (Brown and Goolsbee [2002]), books (Tang *et al.* [2010]), consumer electronics products (Baye *et al.* [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 *et al.* [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; 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.

III. DATA

III(i). *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.⁹ 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 U.S. dollars and are converted into eurocents per liter based on the prevailing exchange rate. While crude oil prices change virtually every day (except weekends), retail prices are more rigid and change on average every 4.35 days.¹⁰

As competition in the retail gasoline market is highly localized (see, e.g., Chamberlin [1948]; Lewis [2008]), 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 data on 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 two 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).

⁹ Since the theoretical search models focus on consumers' incentives to search, 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 per cent 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.

¹⁰ We would prefer using wholesale rather than crude oil prices, but have to rely on the latter data as wholesale prices are not available. Empirical evidence provided by Bachmeier and Griffin [2003] and Chen *et al.* [2005] suggests no asymmetry in price adjustment between crude oil and wholesale prices and that wholesale prices adjust almost instantaneously. See Borenstein *et al.* [1997] and Chen *et al.* [2005] for a discussion on this issue. Furthermore, given that the majority of gasoline stations in Austria are supplied from only one refinery, we expect that temporary changes in refinery margins affect all stations similarly, and thus should not bias our results.

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 *et al.* [2004], Eckert and West [2005], Hastings and Gilbert [2005], Hosken *et al.* [2008], Lewis [2008] or Pennerstorfer [2009].

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.

III(ii). *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.¹⁵ The data comprises information on the commuting behavior of all 3,624,116

¹³ Houde [2012] emphasizes the role of commuters in determining the competitive pressure in local markets. Theoretical models of Claycombe [1991], Raith [1996] and Cooper and Jones [2007] indicate that markets become more competitive if the share of commuters increases.

¹⁴ The period of investigation comprises the years 2003 and 2004, when cell phones, price comparison apps and comprehensive online price comparison sites were not yet available. Data on very cheap gasoline stations were provided by the Austrian Broadcasting Corporation (ORF) via teletext, and the Austrian automobile associations ARBÖ and ÖAMTC provided some information on gas prices online (ARBÖ [2000]) and even via telephone (ÖAMTC [2003]). However, the information provided by these sources was neither comprehensive nor entirely up-to-date. Access to information provided online was limited, as only 37.4% of all Austrian households had internet access in 2003 (Statistics Austria [2019]).

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.

employed individuals in Austria, including the respective place of residence, place of work and mode of transport. 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 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 I shows the summary statistics for prices, costs, as well as the gasoline stations' characteristics. The share of shoppers λ ranges from 20% to 91%, with an average of 54%. Table II shows the correlation between this indicator of consumer information and other station and location characteristics. Stations with a large share of commuters have a smaller number of rival stations within a two kilometer radius (although the distance to the closest rival is a bit smaller). Stations located on highways face a larger share of commuters, as

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.* [2020].

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 V for a discussion.

TABLE I
SAMPLE DESCRIPTION

Variables	Mean	Std. Dev.	Min	Max	# Obs.
<i>Panel/Time Series Variables</i>					
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
First difference of crude oil price (ΔC_t)					
within	0.003	0.282	-1.576	1.124	705
First difference of gasoline price (ΔP_t)					
overall	0.014	0.870	-17.500	19.600	198,105
between	0.014	0.005	0.001	0.027	281
within	0.014	0.870	-17.494	19.596	705
<i>Cross Section Variables</i>					
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

Notes: Prices are in Eurocents per liter.

TABLE II
CORRELATION BETWEEN SHARE OF SHOPPERS AND STATION AND LOCATION
CHARACTERISTICS

	Share of shoppers (λ_i)
# of rival stations within 2 km	-0.40
Distance to nearest rival station (in km)	-0.06
Station is located on the highway	0.12
# of pumps	0.06
Open 24 hours	-0.02
Services offered by station	0.06

expected. Other station characteristics, like the number of pumps, whether the station offers attendant service or is open 24 hours a day, are barely correlated with the share of shoppers.

IV. 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 rate 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 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 analyzed for the cross-section of gasoline stations.

IV(i). *Model Specification and Tests: Time-Series Analysis*

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 gasoline 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 and Perron [1988]) test procedure.¹⁹ 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:²⁰

$$(1) \quad P_{i,t} = \kappa_i + \rho_i C_t + e_{i,t}$$

where $e_{i,t}$ 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 gasoline 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.

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:

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

¹⁹ When testing for unit root and co-integration we use the optimal lag length of two, determined by the Akaike information criteria (AIC).

²⁰ Note that for 49 gasoline stations the parameter estimates of a time trend turned out to be significantly different from zero. We estimate Equation 1 with a time trend for these stations. We also include a dummy variable which captures the effect of an increase in the fuel tax ('Mineralölsteuer') on January 1st, 2004. This dummy variable is set equal to zero before this day and is equal to one on all other days.

We will refer to this equation as the standard error-correction model (ECM).²¹ 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, $ECT_{i,t} \equiv \hat{\varepsilon}_{i,t} = P_{i,t} - \hat{\kappa}_i - \hat{\rho}_i C_t$. The coefficient γ_i measures 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. 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 represent the short-run responses of the retail prices to own changes in the past two days ($A = 2$), and the coefficients δ_2 measure the short-run responses of the retail price to changes in the crude oil price within the last two days ($B = 2$).²² The intercept and the error term are denoted by τ_i and $\zeta_{i,t}$, respectively.

The standard error-correction model (ECM) in Equation 2 allows for different price dynamics across stations. The weakness of this model, however, is that the adjustment process for a particular gas station is restricted to be the same, irrespective of (a) the sign and (b) the size of the cost shock.

Both, theoretical models as well as a large number of empirical studies (see Section II) provide good reasons to doubt this implicit symmetry assumption with respect to the sign of costs shocks (positive or negative). Following an early empirical analysis of pricing asymmetries in the gasoline market (Borenstein *et al.* [1997]), numerous empirical studies estimate variations of an error correction model to account for an asymmetric response in the speed of adjustment to positive and negative costs shocks.²³

The second restriction of the standard error-correction model is that the adjustment pattern is assumed independent of the size of the shock. This implicit assumption is challenged in empirical work (Godby *et al.* [2000]) as well as search-theoretic models (Cabral and Fishman [2012]). Previous empirical contributions investigating asymmetric cost transmission allow prices to respond differently to cost increases versus cost decreases, and thus require the threshold for asymmetric responses to be a zero change in costs.

²¹ More details on empirical applications of this model in the gasoline market are provided in Eckert [2013].

²² 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.e., $I(1)$. Paulsen [1984] and Nielsen [2001] also show that the AIC can be used for both $I(0)$ and $I(1)$ variables.

²³ Indeed, these articles are part of an even larger literature examining (asymmetric) pass-through of upstream cost shocks in a variety of industries. Frey and Manera [2007] and Meyer and von Cramon-Taubadel [2004] provide excellent surveys of the broader literature with a specific focus on the technical issues of modeling and estimation.

Godby *et al.* [2000] extend this literature such that this threshold can take any value, and thus allow small cost changes to be transmitted differently than large cost shocks. Threshold-effects also play an important role in recent search-theoretic models. Cabral and Fishman [2012], for example, suggest that small cost decreases are passed on less quickly than positive or large negative cost shocks. While Godby *et al.* [2000] estimate one threshold only, Cabral and Fishman [2012] suggest that thresholds for price increases and decreases could differ. To account for this potential asymmetry in thresholds, an empirical model with more than one threshold is required.

In the following, we describe and estimate such a flexible threshold error-correction model, which allows for (a) an asymmetric response in the speed of adjustment as well as (b) an asymmetry in the level of thresholds for positive and negative shocks.

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 since 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.²⁴ We apply the approach proposed by Strikholm and Teräsvirta [2015] based on the smooth transition autoregression to determine the number of regimes, and thus run a sequence of tests: First, a linear error-correction model is tested against an error-correction model with two regimes (one threshold). Since the null hypothesis of linearity is rejected for the majority of the stations, in the next step we test the model with two regimes (one threshold) against a model with three regimes (two thresholds). The two-regimes model is also rejected, suggesting that the price transmission process is characterized by three regimes (two thresholds).

To estimate the thresholds we follow 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. However, since there are two thresholds that need to be estimated, a grid search procedure as discussed in Enders and Siklos [2001] is implemented. The estimated residuals from the long-run relationship of Equation 1 are candidates for the thresholds. These residuals are sorted in ascending order. To get consistent estimates of the parameters of the error-correction model, a sufficient number of observations in each regime is needed. Therefore, the smallest and the largest 15% of the estimated residuals were dropped and each of the remaining 70% of the

²⁴ Tsay [1989] proposed the use of residuals from an arranged auto-regression to test for non-linear behavior. Hansen [1996; 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].

values are considered potential thresholds. Note that the choice to drop the smallest and largest 15% is rather arbitrary, but it is important to ensure a sufficient number of observations in each regime. Since large (absolute) values of thresholds imply a small number of observations in the outer regimes, we followed Enders and Siklos [2001] and dropped 15%. Based on a rule of thumb for the minimum number of observations in each regime provided by Hansen [1999], we search from the 20% to 45% of the remaining arranged residual values to find the lower threshold and from the 55% to 80% of the arranged residual values to find the upper threshold. 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 with three regimes is estimated for each gasoline station by means of ordinary least-squares (OLS):

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

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., $|\hat{\theta}^-| < |\hat{\theta}^+|$).

