

Information and heterogeneous tax pass-through:

An application to retail fuel markets*

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February 28, 2023

Abstract

In the presence of information frictions, different consumer types face different price distributions depending on their access to information, and thus possibly also different effective pass-through rates. We estimate a model of consumer search using data from German retail fuel market. We find that search costs are lower in relatively rich areas and decrease over time. Uninformed consumers face higher effective pass-through rates. Given recent increases in commodity prices, this has important distributional implications for regulatory and tax policy responses. Decreasing the VAT rate by 16% leads a 2.3% decrease in transaction prices, but dis-proportionally benefits consumers in areas with high GDP per capita.

Keywords: gasoline, information frictions, search, pass-through optimal taxation

JEL Codes: D83, D22, L11, L15, L81, H21

*Funding from the German Research Foundation (DFG, project 504715884) and the Austrian Science Foundation (FWF, project FG 5 TP 5) is gratefully acknowledged. Computational infrastructure and support were provided by the Centre for Information and Media Technology at Heinrich Heine University Düsseldorf.

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1 Introduction

With energy costs accounting for a large part of household consumption expenditures, recent increases in prices have led to an increased focus on retail fuel markets. Competition authorities have repeatedly expressed concerns regarding a possible lack of competition in these markets and asymmetric cost pass-through in several countries (e.g., for Germany, see Bundeskartellamt, 2011, and Bundesministerium für Wirtschaft und Energie, 2018, and for Austria, see Bundeswettbewerbsbehörde 2011). In view of high and rising commodity prices and inflation (OECD, 2022), possible policy interventions are frequently discussed; by the public, major media outlets, policy makers and academics alike.

The retail fuel market is characterized by substantial price dispersion of the physically homogeneous goods (gasoline and diesel). This implies that different consumers will face different prices or price distributions, depending on the search technology available and their search behavior. To evaluate policy measures like tax changes and their distributional effects, it is therefore necessary to understand how they affect the price distribution and therefore different consumers.

We approach this question through the lens of a model with consumer information heterogeneity in the spirit of Armstrong et al. (2009) and Lach and Moraga-González (2017). In particular, consumers differ in the number of price quotes they obtain prior to making their purchasing decision. This heterogeneity stems from differences in the cost of obtaining quotes, which varies both across consumers and markets. To estimate this model using real-time information on retail fuel prices in Germany, we propose a two-step procedure. In the first step, we obtain a non-parametric estimate of the price distribution conditional on market characteristics from which we can directly infer the cutoff points in the distribution of search costs. This determines the number of price quotes obtained for different customer types. In a second step we match the empirical moments of the price distribution with those generated by the model. This yields the parameters of the firm costs function and the distribution of search costs (see Hong and Shum (2006), Moraga-González and Wildenbeest (2008)).

We obtain reasonable estimates that imply a margin of 10 Euro cent per litre which is close to industry reports. We can directly compute "type-specific" pass-through rates, depending on how well a consumer is informed. We find that pass-through declines from .6 to less than .1 when a consumer moves from sampling only one station to ten stations. Pass-through is higher in markets with wealthier consumers as well as in markets with a higher station density.

Our counterfactual is motivated by a recent tax policy experiment in taxation.

In Germany, retail fuels are subject to value-added tax (VAT), excise tax, and a CO₂ tax. The VAT rate was temporarily reduced in order to stimulate demand during the COVID-19 pandemic. We simulate our model under the reduced VAT rate and find that the tax savings are on average passed through at a rate of 83 percent. Although we estimate our model on pre-pandemic data, this is very much in line with the reduced form findings from Montag et al. (2021), who employ a difference-in-difference strategy exploiting the policy experiment. Our structural model allows us to disentangle this effect. Holding consumer search behavior fixed, the lower tax rate reduces the minimum price and increases dispersion, resulting in higher firm profits. Consumers respond though by intensifying search, as increased dispersion rewards price comparisons, allowing them to obtain a larger share of the increase in surplus due to lower taxes.

The remainder of the paper is organized as follows. Below we discuss the related literature. Section 2 describes the institutional setting, details on our data and sample construction, as well as descriptive evidence. Section 3 introduces the model and characterizes equilibrium pricing, search behavior and pass-through. In Section 4 we describe our estimation method. Section 5 presents estimates of the model parameters and pass-through rates. In Section 6 we conduct and analyze the tax experiment. Section 7 concludes.

1.1 Related literature

Our paper relates to several strands of the literature.

A large body of empirical literature has examined the question on pass-through of input costs to consumer retail prices. Researchers have studied several industries ranging from gasoline markets (Doyle Jr. and Samphantharak, 2008, Montag et al., 2021, Stolper, 2016), electricity markets (Duso and Szücs, 2017, Fabra and Reguant, 2014, Gugler et al., 2023), health markets (Duggan et al., 2016), consumables markets (Besanko et al., 2005, Butters et al., 2022, Renkin et al., 2022), restaurants (Benzarti and Carloni, 2019), cigarette and spirit markets (Harding et al., 2012, Hindriks and Serse, 2019) to the cement industry (Miller et al., 2016) and many others (e.g., Buettner and Madzharova (2021), Carbonnier (2007), Kosonen (2015) and Harasztosi and Lindner (2019)). Results on pass-through rates differ across industries and products from no or limited pass-through (Benzarti and Carloni, 2019, Duggan et al., 2016) to partial pass-through (Duso and Szücs, 2017, Harding et al., 2012, Kosonen, 2015, Montag et al., 2021) or (almost) full pass-through of input costs to consumer prices (Fabra and Reguant, 2014, Miller et al., 2017, Renkin et al., 2022). Several papers exploit natural experiments to identify the pass-through

rates. For instance tax changes are exploited as source of identification for example in Benzarti and Carloni (2019), Benzarti et al. (2020), Doyle Jr. and Samphantharak (2008), Kosonen (2015), Montag et al. (2020), changes in the minimum wage were used to identify pass-through in Harasztosi and Lindner (2019), Renkin et al. (2022). While these papers hence often exploit one-time, salient cost shocks, pass-through of everyday variation in prices (e.g. in Duso and Szücs (2017) or Miller et al. (2017)) might provoke different consumer and firm responses. Benzarti et al. (2020) and Montag et al. (2021) show that even VAT increases and decreases result in substantially different pass-through rates. Ahundjanov and Noel (2021) suggest that also the framing of a tax change can mitigate the resulting demand responses. We contribute to this literature by studying the consumer information channel, which has important consequences for aggregate as well as consumer group-specific pass-through rates.

Another strand of the literature considers how supply-side factors impact pass-through heterogeneity. For example, input substitutability (Benzarti and Carloni, 2019, Harasztosi and Lindner, 2019) and competition intensity as well as incumbency effects (Duso and Szücs, 2017, Gugler et al., 2023, Hindriks and Serse, 2019, Montag et al., 2023, Stolper, 2016) shape pass-through. For the role of competition, Weyl and Fabinger (2013) show theoretically that changes in the competitiveness of market affect pass-through rates in imperfectly competitive environments. Miller et al. (2017) show that pass-through decreases with competition in the US cement industry. On the other hand, Duso and Szücs (2017), Genakos and Pagliero (2022) and Cabral et al. (2018) identify increasing pass-through in more strongly contested electricity, gasoline and medical care markets. Loy et al. (2022) show that pass-through in gasoline markets increases the closer a competitor is located. Doyle Jr. and Samphantharak (2008) find no effect of competition on in station-level pass-through of a sales tax cut. When it comes to the structural estimation of pass-through, many papers consider an imperfectly competitive environment. Recent work (Miravete et al., 2018, 2020) points out that accounting for firms' strategic response in oligopoly affects implications of, for example, tax policy changes. We account both for strategic firm and consumer search behavior in our framework.

Demand-side factors for pass-through heterogeneity across products or consumers though have not been discussed in depth. Duso and Szücs (2017) show that pass-through is higher for electricity tariffs where consumers are likely have higher switching costs. DeCicca et al. (2013) unveil heterogeneous pass-through rates in cigarette prices for consumers who consume heavy or light cigarettes. Doyle Jr. and Samphantharak (2008), Harding et al. (2012) and Stolper (2016) find pass-through

of state-level taxes to be the lowest at state borders as consumers can substitute to buying in cheaper states. Montag et al. (2021) find pass-through rates of VAT rates in the gasoline market to be higher for consumers with more elastic demand. We contribute a new channel via which demand-side heterogeneity shapes pass-through by looking at consumer information in homogeneous product markets. While existing papers look at homogeneous product industries and pass-through (Hindriks and Serse, 2019, Miller et al., 2017), they though do not study how consumer information affect pass-through.

Demand specification also affects pass-through. The curvature of demand impacts pass-through rates under imperfect competition (Bulow and Pfleiderer, 1983, Weyl and Fabinger, 2013) as marginal demand changes differ across price levels. For example, under log-convex demand, one may observe more than full pass-through (Miller et al., 2017). Miravete et al. (2022) show that structural, discrete-choice models, exhibit enough flexibility to accommodate a wide range of pass-through rates.

Our paper is also related to the literature on the estimation of the price elasticity of gasoline demand. On the one hand, a consumer group's price elasticity of gasoline demand is a crucial determinant of pass-through. On the other hand, heterogeneity in the pass-through of input prices is often used to identify the elasticity of gasoline demand (Kilian and Zhou, 2023). Over the last decades, a vast literature has been trying to quantify this key metric. The main challenge is to suitably account for the endogenous correlation of gasoline prices with unobserved demand shocks. Early papers mainly relied on simple conditional quantity-price correlations at a high level of aggregation (e.g., Hughes et al. (2008)), which likely produced biased estimates towards zero. Recent papers turned to identifying the price elasticity of gasoline demand to price changes by using regional variation in tax levels and tax changes (Bento et al., 2009, Davis and Kilian, 2011, Li et al., 2014, Kilian and Zhou, 2023) or spatially pre-determined differences in price pass-through (Kilian and Zhou, 2023) as an instrument for gasoline prices. Papers find short-run elasticities to be quite inelastic, though significantly different from zero. Estimates are in the region of -0.46 (Davis and Kilian, 2011), -0.37 (Coglianese et al., 2017), -0.35 (Bento et al., 2009) or -0.10 (Li et al., 2014). Similar estimates have been obtained using household- or city-level data from Japan (Knittel and Tanaka, 2021) with -0.37 and the US (Levin et al., 2017) with -0.35 as well as in a cross-country approach for Europe (Dieler et al., 2015) with -0.20. While these estimates reflect average demand elasticities, evidence on how demand-side characteristics as well as market-level degrees of competition heterogeneously shape the elasticity of demand is rare.

Only Kilian and Zhou (2023) find that consumers in US states with lower income per capita and from more rural states are more elastic. Bento et al. (2009) show that US households with families and children as well as drivers of SUVs and small trucks are more elastic to changes in gasoline prices. We extend this literature by providing market-level and consumer group-specific results on pass-through.

Furthermore, we contribute to research on gasoline markets - see Eckert (2013) for a survey. While several papers study the role of pass-through in this industry, they have a different focus. Researchers have been trying to understand the asymmetric pass-through of price increases and decreases (Bachmeier and Griffin, 2003, Borenstein et al., 1997, Lewis, 2011, Lewis and Noel, 2011, Loy et al., 2022) and mechanisms which rationalize such pass-through asymmetries (Cabral and Fishman, 2012, Lewis, 2011, Tappata, 2009). For instance Lewis (2011) and Lewis and Noel (2011) find that input cost changes are fully passed-on to consumers, though it can take a month or longer until full pass-through is achieved. In contrast to several papers on pass-through in the gasoline markets (Bachmeier and Griffin, 2003, Borenstein et al., 1997), we are especially interested in empirically estimating pass-through at the station- and market-level instead of at the aggregate industry level. Also, we shed light on distributional implications across consumer groups of different information levels and market characteristics. Other papers on gasoline markets specifically look at the role of consumer information on prices (Chandra and Tappata, 2011, Montag et al., 2023, Pennerstorfer et al., 2020). Though, it remains an open question how information shapes station- and market-level cost pass-through and how the relation between consumer information and prices is mitigated by consumer and market characteristics.

Maybe closest to our paper's institutional setting is work by Doyle Jr. and Samphantharak (2008), Genakos and Pagliero (2022), Montag et al. (2020), and Stolper (2016). The latter study pass-through in the German gasoline market at the example of a short-term, six-month VAT reduction. They find that the VAT cut was passed on to diesel prices by 79% and to gasoline prices by 34%. For the subsequent VAT incline, they find slightly higher pass-through rates. Doyle Jr. and Samphantharak (2008) exploit a similar setting of a tax moratorium in Illinois and Indiana and find pass-through rates for tax cuts and increases of 60-80%. Genakos and Pagliero (2022) exploits exogenous variation in the number of gasoline stations in markets to understand the interaction of competition and tax pass-through. Pass-through increases with a market's competitiveness from 40% in monopolies to 100% in markets with at least four stations. Stolper (2016) is the first paper to exploit state excise tax changes at the example of Spain. Excise tax changes only affect

one cost component of firms instead of sales taxes that proportionally affect all cost components. He finds that excise tax changes are almost perfectly passed on to consumers. We extend the pass-through analysis beyond the setting of single natural experiments and especially dig deeper into pass-through heterogeneity across consumers. In doing so, we give structure to the demand-side response to price changes.

Methodologically, our paper is related to the literature on estimating search costs (Hong and Shum, 2006, Moraga-González and Wildenbeest, 2008, Wildenbeest, 2011)). We contribute to this literature by taking a market-level approach, owing to the wealth of data we have access to, and analysing determinants of the search cost distribution at the market level. In contrast to the earlier literature, which is frequently based on a single market only, we do not match station-level observables, but aggregate across gasoline stations at the market level instead. Therefore, maximum likelihood based approaches otherwise used are not feasible. We use market-level outcomes to form moment conditions. Moreover, non-parametrically estimating price distributions at the market level in the first stage as we are doing has not been previously done in this literature.¹ Several empirical reduced-form studies of retail gasoline markets are based on similar consumer search models (e.g., Chandra and Tappata, 2011, Montag et al., 2020, Montag et al., 2021, Pennerstorfer et al., 2020).

2 Industry background and Data

We study heterogeneous pass-through in the German gasoline market. The industry is ideal to understand and investigate demand-side drivers of pass-through for two reasons: First, firms sell a homogeneous good, so that pass-through heterogeneity across markets cannot be allocated to differences in products. Also, the vast majority of consumers visits gasoline stations to fuel the car, so complementarities or substitution behavior with other products cannot bias pass-through estimates. Second, gasoline markets are narrowly defined (Bundeskartellamt, 2011, Pennerstorfer et al., 2020, Martin, 2020, Chandra and Tappata, 2011). This implies that firms pricing and pass-through behavior likely is a function of local demographics and socio-economic circumstances in the very near vicinity of gasoline stations.

We gather data from three sources. First, we use the universe of diesel prices at German gasoline stations in the years 2015 to 2019. Stations fall under an obli-

¹Martin (2020) also employs a two-stage procedure, but fits a parametric price distribution at the firm level in the first stage.

gation to report all price changes in real-time to the Market Transparency Unit for Fuel (MTU) of the German cartel authority, the Bundeskartellamt. We access this price data through the online portal `tankerkoenig.de`. In our main specification, we focus on 5pm on working days when most people fuel (Bundesministerium für Wirtschaft und Energie, 2018). The price data also includes detailed information on the gasoline stations itself. Coordinates of all stations allow us to specify stations' exact location and to define geographical markets later on. Information on brand affiliation give insights to whether stations are vertically integrated into the upstream crude oil and refinery industries (Bundeskartellamt, 2011). The four firms with the highest market share (ARAL, SHELL, TOTAL, ESSO) hold approximately 50% of all stations.

As is standard practice in the literature (Martin, 2020), we drop all highway stations from the dataset. Even when highway stations are nearby street stations, they typically belong to separate markets (Bundeskartellamt, 2011).

Second, we collect data on brent crude oil prices as main input component of gasoline. The data on brent crude oil prices per gallon in US-Dollar comes from the U.S. Energy Information Administration (EIA). We convert the prices to Euro per litre metrics by using the exchange rate of Euro and US-Dollar downloaded from the website of the European Central Bank. To understand pass-through in the gasoline industry, we, therefore, are interested in how changes in oil prices map into gasoline retail prices. Comparing the time series of average gasoline prices and brent crude oil, both are almost perfectly correlated with each other (s. Figure 1).

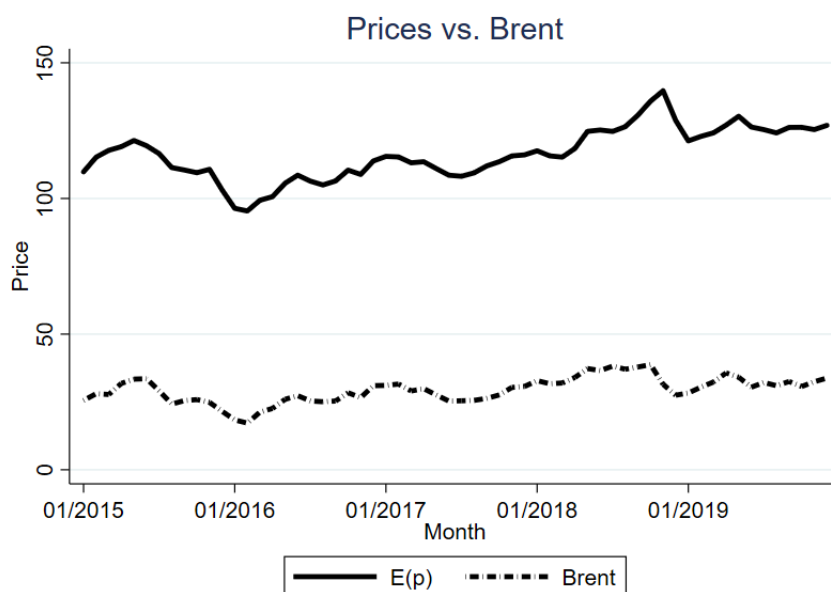


Figure 1: Time Series of Retail Price and Brent Crude Oil

Note: This figure plots the time series of average price and brent crude oil (both in Eurocents per litre).

Besides Brent crude oil, taxes are the main cost driver, which remained constant over the sample period. Retail gasoline is subject to two types of taxes. First, there is an ad-valorem tax, the value-added tax of 19%. Second, there is a per-unit energy tax for each litre of diesel sold (currently 47.04 Eurocents per litre).

We also make use of detailed administrative information on demographic and socio-economic differences across regions in Germany. In detail, we get data on GDP per capita and population density at the county level ($N = 401$) from the Federal Statistical Office and the Statistical Offices of the German States through their online database `regionalstatistik.de`. We exploit the spatial variation in market characteristics to understand heterogeneity in pass-through rates later on.

We delineate markets using a hierarchical clustering algorithm (Carranza et al., 2015, Lemus and Luco, 2021, Martin, 2020), which generates non-overlapping markets. An advantage of this approach relative to using administrative boundaries is that it allows more realistic substitution patterns across artificial boundaries. If instead a fixed radius is drawn around each gasoline station as in Pennerstorfer et al. (2020), then each station ends up indirectly competing with each other, which is again both unrealistic if interpreted at face value, and additionally computationally not feasible for structural estimation and counterfactual equilibrium computation. Exemplarily, Figure 2 displays the market distribution in and around the cities of Aachen and Wuppertal in Germany. The circles' radii indicate the maximum distance from the market's centroid, which is the geographical center of a market, to the station farthest away. For our main specification, we parametrize the clustering algorithm with an upper bound of ten stations per market, and a maximal distance of ten km between stations, which appears reasonable in our setting.

In total, we obtain 2,328 unique markets including, more than 14,000 stations ($\approx 90\%$ of all stations). Table 1 presents a variety of market characteristics. On average, a market has 6.1 stations. Figure 2 shows the distribution of market size. On average, the maximum distance between a station and the market's centroid is 4 km. This is in line with market definitions in other papers which use linear or driving distances of one or two miles as market delineations around stations (Chandra and Tappata, 2011, Hastings, 2004, Pennerstorfer et al., 2020).