While the TECM is very flexible, estimating a large number of coefficients for each gasoline station might lead to imprecisely estimated parameters. We provide simpler, but less flexible models in the sensitivity analysis, where we allow for a smaller number of regimes only, or restrict the parameters to be the same across stations. This enables us to estimate the speed and the pass-through rate more precisely, but limits the scope of investigating asymmetries in cost transmission.

TABLE III
DESCRIPTIVE STATISTICS OF ESTIMATED PARAMETERS

	Mean	Std. Dev.	P 5	P 95
<i>Estimated Parameters from TECM</i>				
Pass-through rate (ρ)	1.294	0.213	0.940	1.701
Positive threshold (θ^+)	1.389	0.825	0.365	2.770
Negative threshold (θ^-)	-1.443	0.610	-2.517	-0.667
Speed upper regime (γ^+)	-0.050	0.034	-0.109	-0.006
Speed middle regime (γ^0)	-0.034	0.225	-0.421	0.266
Speed lower regime (γ^-)	-0.090	0.047	-0.171	0.005
<i>Speed and Asymmetry in Cost Transmission</i>				
Average speed outer regimes ($\frac{ \gamma^+ + \gamma^- }{2}$)	0.071	0.029	0.028	0.132
Asymmetry in speed ($ \gamma^- - \gamma^+ $)	0.040	0.055	-0.466	0.131
Asymmetry in thresholds ($ \theta^+ - \theta^- $)	-0.053	0.869	-1.445	1.575

Notes: The number of observations is 281. P 5 and P 95 denote the 5th and the 95th percentile, respectively.

IV(ii). Estimation Results

Equations 1 and 3 are estimated by OLS for each individual gasoline station. Summary statistics on the most important parameter estimates are provided in Table III. The average parameter value for the long-run pass-through rate, obtained from estimating Equation 1, is $\hat{\rho} = 1.294$.²⁵ Averaging parameter estimates over all gasoline stations, we find that the lower threshold values ($\hat{\theta}^- = -1.443$) are nearly identical to the upper ones ($\hat{\theta}^+ = +1.389$) in absolute terms. The average speed of price increases (i.e., the parameter value in the lower regime $|\hat{\gamma}^-| = 0.090$) exceeds the speed of price decreases (the parameter value estimated for the upper regime $|\hat{\gamma}^+| = 0.050$). The estimated adjustment speed for the middle regime ($|\hat{\gamma}^0| = 0.034$) is smaller in absolute terms than the corresponding parameters for the outer regimes, consistent with Cabral and Fishman [2012].²⁶ Note that small parameter values for the middle regime could be an indicator of sticky prices (rather than the consequence of regular, but small price changes).

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 average of the estimated speed parameters in the outer regimes ($\frac{|\hat{\gamma}^+|+|\hat{\gamma}^-|}{2}$); (ii) The asymmetry in the speed of price transmission is defined by the difference between the lower and the upper speed parameters ($|\hat{\gamma}^-| - |\hat{\gamma}^+|$). (iii) Finally, the asymmetry in the thresholds is defined as $|\hat{\theta}^+| - |\hat{\theta}^-|$.

²⁵ Note that we use gross retail prices, so fully transmitted cost shocks lead to a pass-through rate ρ of 1.2, due to VAT of 20%.

²⁶ Cabral and Fishman [2012] predict cost transmission to be slowest for small cost decreases, suggesting the middle regime to start at $|\theta^+| > |\theta^-| = 0$. Our empirical results suggest hardly any difference between the thresholds $|\theta^+|$ and $|\theta^-|$ and a lower threshold that is substantially smaller than zero.

TABLE IV
TEST RESULTS FOR THE SIGNIFICANCE OF PRICE ADJUSTMENT

Hypothesis	# of observations	Per cent
<i>Speed Estimate in the Upper Regime</i>		
Reject $H_0: \gamma^+ = 0$ at 1% significance level	107	38
Reject $H_0: \gamma^+ = 0$ at 5% significance level	158	56
Reject $H_0: \gamma^+ = 0$ at 10% significance level	191	68
<i>Speed Estimate in the Middle Regime</i>		
Reject $H_0: \gamma^0 = 0$ at 1% significance level	73	26
Reject $H_0: \gamma^0 = 0$ at 5% significance level	118	42
Reject $H_0: \gamma^0 = 0$ at 10% significance level	143	51
<i>Speed Estimate in the Lower Regime</i>		
Reject $H_0: \gamma^- = 0$ at 1% significance level	218	78
Reject $H_0: \gamma^- = 0$ at 5% significance level	235	84
Reject $H_0: \gamma^- = 0$ at 10% significance level	241	86

Notes: The number of observations is 281.

The average speed of adjustment in the outer regimes is $\left(\frac{|\hat{\gamma}^+| + |\hat{\gamma}^-|}{2}\right) = 0.071$, which corresponds well with estimates obtained from a standard error-correction model in Equation 2.²⁷ Regarding the asymmetry in price adjustment, Table III 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 $|\hat{\gamma}^-| - |\hat{\gamma}^+| = 0.040$, which indicates that prices adjust more quickly upwards than downwards in response to cost shocks. Averaging over all gasoline stations, Table III suggests only a small asymmetry in the adjustment thresholds on average ($|\hat{\theta}^+| - |\hat{\theta}^-| = -0.053$).

Note, however, that the parameter estimates for the individual gasoline stations vary considerably (see Tables IV and V). Table IV suggests that the null hypothesis of no price adjustment ($\gamma^0 = 0$) is rejected for about half the gasoline stations (51%) in the inner regime at the 10% significance level. The same null hypothesis is rejected for 68% in the upper regime (for cost decreases) and for 86% of all stations in the lower regime (for cost increases).

Table V 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 75% (69%) 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 43% of all gasoline stations, despite the substantial difference between the estimated parameters γ^- and γ^+ on average (probably due to relatively large

²⁷ The estimated speed parameters $\hat{\gamma}$, obtained from a standard error-correction model, take a mean of 0.064 with a standard deviation of 0.029.

TABLE V
TEST RESULTS FOR ASYMMETRIC PRICE ADJUSTMENT

Hypothesis	# of observations	Per cent
$H_0 : \gamma^+ = \gamma^0$		
Reject H_0 at 1% significant level	91	11
Reject H_0 at 5% significance level	172	61
Reject H_0 at 10% significance level	211	75
$H_0 : \gamma^- = \gamma^0$		
Reject H_0 at 1% significance level	102	36
Reject H_0 at 5% significance level	158	56
Reject H_0 at 10% significance level	194	69
$H_0 : \gamma^- = \gamma^+$		
Reject H_0 at 1% significance level	33	12
Reject H_0 at 5% significance level	79	28
Reject H_0 at 10% significance level	121	43

Notes: The number of observations is 281.

standard errors). The following section aims at investigating these differences between stations more systematically.

IV(iii). *Cost Transmission and Consumer Search: Cross-Section Analysis*

In the second stage we estimate cross-sectional regressions, relating variables indicating the speed and the asymmetry of price transmission to the consumers’ information endowments:

(4)
$$\hat{Y}_i = \alpha_0 + \alpha_1 \lambda_i + X_i \alpha_2 + \xi_i$$

The variable λ_i denotes the share of shoppers for each gasoline station. The vector X_i includes measures of local competition and gasoline station characteristics. α_0 , α_1 and α_2 are parameters to be estimated and ξ_i denotes the error term.

The dependent variable \hat{Y}_i represents our estimates from the first stage, indicating the speed or the asymmetry of cost pass-through. In one variant we use four combinations of specific parameter estimates of the first stage, namely the estimated speed of price transmission (i.e., the average speed in the outer regimes, $\frac{|\gamma^+|+|\gamma^-|}{2}$), the estimated long-run pass-through rate (ρ), the estimated parameters on the asymmetry in speed ($|\gamma^-| - |\gamma^+|$) and the asymmetry in thresholds ($|\theta^+| - |\theta^-|$). Alternatively, we use cumulative price response values (CRV’s) as the dependent variable \hat{Y}_i in the cross-sectional analysis.

The four specifications of regression (Equation 4) based on specific first-stage parameters 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:

$$(5) \quad \hat{Y}_i = \alpha_0 + f(\lambda_i) + X_i\alpha_2 + v_i,$$

We use the two-step procedure outlined in Robinson [1988]. We first obtain non-parametric estimates of $E(\hat{Y}_i|\lambda_i)$ and $E(X_i|\lambda_i)$ and then regress $\hat{Y}_i - E(\hat{Y}_i|\lambda_i)$ on $X_i - E(X_i|\lambda_i)$ to obtain a consistent estimate of α_2 . Finally, we regress $\hat{Y}_i - X_i\hat{\alpha}_2$ against λ_i non-parametrically to obtain our estimate $\hat{f}(\cdot)$.