To match socio-economic variables to the markets, we construct centroids for each market and assign counties accordingly. As markets are narrowly identified, the vast majority of markets does not include stations from more than one county.

A prominent feature of retail gasoline markets is price dispersion. As in Pennerstorfer et al. (2020), we calculate two measures of price dispersion, evaluated per

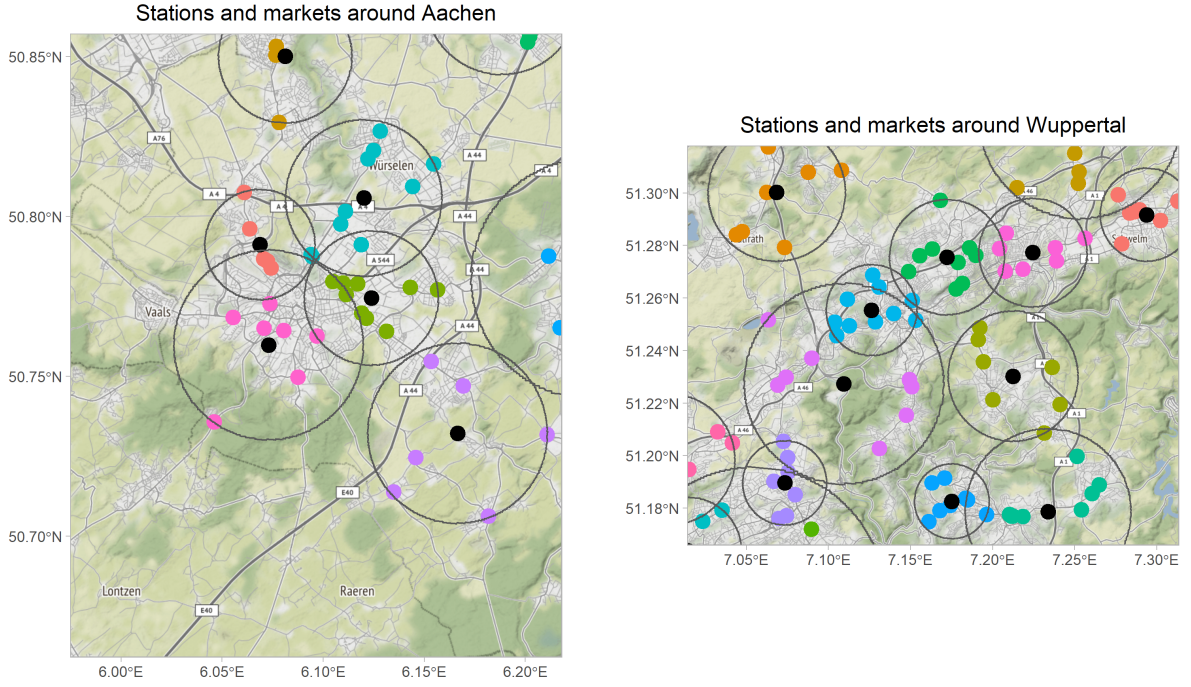


Figure 2: Illustration of market delineation

Note: The figures represent the market delineation done with a hierarchical clustering algorithm. Different colors represent different markets. Black points represent markets' centroids. Circles' radii have the maximum distance between a market's centroid and a station belonging to the market.

market m at a certain time t , given by

$$VOI(p)_{m,t} = E(p) - E_{min}(p)$$

$$Range(p)_{m,t} = E_{max}(p) - E_{min}(p)$$

where VOI denotes the *value of information*, i.e., how much a consumer can gain by purchasing at the cheapest (minimum) price as opposed to the expected price.

Table 1 reports the average price level as well as measures of price dispersion for all markets. On average, prices are 116 Eurocent per litre. However, there is considerable price dispersion in most markets. On average, consumers can gain 1.6 Eurocent per litre when buying at the minimum price instead of the mean price, which is approximately 16% of the gross margin of a typical gasoline station (Scope Investor Services, 2021). The maximum price in a market, on average, is 3.44 Eurocent per litre higher than the minimum price. As approximately 10% of all markets are monopolies, price dispersion in non-monopoly markets is even higher. The degree of price dispersion is slightly larger than, for example, in Pennerstorfer et al. (2020).

Table 1: Summary statistics, markets

Variable	Mean	Std. Dev.	Min.	Max.	N
# stations	6.069	2.95	1	10	2328
Frac. Major	0.418	0.273	0	1	2328
Frac. Integrated	0.072	0.141	0	1	2328
Frac. Other	0.51	0.283	0	1	2328
Max(dist)	4.008	2.357	0	10.891	2328
Area	67.912	64.199	0	372.597	2328
Pop.dens.	0.551	0.862	0.036	4.716	2328
GDP/cap.	35.698	14.223	15.854	167.254	2328
Mean(price)	116.348	1.843	109.539	131.189	2328
Min(price)	114.719	2.064	108.71	131.189	2328
S.d.(price)	1.486	0.597	0	7.165	2159
VOI	1.629	1.012	0	6.154	2328
Range	3.446	1.965	0	15.943	2328

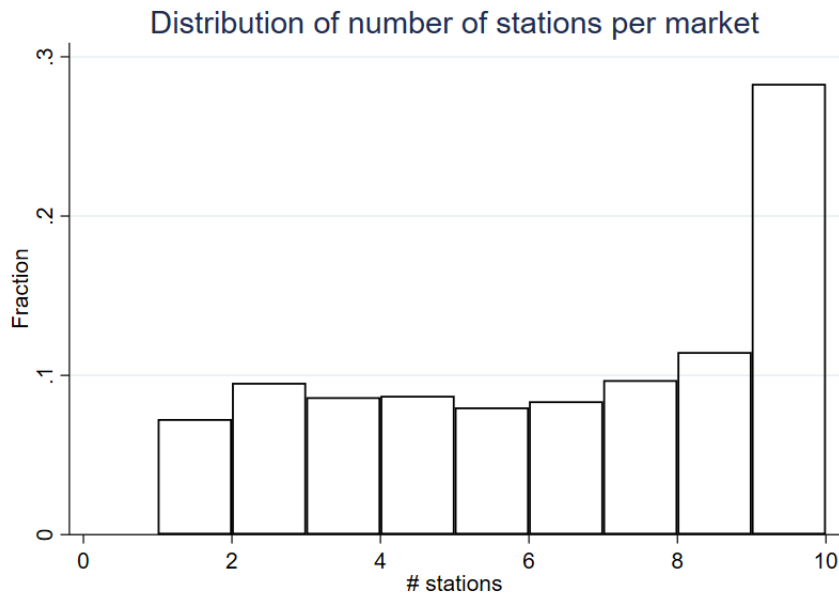


Figure 3: Distribution of number of stations per market

Note: This figure plots reflects the distribution of market size across markets. Market size is restricted to a maximum number of stations of 10.

2.1 Descriptive evidence

In this section, we provide first descriptive insights on how regional differences in socio-economic variables affect market-level price dispersion. We start by looking at markets with a different level of GDP per capita. GDP per capita proxies for disposable income and hence might reflect different degrees of price elasticities and

search behavior. As an illustration, in Figure 4, we show how market-level price dispersion depends by market-level differences in GDP per capita. Price dispersion, measured in VOI, tends to be higher in markets with higher GDP per capita. This could result from consumers searching more intensely in these markets, e.g., because of relatively easier access to price comparison websites or apps.

This pattern does not only hold in the cross-section between markets, but is also persistent over time. Figure 5 shows how the VOI develops for the lowest and highest GDP p.c. decile over time. While the VOI increases with the Brent crude oil price (left panel), the VOI is substantially higher for markets in the highest decile of the distribution. Also, the correlation of the oil price and the VOI is stronger for high GDP p.c. markets.

Naturally, markets which differ in GDP p.c. might also differ in other dimensions such as the station density or population density. Hence, we also provide simple regressions of market-level price dispersion measures on GDP p.c. and other control variables (s. Figure 2). They support a significant conditional correlation between price dispersion and GDP p.c. A 1% increase in GDP p.c. implies an increase in the VOI by 0.17 Eurocent per litre. We estimate similar effects for the range and standard deviation of market-level prices. Also, the highly significant correlation of GDP p.c. and the minimum as well as mean price indicate that GDP p.c. likely shift the distribution along the whole distribution and not just for very low prices. Hence, consumers holding few or much information about prices might be both affected by regional changes in the GDP per capita. Though, the gains from being informed increases with GDP p.c..

Explanations for the observed differences along the GDP p.c. distribution are multi-fold. First, search costs might differ across markets and might be lower in high-GDP p.c. markets. This is suggested by standard models of the consumer search literature (Stahl, 1989, Varian, 1980). But similarly, low-GDP p.c. household might also be more price-elastic and might not differ in search costs from high-GDP households. Then firms need to price near marginal costs and hence price dispersion is small. Lastly, vertical differences in gasoline markets are limited, though the extent of differentiation might differ across markets.

Thus, reduced-form correlations and estimates are not fully informative about the reasons why and mechanisms through which different markets are characterized by different market outcomes. To understand the underlying mechanism in detail, we subsequently setup a model of firm pricing and endogeneous information acquisition on the consumer side through non-sequential search.

Table 2: Baseline price regressions, market level

	(1)	(2)	(3)	(4)	(5)
	Mean(price)	Min(price)	S.d.(price)	VOI	Range
Brent	1.050*** (0.001)	1.027*** (0.001)	0.007*** (0.000)	0.023*** (0.000)	0.021*** (0.001)
Log(GDP/cap.)	1.925*** (0.011)	1.758*** (0.011)	0.020*** (0.003)	0.167*** (0.004)	0.079*** (0.007)
# stations	-0.092*** (0.001)	-0.262*** (0.001)	0.050*** (0.000)	0.170*** (0.000)	0.376*** (0.001)
Log(# stations / sqkm)	-0.110*** (0.002)	-0.035*** (0.002)	-0.070*** (0.001)	-0.074*** (0.001)	-0.156*** (0.001)
Pop.dens.	-0.617*** (0.004)	-0.611*** (0.004)	0.034*** (0.001)	-0.007*** (0.002)	0.046*** (0.003)
Constant	92.215*** (0.049)	92.194*** (0.049)	0.596*** (0.012)	0.021 (0.018)	-0.168*** (0.031)
Observations	2674395	2674395	2663700	2674395	2674395
R^2	0.771	0.750	0.147	0.169	0.219

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

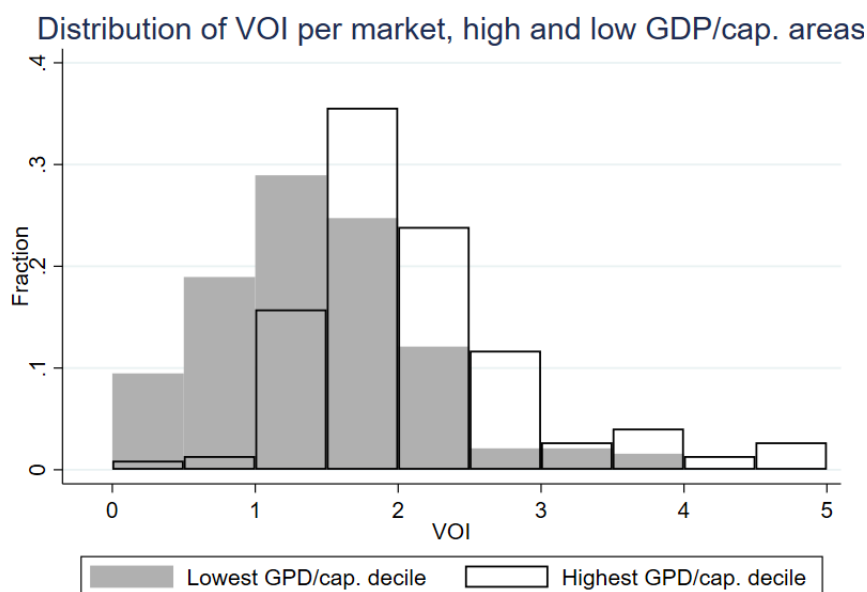


Figure 4: Distribution of VOI per market in low and high GDP p.c. areas

Note: This figure plots the distribution of market-level VOI for the bottom and top decile of the GDP p.c. distribution of markets. VOI is given in Eurocents per litre.

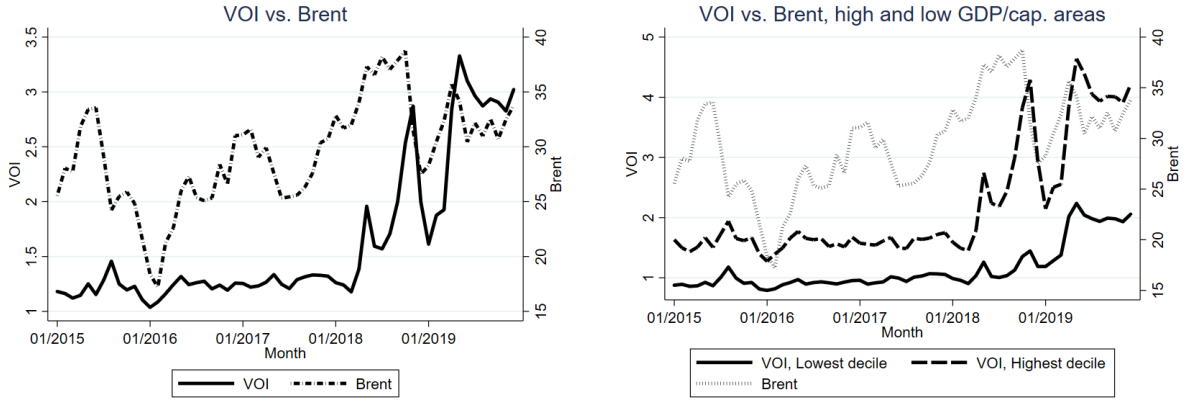


Figure 5: VOI and Brent, including high vs. low GDP/capita areas

Note: The left panel plots the time series of brent crude oil and the average VOI across markets. The right panel plots the time series of brent crude oil and the average VOI for the bottom and top decile of the GDP p.c. distribution.

3 Model

Informed by the descriptive evidence presented above, we present a model that focuses on key features of the market for our application. We assume that the following static game is repeated in every period, independently over time and across markets. Thus, we omit subscript for time period t and markets m for notational clarity in the following.

Specifically, we consider a setting with N firms who simultaneously set prices to sell a homogeneous good with marginal cost of production c . In the empirical application, $c = c_B(1+\eta)$, where c_B denotes the oil price (Brent), which is observed, and η a multiplicative input price component to be estimated.

Consumers with total mass normalized to 1 each have willingness to pay $v > 0$ for one unit of the good. Consumers are heterogeneous in the number of prices $k \in \{1, \dots, N\}$ they observe (we endogenize this distribution through consumer-optimal non-sequential search below). Denote the fraction of consumers observing k prices by μ_k such that $\sum_{k=1}^N \mu_k = 1$. As in Lach and Moraga-González (2017) and Armstrong et al. (2009), we define the probability generating function (PGF) for the number of prices observed as

$$\alpha_N(x) = \sum_{k=1}^N \mu_k(N)x^k$$

for $x \in [0, 1]$.

Denote the k -th derivative of α_N with respect to x by $\alpha_N^{(k)}(x)$, so that $\alpha_N^{(k)}(0) = k!\mu_k$. We assume that $\alpha_N^{(1)}(0) = \mu_1 \in (0, 1)$, i.e., in the terminology of Varian (1980), some, but not all consumers are loyal.

Conditional on purchasing, each consumer demands one unit of the good, resulting in per-consumer net revenue

$$R(p) = \left(\frac{p}{1 + \tau_1} - c - \tau_0 \right)$$

where τ_1 denotes ad-valorem taxes (value-added tax VAT, currently 19% in Germany) and τ_0 per-unit taxes (excise tax, currently 47.04 CPL on diesel).

In this setting, a monopolist would simply charge $p^m = v$. Standard arguments (Stahl, 1989, Lach and Moraga-González, 2017) imply that the unique Nash equilibrium of the game is in mixed strategies. Denoting by $F(p)$ the price distribution of all firms in a symmetric equilibrium, the profits of firm i from charging a price p_i are given

$$\pi_i(p) = \underbrace{\left(\frac{p}{1 + \tau_1} - c - \tau_0 \right)}_{\text{net revenue per consumer}} \underbrace{\frac{\alpha_N^{(1)}(1 - F(p))}{N}}_{\text{expected demand}}.$$

where demand is stochastic given the mixed strategies by competing firms, and weighted by the distribution of consumer types $\{\mu_k\}_{k=1}^N$ and their respective access to information, i.e., the probability $(1 - F(p))^{k-1}$ that all the k prices they observed are higher than p . The upper bound of the price distribution is given by $\bar{p} = p^m = v$. More specifically, the Nash equilibrium is characterized as follows.

Proposition 1. *Firms' equilibrium profit is given by*

$$\pi^* = \pi(\bar{p}) = \left(\frac{v}{1 + \tau_1} - c - \tau_0 \right) \frac{\alpha_N^{(1)}(0)}{N}. \quad (1)$$

Firms draw prices from a continuous distribution $F(p)$ on $[\underline{p}, \bar{p}]$ which is implicitly defined by

$$\left(\frac{p}{1 + \tau_1} - c - \tau_0 \right) \frac{\alpha_N^{(1)}(1 - F(p))}{N} = \pi^* \quad (2)$$

where

$$\underline{p} = \frac{\alpha_N^{(1)}(0)}{\alpha_N^{(1)}(1)} (v - (c + \tau_0)(1 + \tau_1)) + (c + \tau_0)(1 + \tau_1)$$

and $\bar{p} = v$.

Proof. See Stahl (1989), Section II and Lach and Moraga-González (2017). \square

Although $F(p)$ does not admit a closed form solution, its inverse, $q(\phi) = F^{-1}(\phi) = p$, can readily be obtained as (Lach and Moraga-González, 2017):

$$q(\phi) = \frac{\alpha_N^{(1)}(0)}{\alpha_N^{(1)}(1 - \phi)} (v - (c + \tau_0)(1 + \tau_1)) + (c + \tau_0)(1 + \tau_1) \quad (3)$$

A consumer who observes k prices purchases at the cheapest out of k options. The according price distribution is given by

$$F_k(p) = 1 - (1 - F(p))^k$$

$$f_k(p) = k(1 - F(p))^{k-1} f(p)$$

resulting in type- k -specific expected prices

$$E_k(p) = \int_{\underline{p}}^{\bar{p}} p f_k(p) dp = \underline{p} + \int_{\underline{p}}^{\bar{p}} (1 - F(p))^k dp \quad (4)$$

and average *transaction* prices (as opposed to the average *posted* price $E(p)$)

$$E_{tra}(p) = \sum_{k=1}^N \mu_k E_k(p) \quad (5)$$

Given the equilibrium price schedule, all consumers purchase in equilibrium. Under the unit demand assumption, price are simply transfers between consumers and firms and hence total-welfare neutral.

The type- k -specific consumer surplus (excluding search costs) is given by

$$CS_k = v - E_k(p)$$

and hence the aggregate consumer surplus is

$$CS = \sum_{k=1}^N \mu_k CS_k = v - E_{tra}(p)$$

3.1 Non-sequential search

Obtaining information is costly. We embed this consideration in a model of non-sequential search (Burdett and Judd, 1983, Janssen and Moraga-González, 2004, Wildenbeest, 2011, Martin, 2020), i.e., consumers decide upfront how many prices to sample, and subsequently purchase from the firm with the lowest price in their sample. As is common in the literature, we assume that the first search is for free (costless), but obtaining additional price quotes is costly. Consumers are heterogeneous in their search cost s per price quote, where s is drawn from a continuous distribution $G(s)$ without mass points on $(0, \infty)$. In equilibrium, consumer choices are optimal given their search cost s and given the equilibrium price distribution $F(p)$. Thus, a consumer searching k times (weakly) prefers the expected outcome to searching $k' \neq k$ times, i.e.

$$v - E_k(p) - ks \geq v - E_{k'}(p) - k's.$$

Since s has infinite support, in equilibrium there is a set of cutoff points $\{s_k\}_{k=1}^{N-1}$ determined by the marginal consumer who prefers k searches to $k + 1$ searches:

$$v - E_k(p) - (k - 1)s_k = v - E_{k+1}(p) - ks_k$$

and hence

$$s_k = E_k(p) - E_{k+1}(p). \quad (6)$$

Therefore, in equilibrium all consumers with $s \in [s_{k+1}, s_k]$ search k times, resulting in fractions

$$\mu_k = G(s_{k-1}) - G(s_k), \quad k = 2, 3, \dots, N-1 \quad (7)$$

and $\mu_1 = 1 - G(s_1)$ and $\mu_N = G(s_{N-1})$.