Restricting the attention to specific parameters of the first-stage regressions as indicators of the speed or the asymmetry of cost transmission has two potential weaknesses: First, the effects of the short-run changes in prices and costs on retail prices, captured by the parameters δ_1 and δ_2 , are not taken into account. Second, the adjustment of prices to exogenous cost shocks is a combination of the different parameters estimated by Equations 1 and 3. Even if we (do not) observe a significant impact of our measure of consumer information on one of these parameters, the aggregate effect of information (when taking all parameters into account simultaneously) might be different. To accommodate these potential weaknesses, we follow Borenstein *et al.* [1997] and Lewis [2011] and estimate cumulative response functions. These cumulative response values (CRV's) measure the adjustment of retail prices to a one unit change in crude oil prices, and are used as measures of cost transmission \hat{Y}_i when estimating Equation 4.

Following the discussion in Section II, we expect that gasoline stations with large shares of shoppers exhibit higher pass-through rates and higher speed of price transmission than gasoline stations with low shares of shoppers. The effect of the share of shoppers on our measures of asymmetry is theoretically ambiguous.

IV(iii)(a). *Parametric Evidence*

The parametric results on the effects of consumers' information endowments on the speed, the long-run pass-through rate and the asymmetry of cost transmission are reported in Table VI. The first four columns report OLS and WLS regression results for the speed of price transmission (columns 1 and 2) and the pass-through rate (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 rate. The parameter estimates are significantly different from zero at the 1% significance level for the speed of adjustment and at the 5% level for the pass-through rate. The results reported

TABLE VI
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION

	Speed		Pass-through rate		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)	0.031*** (0.011)	0.031*** (0.011)	0.218** (0.108)	0.223** (0.094)	-0.003 (0.025)	-0.001 (0.025)	0.589 (0.411)	0.202 (0.421)
# of stations within 2 km (in 100)	0.179*** (0.029)	0.180*** (0.023)	0.135 (0.158)	0.164 (0.181)	-0.053 (0.058)	-0.015 (0.050)	0.921 (0.714)	1.560* (0.915)
Distance to nearest rival station (in 100 km)	-0.145*** (0.048)	-0.142*** (0.059)	-0.922*** (0.439)	-0.878* (0.499)	-0.351*** (0.117)	-0.338*** (0.130)	1.457 (1.884)	1.186 (2.368)
Station is located on highway	-0.028*** (0.004)	-0.027*** (0.006)	-0.014 (0.031)	-0.002 (0.048)	-0.066*** (0.011)	-0.066*** (0.012)	0.261 (0.159)	0.162 (0.226)
Constant	0.046*** (0.008)	0.043*** (0.007)	1.184*** (0.071)	1.173*** (0.062)	0.056*** (0.017)	0.050*** (0.016)	-0.477* (0.263)	-0.223 (0.277)
# of observations	281	281	281	281	281	281	281	281
R ²	0.327	0.344	0.036	0.042	0.118	0.144	0.015	0.012

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.

in Table VI suggest that the degree of asymmetry in cost transmission is not related to consumers' information endowment. Parameter estimates for the share of shoppers are not significantly different from zero in models for the asymmetry in speed (columns 5 and 6) as well as for the asymmetry in thresholds (columns 7 and 8). Our results thus do not provide empirical support for theoretical models suggesting an impact of consumer information on the asymmetry of thresholds (such as Cabral and Fishman [2012], for example).²⁸

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 *ex-ante* uninformed) to one (perfect information), the speed of price transmission increases by about 0.44 standard deviations of the respective endogenous variable. Furthermore, the increase in consumer information of the same amount causes the pass-through rate to increase by 1.04 standard deviations (referring to the results of the WLS regressions).

With regards to the control variables, Table VI suggests that the speed of cost transmission as well as the pass-through rate increase 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), although not all parameter estimates are significantly different from zero. Regarding the asymmetry in speed, we find that competition is associated with more pass-through asymmetry. According to columns 5 and 6, an increase in the distance to the nearest rival (i.e., a reduction in the intensity of competition) significantly reduces asymmetry in the speed of adjustment (the parameter estimates are significantly different from zero at the 1% significance level). The regression results on the asymmetry in the thresholds are less clear. None of the parameter estimates in column 7 is significantly different from zero and the positive effect of the number of rival stations on threshold asymmetry reported in column 8 is significantly different from zero at the 10% level only. According to Table VI, gasoline stations located on the highway adjust prices more slowly (columns 1 and 2) but have similar long-run pass-through rates (columns 3 and 4). 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 (parameter estimates are significantly different from zero

²⁸ Note that our empirical model is not a formal test of Cabral and Fishman's model. The authors do not make specific predictions about the share of shoppers, because all consumers have homogeneous (and strictly positive) search costs. In their model, retail price volatility induces consumers to search the market and therefore makes the market more competitive, which implies lower profits. If the number of consumers with positive search costs declines (because the share of shoppers increases), discouraging non-shoppers from searching becomes less important. Consequently, the range of cost changes for which prices are sticky should shrink. The asymmetry of thresholds is therefore expected to decline with better informed consumers, a result we do not find in our data.

at the 1% significance level in columns 5 and 6). We do not observe a significant effect of this dummy variable on pricing asymmetry with respect to adjustment thresholds.

IV(iii)(b). *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 Equation 5 are illustrated in Figure 1. The figures are based on a kernel-weighted local polynomial regression.²⁹ The graphs indicate a positive relationship between the share of shoppers and both the speed of cost transmission (Figure 1(a)) and the pass-through rate (b). The effects of consumers' information endowments on the asymmetry in speed (c) is U-shaped, while the asymmetry in thresholds (d) does not suggest a clear relationship with the share of informed consumers. Comparing panels (a) and (b) with (c) and (d), we observe that the confidence bands for the speed and pass-through rate 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 (in panels (c) and (d)).

A test provided by Hardle and Mammen [1993], reported in Table A.I in Appendix A, shows that the non-parametric relationships between the share of shoppers and the variables on the speed and the asymmetry of cost transmission provide a better model fit compared to a simple constant for all endogenous variables, except the asymmetry in speed (c). The test statistics confirm that the model fit of a non-parametric specification is not better than a linear relationship for the pass-through rate (b), while the relationship between the share of shoppers and the speed (a) and the asymmetry in thresholds (d) is nonlinear. Generally, these results confirm the findings of the parametric specifications reported and discussed above: cost changes are passed on more quickly and fully if consumers are better informed, while the influence of consumer information on the asymmetry of price transmission is less clear.

IV(iii)(c). *Investigating Cumulative Response Functions*

The previous cross-sectional analysis investigates individual transmission parameters (adjustment speed, pass-through rate and asymmetry in speed and thresholds) obtained from Equations 1 and 3 separately, while we focus on cumulative price response values (CRV's) as measures of cost transmission here. More specifically, we calculate the values of cumulative response

²⁹ The parametric results on the control variables are similar to the non-parametric regressions reported in Table VI. The results are reported in Table A.I in Appendix A.

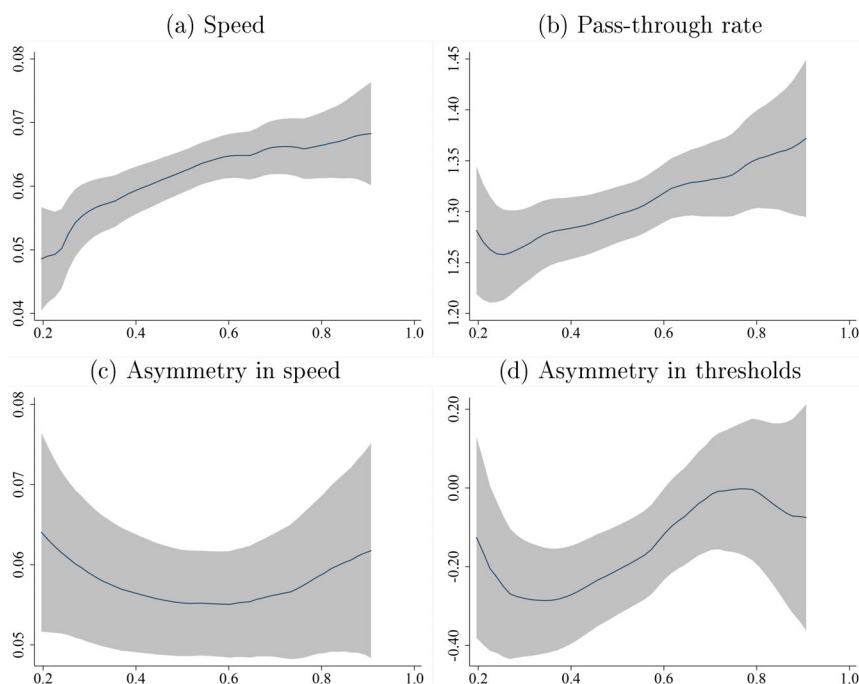


Figure 1

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 pass-through rate, (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 0.09 for the speed, 0.10 for the pass-through rate, 0.12 for the asymmetry in speed and 0.11 for the asymmetry in thresholds. The pilot bandwidth for the standard error calculation is 1.5 times the respective rule-of-thumb bandwidth. [Colour figure can be viewed at wileyonlinelibrary.com]

functions for different scenarios for each individual gasoline station over a period of 30 days, based on the parameter estimates of Equations 1 and 3.