3.2 Equilibrium

In equilibrium, firms take consumer behavior as given (characterized by their information distribution $\{\mu_k\}_{k=1}^N$, resulting in PGF $\alpha_N(x)$), and draw prices according to $F(p; \{\mu_k\}_{k=1}^N)$ in (2) (or alternatively, the quantile expression in (3)).

Consumers, in turn, take firm behavior as given (characterized by $F(p; \{\mu_k\}_{k=1}^N)$), and search according to the cutoff rule $\{s_k\}_{k=1}^{N-1}$ in (6), resulting in $\{\mu_k\}_{k=1}^N$ according to (7).

For computing the equilibrium, it is convenient to rewrite expressions as follows (Wildenbeest, 2011). We use the substitution $y = 1 - F(p)$ and obtain

$$E_k(p) = \int_{\underline{p}}^{\bar{p}} pk(1 - F(p))^{k-1} f(p) dp = \int_0^1 p(y)ky^{k-1} dy$$

so we can write

$$s_k = E_k(p) - E_{k+1}(p) = \int_0^1 p(y)(k - (k+1)y)y^{k-1} dy \quad (8)$$

Next, we introduce a constant $\kappa = (c + \tau_0)(1 + \tau_1)$ and obtain from (3) that

$$q(\phi) = \frac{\alpha_N^{(1)}(0)}{\alpha_N^{(1)}(1 - \phi)}(v - \kappa) + \kappa = \frac{\mu_1(v - \kappa)}{\sum_{k=1}^N k\mu_k(1 - \phi)^{k-1}} + \kappa.$$

By using $p(y) = q(1 - \phi)$ in (8), we can eliminate the dependency on $F(p)$ and write

$$s_k(\{\mu_k\}_{k=1}^N) = \int_0^1 \left(\frac{\mu_1(v - \kappa)}{\sum_{l=1}^N l\mu_l y^{l-1}} + \kappa \right) (k - (k+1)y)y^{k-1} dy$$

and we obtain our equilibrium condition

$$\begin{aligned} \mu_1 &= 1 - G(s_1(\{\mu_k\}_{k=1}^N)) \\ \mu_k &= G(s_{k-1}(\{\mu_k\}_{k=1}^N)) - G(s_k(\{\mu_k\}_{k=1}^N)), \quad k = 2, 3, \dots, N-1 \\ \mu_N &= G(s_{N-1}(\{\mu_k\}_{k=1}^N)) \end{aligned} \quad (9)$$

which using the fact that $\mu_N = 1 - \sum_{k=1}^{N-1} \mu_k$ is a $N-1$ -dimensional fixed point problem.

3.3 Taxes and pass-through

Given a per-unit (excise) tax rate τ_0 and unit demand of a mass 1 of consumers, excise tax revenue is simply

$$TR_0 = \tau_0 \cdot 1$$

and given an ad-valorem (VAT) tax rate τ_1 , VAT tax revenue is given by

$$TR_1 = \sum_{k=1}^N \mu_k TR_{1,k}$$

where

$$TR_{1,k} = \tau_1 E_k(p)$$

and therefore $TR_1 = \tau_1 E_{tra}(p)$, resulting in total tax revenue

$$TR = TR_0 + TR_1 = \tau_0 + \tau_1 E_{tra}(p) \quad (10)$$

The type- k -specific pass-through rate is given by

$$\begin{aligned} \rho_k &= \frac{\partial E_k(p)}{\partial c} \\ &= \frac{\partial \underline{p}}{\partial c} + \frac{\partial \bar{p}}{\partial c} (1 - F(\bar{p}))^k - \frac{\partial \underline{p}}{\partial c} (1 - F(\underline{p}))^k + \int_{\underline{p}}^{\bar{p}} \frac{\partial (1 - F(p))^k}{\partial c} dp \\ &= \int_{\underline{p}}^{\bar{p}} \frac{\partial (1 - F(p))^k}{\partial c} dp \\ &= - \int_{\underline{p}}^{\bar{p}} k (1 - F(p; c))^{k-1} \frac{\partial F(p; c)}{\partial c} dp \end{aligned}$$

and finally we obtain the average pass-through rate as

$$\rho_{avg} = \sum_{k=1}^N \mu_k \rho_k.$$

4 Estimation

Our estimation is based on aggregation at the market-period level. Specifically, we form market-period moments, matching observed $E(p_{m,t})$, $Var(p_{m,t}) = E(p_{m,t}^2) - E(p_{m,t})^2$ and $E(p_{min,m,t})$. We observe market-level objects upfront and perform all calculations at the market-period level.

The model-implied objects like p^m and quantiles of the price distribution can easily be obtained from (3). The respective moments are simple one-dimensional integrals at the market-period level, which we can readily compute using e.g. the trapezoid method.

For computation, it is convenient to calculate using integration by parts as follows:

$$\begin{aligned}
E(\tilde{p}; \theta) &= \int_{\underline{p}}^{\bar{p}} p f(p) dp = \bar{p} - \int_{\underline{p}}^{\bar{p}} F(p) dp \\
E(\tilde{p}^2; \theta) &= \int_{\underline{p}}^{\bar{p}} p^2 f(p) dp = (\bar{p})^2 - 2 \int_{\underline{p}}^{\bar{p}} p F(p) dp \\
E(\tilde{p}_{min}; \theta) &= \int_{\underline{p}}^{\bar{p}} p f_{min}(p) dp = N \int_{\underline{p}}^{\bar{p}} p (1 - F(p))^{N-1} f(p) dp \\
&= \int_{\underline{p}}^{\bar{p}} \underbrace{p}_u \underbrace{N(1 - F(p))^{N-1} f(p)}_{v'} dp \\
&= [-p(1 - F(p))^N]_{\underline{p}}^{\bar{p}} + \int_{\underline{p}}^{\bar{p}} (1 - F(p))^N dp \\
&= \underline{p} + \int_{\underline{p}}^{\bar{p}} (1 - F(p))^N dp
\end{aligned} \tag{11}$$

Then our moments are given by

$$m(\theta) = \frac{1}{T} \begin{pmatrix} z' [E(p_{m,t}) - E(\tilde{p}_{m,t}; \theta)] \\ z' \left[\left(E(p_{m,t}) - \overline{E(p_{m,t})} \right)^2 - \left(E(\tilde{p}_{m,t}; \theta) - \overline{E(\tilde{p}_{m,t}; \theta)} \right)^2 \right] \\ z' [Var(p_{m,t}) - Var(\tilde{p}_{m,t}; \theta)] \\ z' [E(p_{min,m,t}) - E(\tilde{p}_{min,m,t}; \theta)] \end{pmatrix} \tag{12}$$

where z is a instrument matrix for each of our market-period observations. We use the oil price, the number of stations, day-of-the-week dummies, yearly dummies, and market-level demographics as instruments. Then our GMM estimator is given by the solution to

$$\arg \min_{\theta} m(\theta)' W m(\theta) \tag{13}$$

for a weighting matrix W , e.g., the identity matrix.

Our starting point is letting $v = p_{max}$ for each market and month. Alternatively, we could also estimate v by residualizing or through maximum likelihood (Wildenbeest, 2011). We then use a two-stage estimation approach in order to eliminate the necessity to solve the fairly involved fixed-point problem for equilibrium computation for every evaluation of the objective function. Similar to approaches in the auctions literature and in dynamic games, we first estimate (conditional) price distributions, which can subsequently be used as equilibrium beliefs about firm behavior from the consumers' point of view.

More specifically, we non-parametrically estimate the market- m -specific price distribution in period t conditional on the oil price c , $\hat{F}_{m,t}(p|c)$, using the method by Li and Racine (2008).² We can plug this estimated distribution into (4) to compute

²We use the R package “np” for estimation of the conditional price distributions, see Hayfield and Racine (2008).

estimated type- k specific expected prices $\hat{E}_{k,m,t}$. These estimated expected prices serve as input in the estimated equilibrium cutoff points $\hat{s}_{k,m,t}$ in the search costs in (6). Therefore, during estimation of the parameters governing search, we can treat the cutoff points $\hat{s}_{k,m,t}$ as “data”.

We parametrize the search cost distribution as follows, allowing for an annual trend and dependency on market-level observables such as GDP per capita and then number of stations. Search costs s in market m in year y are assumed to follow a log-normal distribution $s \sim \text{Lognormal}(\mu_{y,m}, \sigma_{y,m})$, where

$$\mu_{y,m} = \mu_0 + \mu_1(y - 2014) + \mu_2 \log(\text{GDP}/\text{cap}_m) + \mu_3 \log(n_m/\text{sqkm})$$

$$\sigma_{y,m} = \sigma_0 + \sigma_1(y - 2014) + \sigma_2 \log(\text{GDP}/\text{cap}_m) + \sigma_3 \log(n_m/\text{sqkm})$$

Additionally, we estimate the marginal cost multiplier η . Thus, we are interested in estimating a parameter vector $\theta = (\{\mu_i, \sigma_i\}_{i=0}^3, \eta)$. For each parameter guess θ , we obtain right away the respective fractions of consumers searching k times from (7). Upon plugging these fractions into the equilibrium quantile relationship (3), we compute our moments for GMM estimation.

4.1 Estimating pass-through

We estimate the type- k -specific pass-through rate $\rho_{k,m}$ at the market- m level as follows. We first purge out day-of-the-week and yearly fixed effect from both the oil price and $E_k(p)$ from our non-parametric first stage estimation, yielding residuals \hat{c}_t and $\hat{E}_{k,m,t}(p)$. Afterwards, we obtain the market-level estimate of $\rho_{k,m}$ by

$$\rho_{k,m} = \frac{\text{cov}(\hat{c}, \hat{E}_{k,m,t}(p))}{\text{var}(\hat{c})}. \quad (14)$$

The distribution of consumer types $\{\mu_{k,m,t}\}$ is taken from the respective equilibrium conditions, evaluated at the optimal parameter vector θ^* . The market- m average pass-through is obtained by

$$\bar{\rho}_m = \sum_{k=1}^N \bar{\mu}_{k,m} \rho_{k,m} \quad (15)$$

where $\bar{\mu}_{k,m} = 1/T \sum_{t=1}^T \mu_{k,m,t}$.

5 Estimation results

We proceed with estimation as described in the previous section. Note that we currently use only a subsample from the years 2015-2017, consisting of random 10% of the the entire period in order to reduce computational burden.

Our main estimation results are shown in Table 3.³ On the consumer side, we estimate a parametric log-normal search cost distribution, resulting from an underlying normal distribution with mean μ and standard deviation σ . Search costs are interpreted as finding *a suitable gasoline station*, relative to the costs of filling up an entire tank. We find that μ decreases over time, and also in the markets' GDP/cap. and station density. Thus, search costs tend to lower in higher GDP areas (although the variance is higher). For instance, in the median market, this implies that the median search costs were 1.74 in 2015, and 1.58 in 2017. Relative to filling up an entire tank of 50l, this implies that the relative costs of obtaining one additional price quote is $1.58 \times 50 = 79$ Eurocent, which appears reasonable. As an illustration, the respective search cost distributions are shown in Figure 6, for annual shifts (top left panel), shifts depending on high and low GDP/cap. areas (top right panel), and shifts depending on station density (lower panel).

Our estimates for the multiplicative marginal cost term η is 0.31, i.e., an additional 31% on top of the oil price are. Although we are not matching an aggregate margin moment, the estimated margin are very close to those provided industry reports (Scope Investor Services, 2021).

The estimated search cost distributions are primitives of the model. We now discuss how search costs translate into consumer information in equilibrium, which in our setup is crucial for firm pricing. In the left panel of Figure 7, we depict the distribution (across market-periods) of the mean number of stations k observed per consumer. Note that this comparison is not entirely straight-forward, since markets differ in their number of stations to start with. Yet, the observed heterogeneity across markets appears relevant.

In the right panel of Figure 7, we only consider markets with six stations for better comparability. On average, 70 % of consumers observe only one station, and thus purchase at the expected prices. Due to their relatively high search costs, they still prefer that outcome to searching for cheaper offers. Over 20% of consumers observe at least two stations and thus purchase at $E_2(p)$, i.e, the expected minimum from two prices quotes. Excluding of search costs, their expected surplus equals the value of $VOI_2 = E(p) - E_2(p)$.

³Standard errors are obtained from the variance-covariance matrix evaluated at the optimum θ , numerically approximated with finite differences ($h = 10^{-9}$). Thus, the reported standard do not consider noise stemming from the first-stage estimation, which would require bootstrapping.

Table 3: Estimation results

Variable	Estimate			
	Const.	Trend	log(GDP/cap.)	# stations
Search cost μ	1.78 (0.04)	-0.05 (0.00)	-0.34 (0.01)	-0.00 (0.00)
Search cost σ	0.21 (0.01)	0.02 (0.00)	0.03 (0.00)	-0.04 (0.00)
Marginal costs multiplier η	0.31 (0.00)			
Med(s), 2015	1.74			
Med(s), 2017	1.58			
Med(s), Low GDP/cap.	1.76			
Med(s), High GDP/cap.	1.36			
Med(s), Low stat.dens.	1.59			
Med(s), High stat.dens	1.57			
Mean(margin)	10.34			

Note: Standard errors in parentheses (see main text for details).

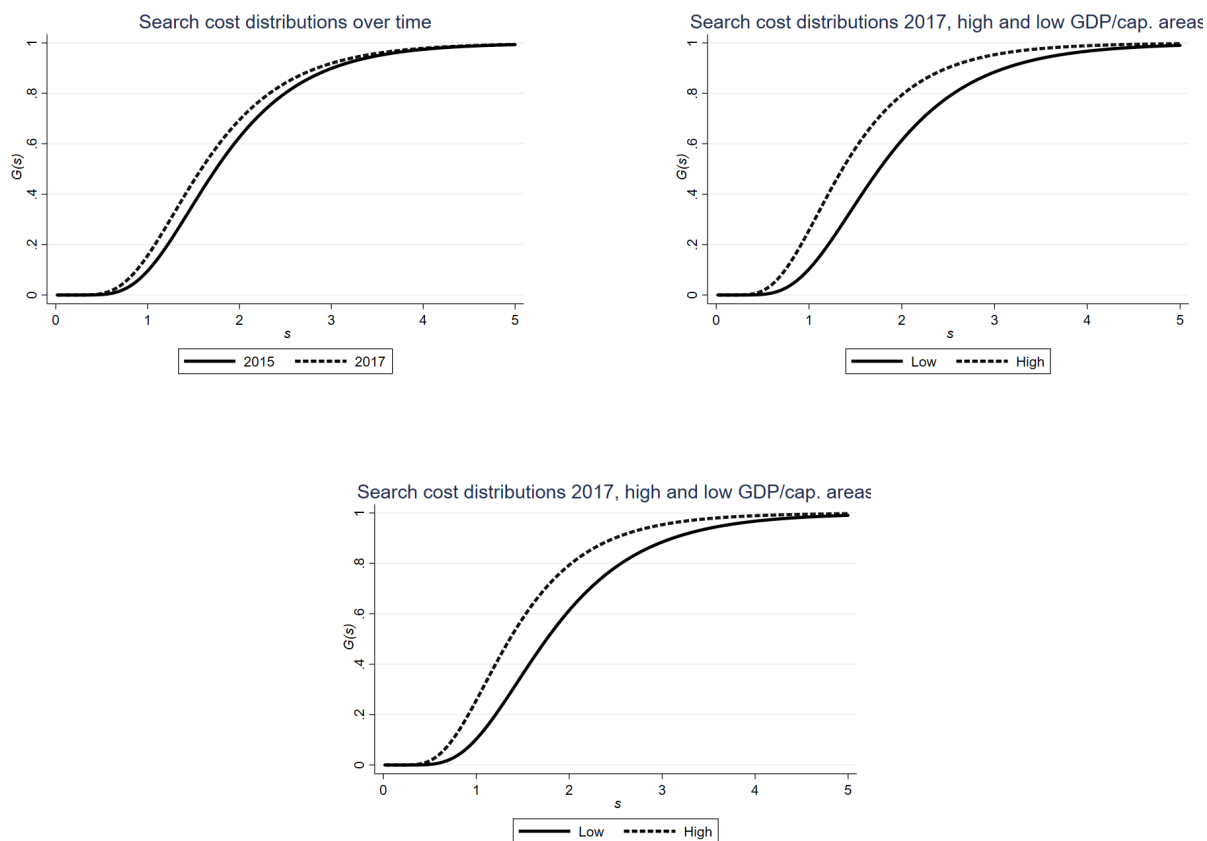


Figure 6: Estimated search cost distributions

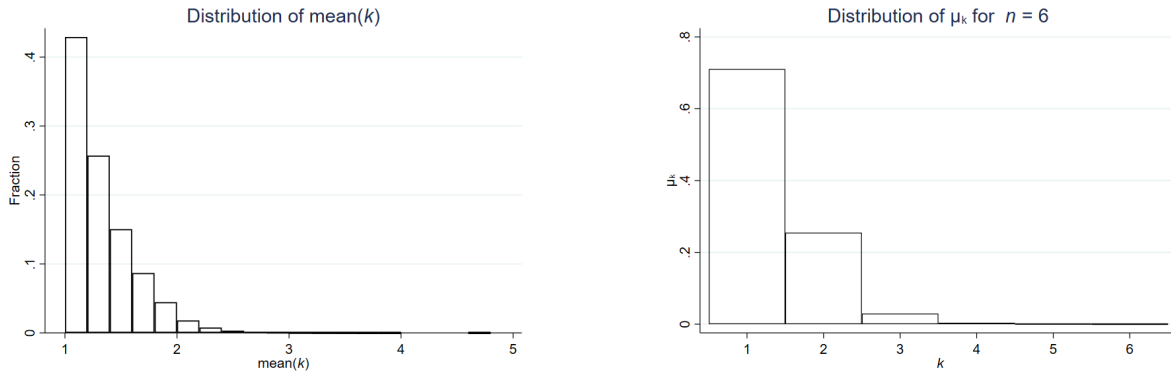


Figure 7: Number of stations observed

5.1 Pass-through

We now turn to the analysis of the implied input-cost pass-through rates, using the approach described in Section 4.1.

Consider first the estimated pass-through rates for consumer type k , shown in Figure 8. Recall that a consumer type $k = 1$ purchase at the expected prices $E(p)$, whereas a consumer type $k = n$ purchases at the *minimum* of N draws from the price distribution $F(p)$, i.e., $E_{min}(p)$, which by definition is less than $E(p)$. However, as the figure shows, consumer types who observe more prices face *lower* pass-through in equilibrium, i.e., their transaction prices are less sensitive to changes in input costs.

In Figure 9, we separately depict estimate pass-through rates by decile of the respective market in the GDP/capita distribution. Since markets differ in their characteristics, and in particular, in their number of stations and the respective search cost distribution on the consumer side, also the distribution of consumer information differs across markets. We therefore also consider the market-level average pass-through rate ρ_{avg} , which is weighted by the measure of type- k consumers. All pass-through rates are higher in areas with high GDP/capita.

Finally, in Figure 10, we separately depict estimate pass-through rates depending on station density in the respective market. For all pass-through rates, we find a very consistent pattern, namely that the markets pass-through is higher in areas with more stations, which seems plausible.