The left panel (a) of Figure 2 compares the average cumulative response values for two groups of gasoline stations:³⁰ gasoline stations with the largest share of informed consumers (i.e., the 28 stations above the 90th percentile in the distribution of the share of shoppers) and those with the smallest share (i.e., the 28 stations below the 10th percentile). Consistent with theoretical models of consumer search, we find that the rate of price transmission is

³⁰ To be consistent with our definition of the speed parameter, the cumulative response values are calculated based on the parameters of Equation 1 and Equation 3 using the average speed of adjustment in the outer regimes $\frac{|\gamma^+| + |\gamma^-|}{2}$.

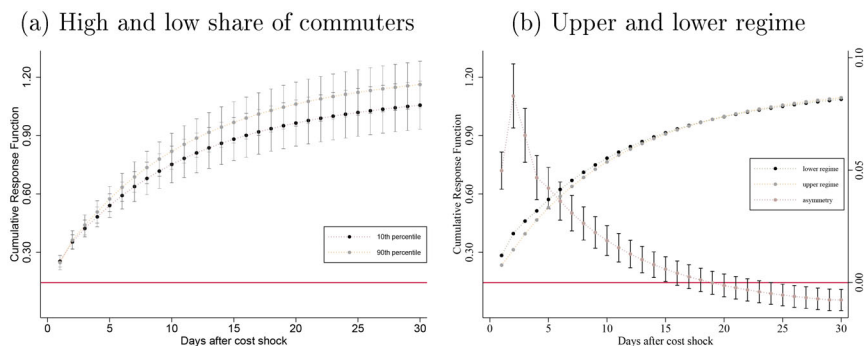


Figure 2
Cumulative Response Function Estimates

Notes: In the left panel (a) we report mean values of the cumulative response estimates for stations located in the lowest (below the 10th percentile) and highest (above the 90th percentile) of the distribution of shoppers. For each point estimate the respective 95% confidence interval is shown. In the right panel (b) we report mean values of the cumulative response estimates over all stations for the upper and lower regime as well as the estimate of the difference between the mean cumulative response values in the lower and upper regime with the respective 95% confidence interval for the asymmetry. Standard errors for each point estimate of the individual stations are calculated using the delta method. [Colour figure can be viewed at wileyonlinelibrary.com]

permanently higher for gasoline stations with a large share of informed customers. Furthermore, we observe that the rate of price transmission for both groups of stations approaches a one-for-one transmission (a cumulative response value of 1.2 with a VAT of 20%) by the end of one month. Taking all parameter estimates of Equations 1 and 3 into account, a one-for-one transmission in the long run cannot be rejected for each of the two groups (above the 90th percentile and below the 10th percentile).

To investigate transmission asymmetries, the right panel (b) of Figure 2 shows the cumulative response values (averaged over all stations) for each period in the upper and lower regime. The cumulative response estimates again approach 1.2 (i.e., a one-for-one transmission with a VAT of 20%) by the end of the 30-day period. We further observe that the estimated response values are significantly larger in the lower regime compared to the upper regime during the first two weeks after the cost shock: in the short-run, an increase in crude oil prices is transmitted into retail prices more quickly than a cost reduction, which corresponds to the ‘rockets and feathers phenomenon.’ T-tests suggest that this ‘rockets and feathers’ asymmetry disappears by the end of the second week.

To investigate the effect of consumer information on stations’ price responses, we regress the cumulative price response values (CRV’s) in the different regimes on the share of shoppers λ (and all control variables) for each period after the cost shock. For the sake of brevity, Table VII reports results

TABLE VII
ESTIMATION RESULTS FOR THE SHARE OF SHOPPERS (λ) ON CUMULATIVE RESPONSE VALUES (CRV's)

Dependent Variable	$t = 1$	$t = 2$	$t = 3$	$t = 4$	$t = 5$	$t = 6$	$t = 10$	$t = 15$	$t = 20$	$t = 30$
CRV in Upper Regime (UR)	0.002 (0.046)	0.085* (0.045)	0.096** (0.041)	0.118** (0.049)	0.135** (0.059)	0.152** (0.070)	0.212** (0.105)	0.264** (0.130)	0.295** (0.144)	0.317** (0.155)
CRV in Lower Regime (LR)	-0.013 (0.050)	0.051 (0.067)	0.066 (0.073)	0.091 (0.076)	0.116 (0.087)	0.137 (0.097)	0.209* (0.124)	0.268* (0.144)	0.301* (0.154)	0.325** (0.163)
Difference between CRV in LR and UR	-0.011 (0.035)	-0.031 (0.060)	-0.030 (0.047)	-0.027 (0.036)	-0.020 (0.034)	-0.015 (0.031)	-0.003 (0.022)	0.003 (0.017)	0.006 (0.014)	0.007 (0.012)

Notes: CRV refers to cumulative response value and UR (LR) denotes the upper (lower) regime. Standard errors are reported in parentheses. The table shows OLS estimates for the parameters of the variable 'share of shoppers' (λ) with standard errors based on a robust variance estimator. Parameter estimates for all variables (including control variables) are reported in Table C.I, Table C.II and Table C.III in Online Appendix C. *** significant at 1%, ** significant at 5%, * significant at 10% level.

of parameter estimates for the share of shoppers λ only for $t = 1, \dots, 6$ and $t = 10, 15, 20$ and 30 days after the cost change. The full estimation results, including parameter estimates for all control variables, are provided in Online Appendix C, available on the Journal's editorial web site.

The first line of Table VII summarizes the results for the upper regime, i.e., following a reduction in crude oil prices. The share of shoppers λ has a positive effect on cumulative price response values (CRV's), which is significantly different from zero for all but the first day after the cost shock. The degree of transmission significantly increases with our measure of consumer information.

We also observe positive parameter estimates for λ (with the exception of $t = 1$) in the second line, which reports point estimates for the share of shoppers in the lower regime (following an increase in crude oil prices). However, these estimates are smaller and significantly different from zero (at the 10% level) only after ten days following the cost shock. Taken together, these results are consistent with those reported in Table VI: the share of informed consumers increases the degree of price transmission to cost shocks in the long-run.

In addition, a comparison between the upper and the lower regime (results from the first and second line of Table VII) seems to suggest an impact of consumer information on the asymmetry in price adjustment in the short-run. While the transmission of cost increases remains unchanged, the short-run transmission of cost reductions increases significantly with the share of informed consumers. This would imply that the short-run 'rockets and feathers' asymmetry is weaker in markets with better informed customers. However, the results reported in the third line of Table VII suggest that this effect does not stand up to scrutiny. The share of shoppers λ does not exert a significant impact on the asymmetry in price adjustment measured as the difference between the CRV's in the lower and the upper regime. We thus (again) do not find evidence of a significant relationship between consumer information and the asymmetry of price transmission.

V. ALTERNATIVE INTERPRETATION AND ADDITIONAL SENSITIVITY TESTS

V(i). *Imperfect Information vs. Transportation Costs*

Our strategy to identify the impact of information on price transmission rests on the assumption that commuters are better informed about gasoline prices than non-commuters: spatial variation in the share of informed consumers (i.e., commuters) explains the observed differences in the degree of price transmission. An alternative interpretation of our empirical results focuses on differences in transportation costs between commuters and non-commuters: commuters can reach any site located on their route to work without incurring incremental travel costs (Claycombe [1991]). Free transportation along

a commute intensifies the degree of competition between firms on this route, which influences firms' price setting behavior. Any effect of the share of commuters on spatial differences in firms' prices could then be the result of different transportation costs between commuters and non-commuters instead of a different information endowment.³¹

A few theoretical models study the impact of different transportation costs between commuters and non-commuters on product prices in a spatial context (Claycombe [1991]; Raith [1996]; Cooper and Jones [2007]). These studies indeed find that the level of prices depends on the share of commuters. Unfortunately, none of these studies investigates the impact of (the share of) commuters on price transmission, which is the main focus of the present analysis.

Extending Claycombe's [1991] analysis, Raith [1996] studies the consequences of commuting in a Hotelling model. For small commuting distances (compared to the distance between firms), the author finds that prices are decreasing in the proportion of commuting consumers. For larger commuting distances, a price equilibrium does not exist. Marginal production costs, however, are normalized to zero and the transmission of cost shocks into prices is not studied.

In a similar context, Cooper and Jones [2007] focus on asymmetries in transportation costs. When commuting to work, consumers pass by every firm on the inner portion of the market (relative to their home). Consumers thus have no transportation costs for these firms. If, instead, consumers choose to buy from a station located on the outer portion of the market, they must make an extra trip to purchase the product and thus face positive transportation costs. The authors find that the directional flow of commuting determines the level of prices.³² While commuters influence the level of prices in Cooper and Jones [2007], it turns out that the rate of price transmission to exogenous cost shocks is independent of commuters in this framework. More specifically, for all specifications reported in their theoretical analysis, the transmission of marginal costs into prices is constant ($\frac{\partial p}{\partial c} = 1$).

While a number of theoretical models in the context of consumer search and information are available that provide detailed predictions on firms' short-run price dynamics (the degree and asymmetry of price transmission), the existing theoretical literature using spatial models (where consumers face transportation costs when visiting a store) devotes rather limited attention to the issue of

³¹ We are very thankful to a referee for making us aware of this argument.

³² In their empirical analysis, Cooper and Jones [2007] treat the market segments on each side of a firm as distinct sub-markets and indeed find empirical evidence for an asymmetry in transportation costs because of commuting. The authors further argue that asymmetries in transportation costs also generate price differences between otherwise identical firms (i.e., price dispersion). Cooper and Jones's [2007] theoretical model could thus help explain empirical evidence for a relationship between the share of commuters and the degree of price dispersion in spatial markets (see, for example, Pennerstorfer *et al.* [2020]).

short-run price dynamics and price transmission. A theoretical analysis that would allow differentiating between the impact of transportation costs and information endowments of commuters and non-commuters on the degree of price transmission is not yet available.

Empirically, it is difficult to distinguish between the effects of information and transportation costs in a spatial context, because both channels are closely related. With respect to non-commuters, we include variables on the distance to the nearest station and on the number of stations in the vicinity to account for the heterogeneity in transportation costs of this consumer group.³³ Commuters are characterized by both better information and lower transportation costs than non-commuters. If the information channel is more important in explaining the effects of commuters on price transmission, the share of commuters should have a stronger effect if commuters pass by a larger number of gas stations (because they can acquire more information). If low transportation costs are the dominant mechanism, the share of shoppers should have a larger influence if commuters travel longer distances. We use the heterogeneity of commuters regarding the number of gas stations they pass and with respect to the length of their commuting routes in an attempt to separate out the information from the transportation cost effect.

For each gas station, we can identify for all commuters (driving past the respective station) both the commuting distances and the number of (other) stations they pass when commuting to work. We can thus investigate whether stations facing commuters with very low transportation costs (because they travel on average long distances) or locations confronted with well-informed commuters (because they drive past a large number of stations) pass on cost changes more quickly. As the average travel distance and the number of stations along the commuting routes are obviously correlated, we estimate the average commuting distance conditional on the number of gas stations commuters drive past. We therefore regress the average distance on the average number of gas stations non-parametrically, and use the residual of this regression as an additional variable in the cross-section regression. This variable is positive if commuters travel a relatively long distance to work (conditional on the number of stations they pass), and negative if commuting distances are relatively short.

The regression results, including the average commuting distance conditional on the number of gas stations, are reported in Table VIII. While the parameter estimates of the average commuting distance on the pass-through rate are significantly positive, these variables do not seem to influence the speed of cost transmission. The parameter estimates of the share of shoppers are hardly affected by including the average commuting distance as an

³³ Many stations in the vicinity, however, might also indicate low (sequential) search costs for non-commuters.

TABLE VIII
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION CONTROLLING FOR COMMUTER
HETEROGENEITY

	Speed		Pass-through rate		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)	0.032*** (0.011)	0.032*** (0.011)	0.224** (0.109)	0.228** (0.094)	-0.004 (0.025)	-0.001 (0.024)	0.671 (0.410)	0.271 (0.424)
Average commuting distance (conditional on # of stations)	-0.000 (0.000)	0.000 (0.000)	0.005** (0.003)	0.005** (0.002)	0.002*** (0.001)	0.002*** (0.001)	-0.005 (0.010)	-0.001 (0.010)
# of stations within 2 km (in 100)	0.179*** (0.029)	0.181*** (0.023)	0.204 (0.163)	0.225 (0.182)	-0.030 (0.057)	0.005 (0.050)	0.913 (0.731)	1.608* (0.917)
Distance to nearest rival station (in 100 km)	-0.141*** (0.049)	-0.143*** (0.061)	-1.164** (0.468)	-1.129** (0.510)	-0.440*** (0.129)	-0.430*** (0.131)	1.775 (1.947)	1.338 (2.450)
Station is located on highway	-0.028*** (0.004)	-0.027*** (0.006)	-0.006 (0.030)	0.004 (0.048)	-0.062*** (0.012)	-0.063*** (0.012)	0.243 (0.159)	0.152 (0.226)
Constant	0.045*** (0.008)	0.043*** (0.007)	1.181*** (0.071)	1.172*** (0.062)	0.056*** (0.017)	0.050*** (0.016)	-0.521** (0.262)	-0.262 (0.279)
# of observations	280	280	280	280	280	280	280	280
R ²	0.328	0.345	0.052	0.059	0.148	0.176	0.017	0.013

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.

additional variable in all model specifications. These results suggest that transportation costs seem to play some role in explaining price transmission in addition to the information effect. We have to acknowledge that this procedure is far from ideal in separating the information from the transportation cost effect, because commuters are heterogeneous in many dimensions. Commuters travelling long distances, for example, are not only characterized by low transportation costs, but also by high demand. A tentative interpretation of the results, however, points in the direction that consumers' information endowments are indeed important in firms' decisions on how to pass through cost shocks to consumers.

V(ii). *Results Using Less Flexible Model Specifications*

Compared to previous empirical studies, we use a TECM specification in the first stage of the present analysis, because this approach is very flexible: the model estimates a large number of parameters separately for each station, allows for a large degree of heterogeneity across firms, and thus enables us to investigate predictions on the speed and the asymmetry of cost transmission derived from a variety of theoretical papers. The downside of this flexible approach is that some parameters might be imprecisely estimated. Table III shows substantial differences in parameter estimates across stations in the first stage, and Table IV indeed suggests large standard errors for many of them. For example, the speed parameters γ reported in Table IV are not significantly different from zero at the 10% significance level for 32% (14%) of all stations in the upper (lower) regime. When we estimate a standard ECM (Equation 2) instead of the flexible TECM (Equation 3), the speed parameters are significantly different from zero for all 281 stations in our sample, because standard errors of the parameter estimates are substantially smaller. In the following sensitivity analysis, we estimate regression models based on simpler and less flexible specifications for the first step of the analysis to obtain parameter estimates which are more precisely estimated.

We first evaluate the speed of price adjustment and estimate an asymmetric ECM with one threshold exogenously set to zero.³⁴ The estimated speed parameters γ^+ and γ^- allow us to investigate the average and the asymmetry of the adjustment speed. Cross-section results using these parameter estimates are reported in Table IX. Consistent with our previous results, columns 1 and 2 of Table IX show that the average speed of price adjustment increases with the share of shoppers λ . Again, we do not observe a significant relationship between the share of shoppers and the asymmetry in the speed of price adjustment (see columns 3 and 4). In this less flexible model, any asymmetric price adjustment is captured by asymmetries in the adjustment speed since (asymmetric) threshold effects are not included in this specification. If we further

³⁴ This approach is used by Galeotti *et al.* [2003] and Grasso and Manera [2007], for example.

TABLE IX
ESTIMATION RESULTS FOR SPEED AND ASYMMETRY OF PRICE TRANSMISSION BASED ON SIMPLER ERROR CORRECTION MODELS

Model used in time-series analysis	Speed asymmetric ECM (one threshold: $\theta = 0$)		Asymmetry in speed asymmetric ECM (one threshold: $\theta = 0$)		Speed standard ECM (no threshold)	
	OLS [1]	WLS [2]	OLS [3]	WLS [4]	OLS [5]	WLS [6]
Share of shoppers (λ)	0.027** (0.013)	0.025* (0.013)	0.005 (0.025)	0.006 (0.025)	0.038*** (0.011)	0.037*** (0.011)
# of stations within 2 km (in 100)	0.172*** (0.038)	0.163*** (0.028)	-0.074 (0.054)	-0.013 (0.051)	0.181*** (0.026)	0.180*** (0.023)
Distance to nearest rival station (in 100 km)	-0.080 (0.098)	-0.094 (0.069)	-0.274** (0.113)	-0.261** (0.128)	-0.121** (0.049)	-0.104* (0.054)
Station is located on highway	-0.020*** (0.004)	-0.018*** (0.006)	-0.061*** (0.009)	-0.060*** (0.012)	-0.026*** (0.005)	-0.025*** (0.005)
Constant	0.065*** (0.009)	0.064*** (0.009)	0.057*** (0.018)	0.049*** (0.016)	-0.034*** (0.007)	-0.030*** (0.007)
# of observations	281	281	281	281	281	281
R ²	0.193	0.201	0.092	0.121	0.313	0.345

Notes: Regression results in columns 1 to 4 are based on an asymmetric ECM with one threshold exogenously set to zero. Results in columns 5 and 6 are based on a standard ECM. 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.

simplify the analysis and estimate a standard ECM (without any thresholds), we obtain only one speed parameter γ for each station. Using these parameter estimates in a cross-section analysis, we again conclude that the adjustment speed depends positively on the share of informed consumers, as reported in columns 5 and 6 of Table IX. Note that the influence of the share of shoppers λ on the speed of price transmission is virtually identical to the results obtained from the flexible TECM, reported in Table VI.