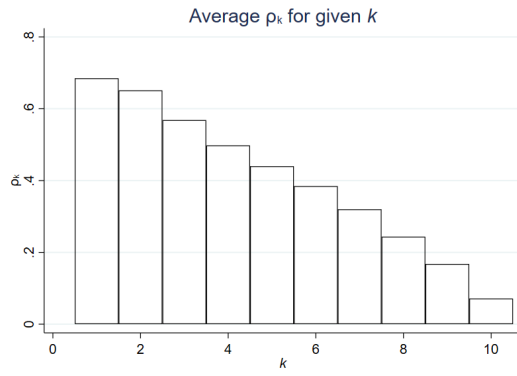


Figure 8: Estimated pass-through rates for consumer type k

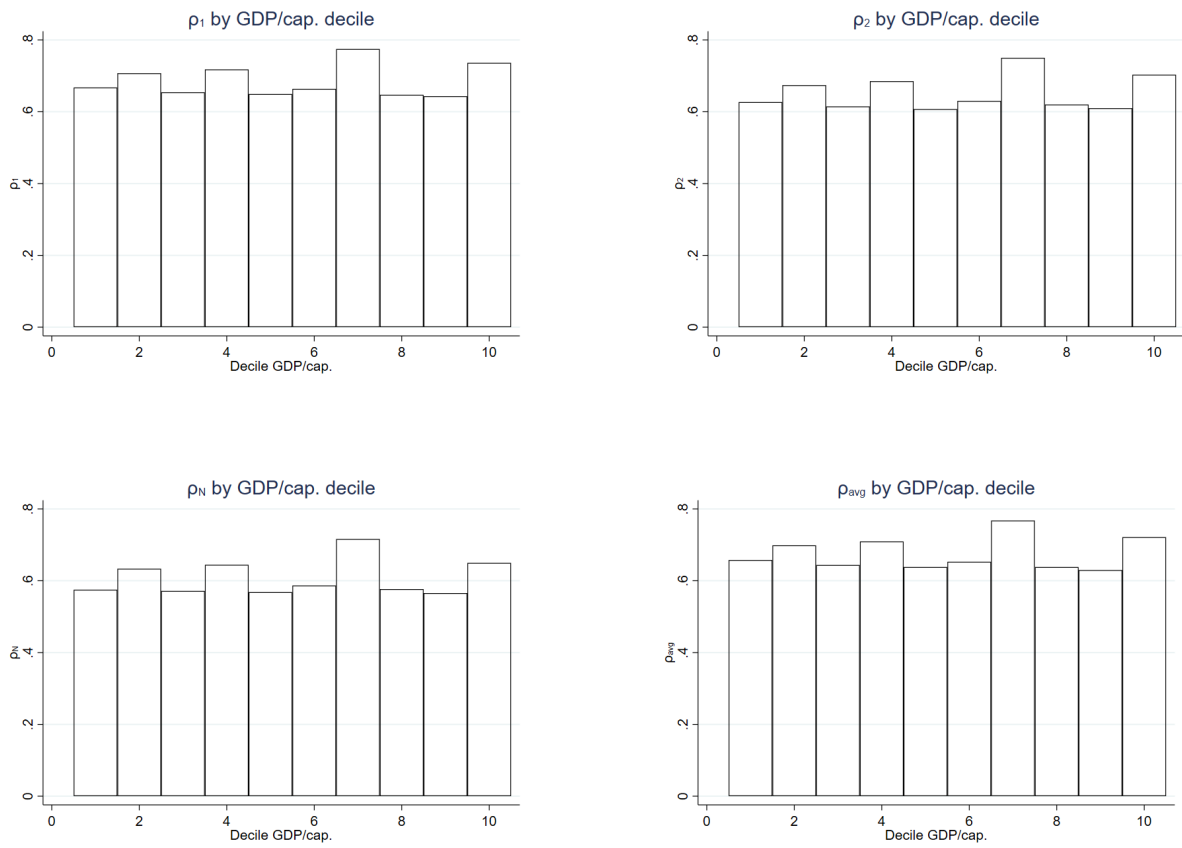


Figure 9: Pass-through, depending on GDP/cap. deciles

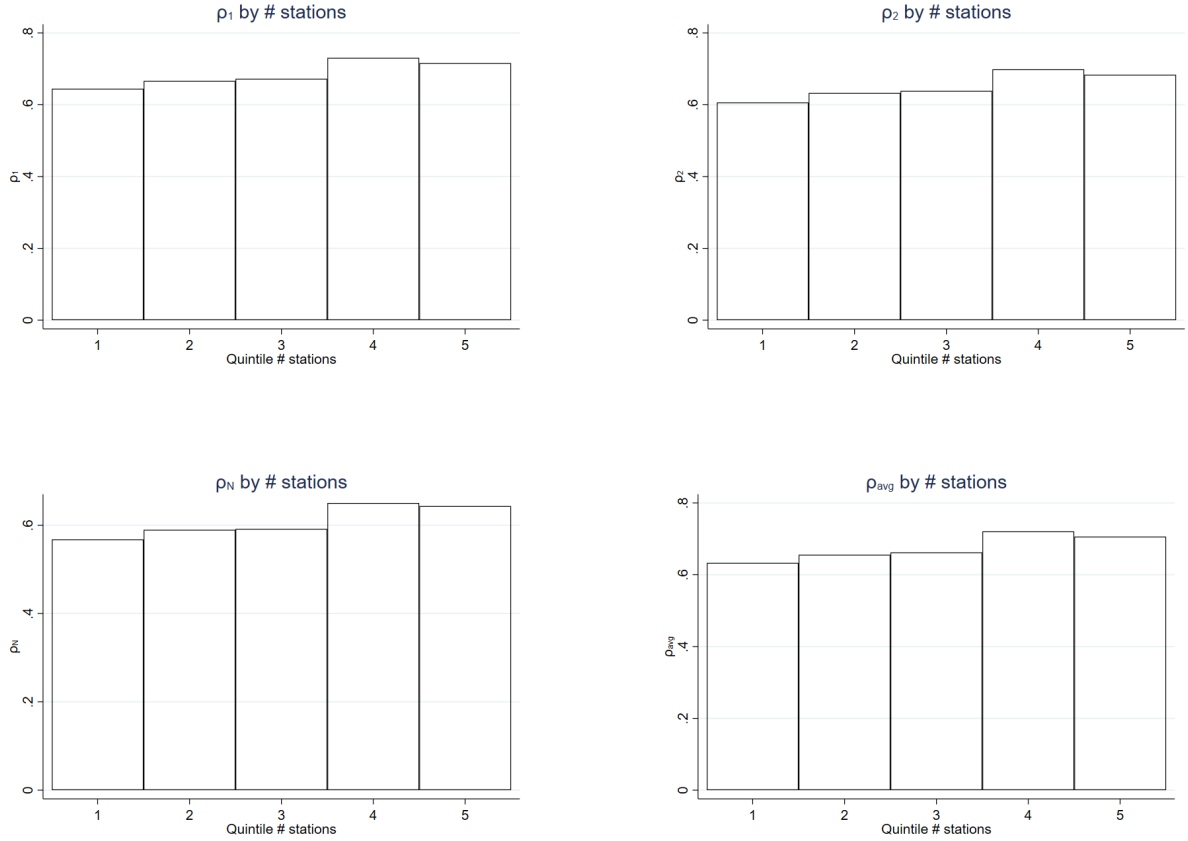


Figure 10: Pass-through, depending on number of stations

6 Counterfactual analysis

We simulate a tax change that was actually implemented in Germany from July to December 2020 in view of the COVID-19 pandemic, namely a VAT reduction from 19% to 16%, i.e., a reduction by around 16.6%. The pass-through rate of this tax change is given by (Montag et al., 2020)

$$\rho_\tau = \frac{\partial p}{\partial \tau} \frac{1 + \tau}{p},$$

where under full pass-through, prices should adjust by -2.52% . Montag et al. (2020) find a price reduction of -1.99% for diesel, i.e., a pass-through rate of 79%. However, since this tax reduction was precisely in response to major changes on the supply and demand side due to the pandemic, it is difficult to isolate the underlying channels.

We thus analyse the tax change in a counterfactual manner instead. Based on our estimates of the structural parameters, we now compute status-quo and counterfactual equilibria (see Section 3.2). Although this is a relatively involved $N - 1$ -dimensional fix point problem at the market level (searching for the distribution of consumer types $\{\mu_k\}$), computation is facilitated by the fact that it can be

parallelized at the market-period level, owing to our non-overlapping markets and our static model assumption.

We separately consider possible short-term and long-term consequences of the tax policy change. In the short-term, we allow only firms to adjust their prices responding to the tax change, but hold the distribution of consumer types $\{\mu_k\}_{k=1}^N$ fixed, as implied by the equilibrium in the baseline specification. As such, this outcome represents only a partial equilibrium analysis, since consumer behavior remains fixed.

In the long-term, we additionally allow consumers to adjust their non-sequential search behavior in an optimal way, such that consumer and firms are again in equilibrium, taking behaviour on the other market side as given.

In Table 4, we depict several outcomes of interest, taking the average across all our markets. x_0 denotes baseline quantities, and Δ_{short} and Δ_{long} the relative percentage change over the short and long run, respectively. Both in the short and long run, prices decrease and price dispersion increases when the VAT rate is reduced to 16%. Posted prices decrease by 2.10% in the long run. This implies a pass-through rate of 83%, slightly above the estimate from Montag et al. (2020). Naturally, the expected minimum price $E_{min}(p)$ and the average transaction price $E_{trans}(p)$ decrease even more, because consumers dis-proportionally purchase at lower prices. Cross-sectional price dispersion $s.d.(p)$ increases, because firm find it relatively more attractive to offer low prices targeted to the informed consumer segment only, since their effective marginal costs are reduced.

In the short run, firms' profit increases by 19.69%, mostly because they effectively face lower marginal costs and consumer search behavior still remains unchanged. This is also highlighted in the reported objects concerning consumer information: μ_x and the resulting mean number of stations k observed are unchanged in the short run.

In the long run, however, consumers understand that they should search more in the new environment in which taxes are lower, which leads to lower prices, more price dispersion, and hence higher gains of search. Indeed, we find that more consumers find it worthwhile to obtain two prices quotes (μ_2 increases) instead of one price quote only (μ_1 decreases). This puts additionally competitive pressure on the firms since consumers are effectively more price elastic, leading to lower prices than in the short run, and importantly, profits that are *even lower* than under the baseline tax regime. The combination of these effects also leads to an increase in consumer surplus that is twice as large in the long run than in the short run.