Furthermore, we evaluate the long-run relationship between retail prices and costs (see Equation 1) together with the standard ECM (Equation 2) using a one-step approach. We start by applying a pooled mean-group (PMG) estimator, outlined in Pesaran *et al.* [1999], which allows the short-run coefficients (in particular the speed parameters in the standard ECM) to vary across stations, but constrains the long-run pass-through rate ρ to be the same for all stations.³⁵ The results obtained from this model, reported in column 1 of Table X, show that the parameter estimates of the pass-through rate ρ (for C_{t-1}) and the transmission speed γ (for ECT_{t-1}) are similar to the average of the parameter values obtained when estimating the time series separately for each station (as reported in Table III). Including an interaction term between costs C_{t-1} and the share of shoppers λ in column 2 shows that the interaction term is positive and significantly different from zero at the 1% level. This suggests that the pass-through rate is higher if consumers are better informed, which supports the results of our main specification. To further simplify the specification, we follow Deltas [2008] and restrict the parameters in the standard ECM to be identical for all stations, and allow for different intercepts only. With this dynamic fixed-effects estimator, the long-run relationship between costs and prices (Equation 1) and the standard ECM (Equation 2) are estimated simultaneously in one panel model.³⁶ The results, reported in the final column (3) of Table X, again suggest a significantly higher pass-through rate ρ for stations facing better informed consumers.

V(iii). *Additional Sensitivity Analyses*

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. The results confirm the main findings reported above.

³⁵ We employ the procedure discussed by Blackburne and Frank [2007], who implement the PMG estimator in Stata. We also perform specification tests for panel data before estimation: Testing the error terms of the dynamic panel models (pmg and dfe) for weak cross-sectional dependence, as proposed by Pesaran [2015], indicates no cross-sectional dependence in the data. The cointegration tests of Kao [1999], Pedroni [1999], Pedroni [2004] and Westerlund [2005] suggest that we can reject the null hypothesis of no cointegration in all panels.

³⁶ The results are based on a reduced-form fixed effects panel estimation, and the parameters for the long-run relationship are recovered from this estimation. See Borenstein *et al.* [1997] or Blackburne and Frank [2007] for details.

TABLE X
PANEL MEAN GROUP (PMG) AND DYNAMIC FIXED EFFECTS (DFE) ESTIMATES

	PMG [1]	PMG [2]	DFE [3]
Long-Run Relationship			
C_{t-1}	1.321*** (0.013)	1.183*** (0.044)	1.198*** (0.048)
Indicator Var. for year 2004	0.033*** (0.001)	0.033*** (0.001)	0.034*** (0.001)
$C_{t-1} \times \text{SIC}$		0.261*** (0.080)	0.234*** (0.085)
Short-Run Relationship			
ECT_{t-1}	-0.059*** (0.002)	-0.059*** (0.002)	-0.055*** (0.001)
ΔP_{t-1}	-0.104*** (0.004)	-0.104*** (0.004)	-0.125*** (0.002)
ΔP_{t-2}	-0.022*** (0.003)	-0.022*** (0.003)	-0.034*** (0.002)
ΔC_t	0.112*** (0.004)	0.104*** (0.004)	0.108*** (0.007)
ΔC_{t-1}	0.078*** (0.006)	0.078*** (0.006)	0.087*** (0.007)
ΔC_{t-2}	0.047*** (0.004)	0.047*** (0.004)	0.058*** (0.007)
Constant	0.039*** (0.001)	0.039*** (0.001)	0.036*** (0.001)
# of observations	197,262	197,262	197,262

Notes: Regression results in columns 1 and 2 are obtained by using the panel mean group estimator. Results in column 3 are based on a dynamic fixed effects estimator. Standard errors are reported in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10% level.

For reasons of space, they are only briefly mentioned here and are reported in Appendix A.

First, we use a rather parsimonious model in the main specifications. Table A.II 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 barely affected by this modification, indicating that there is no omitted variable bias with respect to station heterogeneity.

Second, the same analysis is carried out for sub-samples only: In one specification we estimate the same regression as reported in Table VI, but exclude highway locations. Stations located on highways are often considered to constitute a separate market,³⁷ 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

³⁷ 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]).

without these stations, reported in Table A.III, however, indicate that the results are hardly affected by this modification. In a second specification we exclude stations that do not change prices very often. In the time period under scrutiny, prices are changed every 4.35 days on average. If we exclude 10% of stations that adjusted their prices least often, the parameter estimates of the share of shoppers are hardly affected, as reported in Table A.IV. In another specification, we exclude stations with the highest or the lowest estimated pass-through rates $\hat{\rho}$, to ensure that our results are not driven by outliers. The regression results excluding the 5% of stations with either the highest or the lowest pass-through rates are reported in Table A.V. Again, the point estimates are very similar compared to the main results (reported in Table VI).

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 A.VI in Appendix A. The number of commuters has a significantly positive effect on the speed and the pass-through rate, as well as on the asymmetry in speed. We find the opposite effects for non-shoppers. A larger number of uninformed customers reduces the speed of cost transmission and the pass-through rate significantly. No significant effect of non-shoppers is identified for the asymmetry in speed and pricing thresholds. This seems to suggest that it does not matter whether a large share of shoppers λ is due to many shoppers or a few non-shoppers. Both consumer groups are not significantly related to the asymmetry in thresholds, in line with the results of the main specifications reported in Table VI.

Fourth, we use two alternative ways to construct the share of informed consumers λ by weighting one or both consumer groups differently: (i) In the first estimation experiment, we refrain from weighting commuter flows by the number of potential routes when calculating the share of informed consumers λ .³⁸ (ii) In a second estimation exercise, we weight commuters (non-commuters) by the number of gas stations along their commuting route (in their municipality of residence). This is motivated by the notion that 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's attracting a non-commuter declines with the number of rival stations located in the same municipality. The regression results for both estimation experiments are reported in Table A.VII and Table A.VIII, respectively. In both cases, the impact of the share of shoppers on the speed and the pass-through rate of price transmission is positive and significantly different from zero, while we do not observe a significant effect for our measures of consumer information on the asymmetry of price adjustment.

³⁸ Note that in the main specification, transit commuters are weighted by the share of possible routes passing by a particular gasoline station (see footnote 16).

And finally, we examine the sensitivity of our results to data frequency. It is well known that aggregation over time can lead to biased parameter estimates if the intertemporal lag distribution is not properly specified (Geweke [1978]; Bachmeier and Griffin [2003]; Chesnes [2016]). Geweke [1978] suggests a 'practical procedure which will indicate in a qualitative way the extent of the temporal aggregation problem in a particular application,' which involves estimating the relation of interest 'at two different levels of aggregation, the finest possible and one other' (p. 654). Following this suggestion, we re-estimate our model using weekly instead of daily price observations. More specifically, we use prices of each gasoline station on every Tuesday³⁹ and estimate first the long-run relationship between retail prices and costs of Equation 1 and then the error-correction models of Equations 2 and 3.⁴⁰ The sequential test procedure to test for the number of regimes, as outlined in Section IV(i), supports a model with three regimes for 224 out of 281 gasoline stations at the 5% significance level, whereas for 57 stations the test suggests a linear error-correction model.

Using weekly price data, the parameter estimates for the pass-through rate (ρ) and affected, as reported in Table A.IV the thresholds (θ^+ and θ^-) are similar to those based on daily retail prices, reported in Table III. The speed parameters γ are substantially larger in absolute terms when using lower-frequency data, because they describe the adjustment process within a week rather than within a day (see Table C.IV in Online Appendix C for details). Based on these parameter estimates, we re-estimate the cross-section regression (4). Comparing the results based on weekly data, reported in Table A.IX, with the analysis based on daily price observations (see Table VI) suggests that data frequency does not influence the impact of consumer information on most dimensions of price transmission. The share of shoppers λ exerts a significant and positive impact on the speed of price adjustment as well as on the pass-through rate, and does not contribute significantly to the variation in the asymmetry in speed. In contrast to Table VI, however, Table A.IX suggests a significant and negative impact on the asymmetry in thresholds: a large share of informed consumers significantly reduces asymmetries in thresholds, which underlines the importance of investigating pricing thresholds (as suggested by Cabral and Fishman [2012], for example). Data frequency thus seems to matter when investigating pricing asymmetries in thresholds.

³⁹ We select prices on every Tuesday, since it turns out that prices are most likely to adjust on this day of the week. An alternative procedure (not chosen here) involves calculating (moving) averages over a period of seven days. This would imply that the calculated price possibly never actually has been chosen. Using the weekly price series based on a particular day of the week avoids this issue.

⁴⁰ Similarly to the analysis with daily data, we use the Akaike information criteria (AIC) test statistics to select the optimal lag order for each gasoline station. For the majority of the gasoline stations we use a lag order of two.

VI. DISCUSSION AND CONCLUSIONS

This article 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 of cost shocks (changes in crude oil prices) on the various dimensions of price transmission (i.e., the pass-through rate as well as the speed and asymmetry of price adjustment). Our measure of consumer information is constructed by 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 and up-to-date information on gasoline prices were not yet available and visiting a specific gasoline station was the only way for most 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 larger cost pass-through rates and adjust prices more quickly to exogenous cost shocks. This finding is consistent with implications of search-theoretic models (see Tappata [2009]; Yang and Ye [2008]; Lewis [2011]). It also 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 (Dewenter *et al.* [2017]; 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.⁴¹

Our analysis further contributes to the large empirical literature on asymmetries in price adjustments (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 endogenously identifies multiple regimes by applying a sequential model

⁴¹ 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.

selection approach. This procedure suggests 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. The empirical analysis reveals (a) significant asymmetries in price adjustment for a large number of gasoline stations and (b) substantial heterogeneity between gasoline stations with respect to both measures of adjustment asymmetries. However, our results do not provide unambiguous support for theoretical models suggesting that pricing asymmetries are related to the degree of consumer information. We do not observe a significant impact of the share of commuters (informed consumers) on asymmetries in speed, and the relationship between consumer information and asymmetries in pricing thresholds seems to depend on data frequency.

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.* [2020] draw on similar measures of consumer information based on the same data on commuting, and 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. Their empirical investigation—covering a longer time period (from October, 1999, to March, 2005) and a larger number of gas stations—draws on price information collected much less frequently and uses quarterly data. Pennerstorfer *et al.* [2020] are interested in long-run differences in price levels and price dispersion between local markets with poorly and well informed consumers only. In contrast, the present article uses high-frequency information on both prices and marginal costs, which allows us to investigate short-run (in fact, daily) price responses to cost changes as well as their relation to consumer information. Based on the findings of both studies, 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.

In the end, we point out three important issues in this research area which have not been convincingly addressed so far (including the present analysis). First, while commuting is a source of information for consumers (rather than firms) and generates an arguably exogenous measure of consumer information, it is important to note that commuters and non-commuters also differ in the transportation costs they incur when visiting gasoline stations. We provide a first attempt to differentiate between the impact of transportation costs and consumer information on price transmission in this article. More detailed empirical and theoretical work on this issue must be postponed to future research. Second, consumer information could also influence market structure. A higher share of informed consumers increases the price elasticity of demand, lowers firms' price-cost margins and thus reduces the number of firms in equilibrium. In the context of the present paper, this would imply

that consumer information could influence price transmission indirectly via a ‘market structure channel.’⁴² While the impact of information (transparency) on market structure (number of firms and product variety) is well understood in theory (Schultz [2009]; Gu and Wenzel [2011]), a careful empirical analysis (extending Seim’s [2006] analysis, for example) is still lacking. Third, this analysis applies various measures of the gradual adjustment of individual prices. However, we do not explicitly address one important dimension of price adjustment: the frequency of price changes. Prices do change infrequently for many retail transactions and various explanations have been promoted for explaining different spells of unchanged prices (Wolman [2007]; Nakamura and Steinsson [2008]). Investigating the impact of consumer information on the frequency of price adjustment would further improve our understanding about the dynamics of price adjustment and thus the functioning of markets.

APPENDIX A

ADDITIONAL REGRESSION TABLES

TABLE A.I
PARAMETRIC RESULTS OF SEMI-PARAMETRIC REGRESSIONS

	Speed	Pass-through rate	Asymmetry in speed	Asymmetry in threshold
# of stations within 2 km (in 100)	0.181*** (0.024)	0.167 (0.208)	−0.059 (0.052)	1.430* (0.851)
Distance to nearest rival station (in 100 km)	−0.158** (0.074)	−1.356** (0.653)	−0.505*** (0.163)	−0.598 (2.668)
Station is located on highway	−0.027*** (0.006)	−0.007 (0.056)	−0.062*** (0.014)	0.264 (0.227)
# of observations	281	281	281	281
R ²	0.292	0.025	0.124	0.015
Hardle and Mammen [1993] specification test statistic				
polynomial of degree 0	4.034 [p = 0.00]	1.832 [p = 0.06]	0.535 [p = 0.48]	2.119 [p = 0.04]
polynomial of degree 1	1.877 [p = 0.05]	0.979 [p = 0.34]	1.132 [p = 0.32]	2.776 [p = 0.00]
polynomial of degree 2	1.468 [p = 0.12]	1.045 [p = 0.29]	0.429 [p = 0.76]	2.418 [p = 0.00]

Notes: Standard errors are reported in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10% level. Hardle and Mammen [1993] specification tests evaluate whether the non-parametric fit can be approximated by a parametric adjustment of order zero, one or two, respectively (H0: parametric and non-parametric fits are not different). Inference is based on a wild bootstrap testing procedure with 100 replications.

⁴² We are thankful to a referee for making us aware of this potential effect.

TABLE A.II
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION, CONTROLLING FOR STATION CHARACTERISTICS

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.031*** (0.011)	0.031*** (0.011)	0.224** (0.110)	0.229** (0.094)	0.002 (0.025)	0.004 (0.024)	0.567 (0.415)	0.181 (0.422)
# of stations within 2 km	0.186*** (0.030)	0.186*** (0.024)	0.215 (0.169)	0.230 (0.190)	-0.011 (0.064)	0.027 (0.052)	0.531 (0.743)	1.088 (0.958)
Distance to nearest rival station (in 100 km)	-0.133*** (0.048)	-0.130** (0.059)	-0.870** (0.439)	-0.842* (0.502)	-0.324*** (0.115)	-0.309** (0.129)	1.112 (1.814)	0.652 (2.378)
Station is located on highway	-0.016* (0.009)	-0.015* (0.008)	0.026 (0.062)	0.031 (0.070)	-0.024 (0.017)	-0.024 (0.018)	-0.063 (0.341)	-0.256 (0.319)
# of pumps	0.002 (0.001)	0.002 (0.001)	0.002 (0.010)	0.001 (0.010)	-0.001 (0.003)	-0.000 (0.003)	-0.026 (0.048)	-0.019 (0.048)
Open 24 hours	-0.002 (0.004)	-0.001 (0.004)	-0.053 (0.033)	-0.043 (0.030)	-0.014* (0.007)	-0.014* (0.008)	0.214 (0.135)	0.193 (0.139)
Attendant service	-0.017** (0.008)	-0.017** (0.007)	-0.006 (0.038)	-0.003 (0.055)	-0.035** (0.014)	-0.038*** (0.015)	0.259 (0.269)	0.403 (0.261)
Constant	0.040*** (0.008)	0.039*** (0.008)	1.180*** (0.075)	1.171*** (0.067)	0.056*** (0.018)	0.049*** (0.017)	-0.406 (0.286)	-0.171 (0.299)
# of observations	281	281	281	281	281	281	281	281
R ²	0.345	0.362	0.045	0.049	0.146	0.175	0.027	0.027

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 A.III
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION, EXCLUDING STATIONS LOCATED ON THE HIGHWAY

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.030** (0.012)	0.030** (0.012)	0.217* (0.113)	0.223** (0.099)	-0.005 (0.026)	-0.003 (0.026)	0.584 (0.431)	0.169 (0.438)
# of stations within 2 km (in 100)	0.178*** (0.029)	0.179*** (0.024)	0.123 (0.162)	0.152 (0.188)	-0.056 (0.059)	-0.018 (0.051)	0.921 (0.727)	1.529 (0.939)
Distance to nearest rival station (in 100 km)	-0.159*** (0.053)	-0.156** (0.063)	-1.032** (0.492)	-0.988* (0.538)	-0.373*** (0.127)	-0.363*** (0.138)	1.360 (2.043)	0.921 (2.524)
Constant	0.047*** (0.008)	0.044*** (0.008)	1.188*** (0.074)	1.176*** (0.065)	0.058*** (0.018)	0.052*** (0.017)	-0.473* (0.277)	-0.198 (0.290)
# of observations	264	264	264	264	264	264	264	264
R ²	0.256	0.263	0.037	0.044	0.027	0.028	0.008	0.011

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 A.IV
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION EXCLUDING STATIONS WITH MOST RIGID PRICES