In Table 5, we break down the analysis by separately considering only markets in

the last (x^{high}) and the first decile (x^{low}) of the GDP/cap. distribution, respectively. Both in the short run and in the long run, high GDP/cap. markets experience a stronger price effect, owing to lower search costs, which lead to better informed consumers ex-ante. Thus, high GDP/cap. areas also benefit more from the tax reduction. However, the difference is less pronounced in the long run, because consumer information endogeneously responds more strongly in low GDP/cap. markets (mean k increases by 0.90%, as opposed to a 0.26% decrease in high GDP/cap. markets). Our analysis shows that not only average search costs matter for equilibrium outcomes, but the shape of the entire distribution, a point also made in Wildenbeest (2011)

Table 4: Counterfactual results

	x_0	$\Delta_{short}\%$	$\Delta_{long}\%$
$E(p)$	106.53	-1.11	-2.10
$s.d.(p)$	3.13	13.37	13.23
$E_{min}(p)$	103.69	-1.52	-2.31
$E_{trans}(p)$	105.46	-1.26	-2.28
Π	0.01	19.69	-0.91
μ_1	0.46	0.00	-12.42
μ_2	0.50	0.00	13.58
μ_N	0.07	0.00	-5.66
mean(k)	1.65	0.00	0.23
TR_1	0.20	-16.85	-17.71
CS	0.10	12.83	23.33

Table 5: Counterfactual results, high and low GDP/cap. areas

	x_0	$\Delta_{short}\%$	$\Delta_{long}\%$	x_0^{high}	$\Delta_{short}^{high}\%$	$\Delta_{long}^{high}\%$	x_0^{low}	$\Delta_{short}^{low}\%$	$\Delta_{long}^{low}\%$
$E(p)$	106.53	-1.11	-2.10	104.93	-1.38	-2.17	108.31	-0.82	-1.90
$s.d.(p)$	3.13	13.37	13.23	3.21	13.74	9.69	2.74	13.19	18.64
$E_{min}(p)$	103.69	-1.52	-2.31	102.08	-1.82	-2.29	105.78	-1.16	-2.21
$E_{trans}(p)$	105.46	-1.26	-2.28	103.68	-1.56	-2.33	107.47	-0.92	-2.08
Π	0.01	19.69	-0.91	0.00	17.96	5.53	0.01	19.88	-2.35
μ_1	0.46	0.00	-12.42	0.34	0.00	-12.73	0.60	0.00	-11.40
μ_2	0.50	0.00	13.58	0.61	0.00	8.39	0.37	0.00	22.38
μ_N	0.07	0.00	-5.66	0.02	0.00	-30.33	0.11	0.00	3.34
mean(k)	1.65	0.00	0.23	1.78	0.00	-0.26	1.52	0.00	0.90
TR_1	0.20	-16.85	-17.71	0.20	-17.10	-17.75	0.20	-16.57	-17.54
CS	0.10	12.83	23.33	0.12	13.26	19.81	0.08	12.67	28.44

7 Conclusion

The contribution of regulatory interventions to the efficient allocation of resources is one of *the* central themes in economics, especially in the view of rising commodity prices and inflation. Our study shows an important channel that modulates the effectiveness and the distributional consequences of taxation, namely through endogenous information acquisition on the consumer side.

Specifically, we adjust a non-sequential consumer search model to the German retail fuel market, in which cross-sectional price dispersion is a central feature. We find that search costs are decreasing over time. Moreover, median search costs are 22% lower in the markets with very high GDP/cap. than in markets with very low GDP/cap. (the last and first decile in the GDP/cap. distribution, respectively). Besides its first-order relevance in its own right, this finding also informs the theoretical literature on consumer search, which typically is agnostic about whether high-valuation consumers also have higher search costs. To the best of our knowledge, this is the first paper that directly speaks to that question.

Endogenously searching for prices leads to an atypical form of price discrimination. Although each firm posts one price only and does not discriminate directly, consumers differ in the number of price quotes they obtain (chosen endogenously given their respective search costs). Hence, they also differ in their expected transaction prices. A consumer who samples only one firm observes one price realization only, whereas a consumer who samples ten firms may pick the cheapest out of these ten. This implies that consumers also differ in their *effective* pass-through rates they are faced with. According to our structural estimates, consumers with better access to information pay lower prices, but also their effective pass-through rates are lower.

Based on our model estimates, we compute a counterfactual in which the VAT rate is reduced from 19% to 16%. We find that posted prices decrease by 1.11% in the short run and by 2.10% in the long run, which implies an average pass-through rate of 83%. The long run effect is stronger due to an adjustment in the endogenous information acquisition on the consumer side, which makes searching for cheap offers more attractive, putting additional competitive pressure on the firms.

Finally, analyzing separately markets with high and low GDP/cap., respectively, we find that the price reduction following the VAT change is stronger in market with high GDP per capita. The main reason is that search costs tend to be lower in these areas. Thus, our analysis shows that the information channel has first-order distributional consequences that should be taken into account by policy makers.

Appendix

A Additional figures

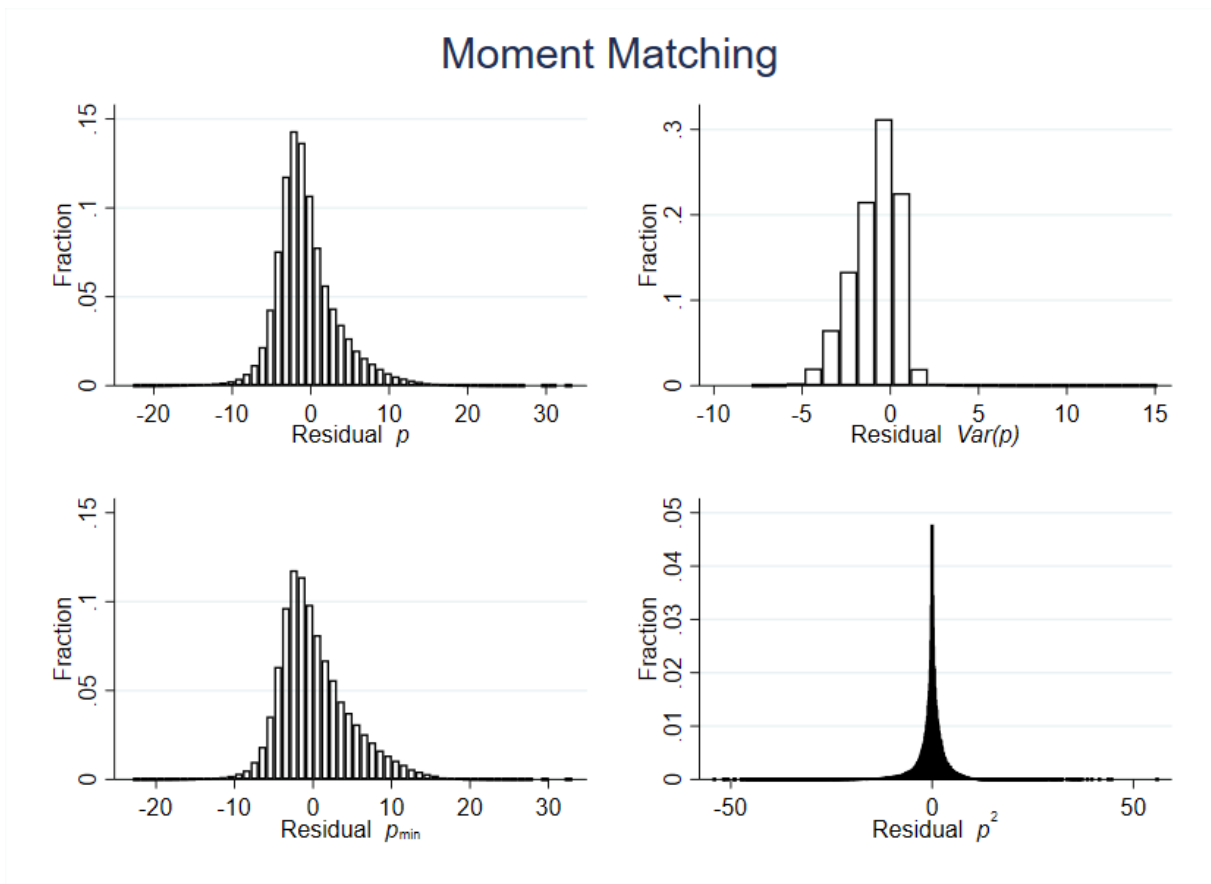


Figure 11: Moment matching

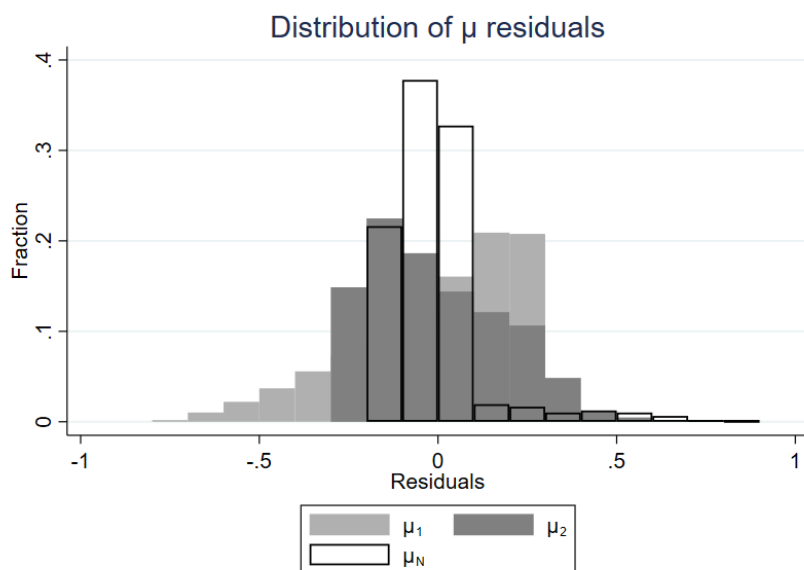


Figure 12: Residuals of $\mu_k = \alpha_0 + \alpha_1 n + \varepsilon$

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