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.031*** (0.011)	0.032*** (0.011)	0.225* (0.118)	0.233** (0.103)	-0.007 (0.026)	0.004 (0.025)	0.691 (0.445)	0.414 (0.457)
# of stations within 2 km (in 100)	0.166*** (0.030)	0.162*** (0.023)	0.092 (0.170)	0.117 (0.195)	-0.087 (0.059)	-0.011 (0.051)	0.889 (0.744)	0.859 (0.935)
Distance to nearest rival station (in 100 km)	-0.118*** (0.045)	-0.103* (0.057)	-0.955* (0.490)	-0.919 (0.557)	-0.297** (0.119)	-0.244* (0.124)	1.829 (2.103)	1.485 (2.318)
Station is located on highway	-0.003 (0.020)	-0.009 (0.015)	-0.146 (0.148)	-0.124 (0.150)	0.009 (0.014)	0.007 (0.034)	-0.052 (1.104)	-0.478 (0.638)
Constant	0.048*** (0.008)	0.043*** (0.007)	1.188*** (0.077)	1.177*** (0.068)	0.063*** (0.018)	0.048*** (0.016)	-0.524* (0.287)	-0.356 (0.301)
# of observations	254	254	254	254	254	254	254	254
R ²	0.226	0.234	0.037	0.043	0.024	0.018	0.010	0.007

Notes: 10% of all stations adjusting their prices least often within the sample period are excluded from the analysis. 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 A.V
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION EXCLUDING STATIONS WITH HIGHEST AND LOWEST PASS-THROUGH RATES

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (λ)	0.030** (0.013)	0.030** (0.013)	0.130* (0.067)	0.142** (0.064)	-0.010 (0.027)	-0.008 (0.027)	0.846* (0.451)	0.474 (0.457)
# of stations within 2 km (in 100)	0.175*** (0.030)	0.177*** (0.025)	0.136 (0.113)	0.153 (0.120)	-0.063 (0.060)	-0.022 (0.053)	1.030 (0.738)	1.862* (0.948)
Distance to nearest rival station (in 100 km)	-0.149*** (0.050)	-0.147** (0.064)	-0.677** (0.316)	-0.685** (0.335)	-0.353*** (0.123)	-0.344** (0.137)	1.778 (2.000)	1.472 (2.461)
Station is located on highway	-0.028*** (0.004)	-0.028*** (0.006)	-0.018 (0.026)	-0.006 (0.031)	-0.067*** (0.012)	-0.067*** (0.013)	0.215 (0.163)	0.125 (0.230)
Constant	0.047*** (0.009)	0.044*** (0.008)	1.232*** (0.043)	1.218*** (0.042)	0.061*** (0.019)	0.055*** (0.018)	-0.602** (0.289)	-0.367 (0.298)
# of observations	251	251	251	251	251	251	251	251
R ²	0.324	0.343	0.047	0.053	0.126	0.153	0.021	0.017

Notes: Stations with the 5% highest and lowest values of the pass-through rate ρ are excluded from the analysis. 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 A.VI
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION, USING ABSOLUTE # OF SHOPPERS AND NON-SHOPPERS

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
# of shoppers (in logs)	0.010*** (0.003)	0.011*** (0.003)	0.062** (0.031)	0.070*** (0.026)	0.015** (0.008)	0.015** (0.007)	-0.007 (0.114)	-0.065 (0.114)
# of non-shoppers (in logs)	-0.007*** (0.003)	-0.007*** (0.002)	-0.051*** (0.025)	-0.053*** (0.021)	-0.003 (0.006)	-0.003 (0.005)	-0.094 (0.092)	-0.022 (0.093)
# of stations within 2 km (in 100)	0.148*** (0.036)	0.143*** (0.027)	0.015 (0.150)	-0.001 (0.214)	-0.168*** (0.060)	-0.142** (0.058)	1.825** (0.862)	2.477** (1.111)
Distance to nearest rival station (in 100 km)	-0.091* (0.054)	-0.081 (0.065)	-0.726 (0.489)	-0.567 (0.554)	-0.124 (0.128)	-0.109 (0.139)	-0.490 (2.403)	-0.427 (2.569)
Station is located on highway	-0.025*** (0.004)	-0.024*** (0.006)	-0.002 (0.035)	0.015 (0.049)	-0.055*** (0.012)	-0.055*** (0.012)	0.176 (0.165)	0.098 (0.229)
Constant	0.035** (0.014)	0.029** (0.013)	1.195*** (0.107)	1.140*** (0.111)	-0.052* (0.029)	-0.059** (0.028)	0.705 (0.491)	0.620 (0.503)
# of observations	281	281	281	281	281	281	281	281
R ²	0.335	0.356	0.038	0.048	0.161	0.189	0.025	0.020

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 A.VII
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION, WITHOUT ROUTE WEIGHTS

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers ($\lambda^{no\ weights}$)	0.041*** (0.008)	0.041*** (0.009)	0.237*** (0.082)	0.231*** (0.077)	-0.004 (0.020)	-0.002 (0.020)	0.620* (0.345)	0.293 (0.352)
# of stations within 2 km (in 100)	0.173*** (0.026)	0.174*** (0.021)	0.062 (0.141)	0.076 (0.166)	-0.052 (0.053)	-0.015 (0.046)	0.713 (0.659)	1.544* (0.855)
Distance to nearest rival station (in 100 km)	-0.132*** (0.047)	-0.129** (0.058)	-0.900** (0.423)	-0.869* (0.492)	-0.352*** (0.116)	-0.340*** (0.129)	1.491 (1.840)	1.325 (2.348)
Station is located on highway	-0.029*** (0.004)	-0.028*** (0.006)	-0.017 (0.031)	-0.005 (0.048)	-0.066*** (0.011)	-0.066*** (0.012)	0.255 (0.159)	0.153 (0.226)
Constant	0.038*** (0.006)	0.037*** (0.006)	1.168*** (0.057)	1.164*** (0.053)	0.057*** (0.015)	0.051*** (0.014)	-0.509** (0.233)	-0.285 (0.245)
# of observations	281	281	281	281	281	281	281	281
R ²	0.354	0.370	0.047	0.053	0.118	0.144	0.019	0.014

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 A. VIII
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION, USING ALTERNATIVE WEIGHTS

	Speed		Pass-through rate		Asymmetry in speed		Asymmetry in threshold	
	OLS	WLS	OLS	WLS	OLS	WLS	OLS	WLS
Share of shoppers (<i>alternative weights</i>)	0.040*** (0.009)	0.041*** (0.010)	0.306*** (0.082)	0.281*** (0.080)	0.013 (0.021)	0.015 (0.021)	0.202 (0.383)	-0.066 (0.381)
# of stations within 2 km (in 100)	0.138*** (0.026)	0.138*** (0.021)	-0.166 (0.143)	-0.136 (0.165)	-0.055 (0.051)	-0.020 (0.046)	0.340 (0.701)	1.399* (0.842)
Distance to nearest rival station	-0.131*** (0.040)	-0.128*** (0.058)	-0.797* (0.408)	-0.794 (0.491)	-0.330*** (0.118)	-0.317** (0.129)	0.981 (1.780)	0.812 (2.359)
Station is located on highway	-0.029*** (0.005)	-0.029*** (0.006)	-0.026 (0.033)	-0.013 (0.048)	-0.067*** (0.012)	-0.067*** (0.012)	0.276* (0.163)	0.180 (0.227)
Constant	0.054*** (0.003)	0.052*** (0.003)	1.242*** (0.035)	1.241*** (0.029)	0.051*** (0.008)	0.046*** (0.008)	-0.164 (0.121)	-0.082 (0.135)
# of observations	281	281	281	281	281	281	281	281
R ²	0.349	0.367	0.063	0.064	0.119	0.146	0.009	0.011

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 A.IX
ESTIMATION RESULTS FOR SPEED, PASS-THROUGH RATE AND ASYMMETRY OF PRICE TRANSMISSION BASED ON WEEKLY DATA

	Speed		Pass-through rate		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)	0.080** (0.039)	0.082* (0.042)	0.364*** (0.094)	0.342*** (0.091)	0.135 (0.120)	0.126 (0.128)	-1.063** (0.411)	-1.326*** (0.434)
# of stations within 2 km (in 100)	0.267*** (0.071)	0.281*** (0.082)	0.250 (0.154)	0.280 (0.180)	-0.413* (0.218)	-0.363 (0.248)	-2.322*** (0.692)	-2.731*** (0.898)
Distance to nearest rival Station (in 100 km)	-0.059 (0.327)	-0.050 (0.324)	0.132 (0.397)	0.139 (0.508)	-0.392 (1.029)	-0.387 (0.985)	-6.593** (3.035)	-5.686* (3.022)
Station is located on the Highway	-0.022 (0.025)	-0.022 (0.022)	0.030 (0.039)	0.036 (0.049)	-0.038 (0.094)	-0.039 (0.067)	0.254 (0.238)	0.189 (0.190)
Constant	0.219*** (0.026)	0.212*** (0.027)	1.100*** (0.066)	1.103*** (0.060)	0.077 (0.078)	0.073 (0.083)	0.951*** (0.267)	1.108*** (0.281)
# of observations	224	224	281	281	224	224	224	224
R ²	0.067	0.071	0.051	0.053	0.030	0.023	0.051	0.064

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.

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