Indirect taxation in consumer search markets: The case of retail fuel*

Kai Fischer† Simon Martin‡ Philipp Schmidt-Dengler§

May 15, 2024

Abstract

When consumers have heterogeneous access to information about prices, they face different observed price distributions and thus possibly different effective pass-through rates. We estimate a model of consumer search using data from the German retail fuel market. We find that informed consumers face higher effective pass-through rates, with important distributional implications for regulatory and tax policies. Lowering the VAT rate from 19% to 16% decreases transaction prices by 1.9% on average, but disproportionally benefits consumers in high-income markets. We further show that a tax-revenue-equivalent excise tax reduction would have benefited consumers more than a VAT cut, thus generalizing known results in public economics to markets with imperfect information.

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

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

*We would like to thank seminar and conference participants at Toulouse School of Economics, KU Leuven, DICE, CLEEN (Mannheim, 2023), Verein fuer Socialpolitik Annual Meeting (Regensburg, 2023), EARIE (Rome, 2023), Consumer Search and Switching Costs Workshop (Rotterdam, 2023), and the Asia Meeting of the Econometric Society (Delhi, 2024) for their valuable feedback. This project also benefited from comments by Nicolas de Roos, Natalia Fabra, José Luis Moraga-Gonzalez, Helena Perrone, Mathias Reynaert, Nicolas Schutz, Joel Stiebale, Jo Van Biesebroeck, Frank Verboven, Matthijs Wildenbeest, and Biliana Yontcheva. Funding from the German Research Foundation (DFG, project 504715884 and 235577387/GRK1974) 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.

†kfischer@dice.hhu.de. Düsseldorf Institute for Competition Economics (DICE) at Heinrich-Heine-Universität Düsseldorf

‡simon.martin@dice.hhu.de. Düsseldorf Institute for Competition Economics (DICE) at Heinrich-Heine-Universität Düsseldorf, also affiliated with CEPR and CESifo

§philipp.schmidt-dengler@univie.ac.at. University of Vienna, also affiliated with CEPR, CESifo, and WIFO

1 Introduction

Consumption taxes are among the most visible components of policy interventions, with an average standard VAT rate of 19.2% in OECD countries (OECD, 2022). At the same time, they are a major source of government finances, generating a total tax revenue of around 10% of GDP. Apart from transferring resources between consumers, firms, and the government, taxes also serve a redistributive role between different groups of consumers and households, e.g., through a progressive income tax schedule. Noteworthy, most of the literature on taxation and tax incidence, dating back to Ramsey (1927) and Mirrlees (1976), operates under the assumption that consumers are perfectly informed about prices.

The debate among the public, media, and academics regarding policy interventions in the form of tax reductions has garnered substantial attention, particularly in light of the recent rise in commodity prices and inflation. Prices rose particularly in energy markets, which account for a large part of household consumption expenditures.[1] Among the interventions discussed in energy markets, tax cuts in gasoline markets were featured prominently and as a result have been introduced in several European countries.

In this paper, we study the distributive role of taxation in markets with imperfect consumer information. Specifically, we address the following questions: How are different consumer types heterogeneously affected by tax changes, depending on their access to information? And does the welfare-superiority of ad valorem taxes over unit taxes (Delipalla and Keen, 1992, Anderson et al., 2001a) continue to hold under imperfect consumer information?

We empirically investigate the effect of taxes in the German retail gasoline market, which serves as an ideal setting to study these questions. First, there is considerable price dispersion, both cross-sectional and intertemporal, despite the fact that the good is physically homogeneous. Second, given this substantial price dispersion, consumer information is key in determining effective prices paid. For example, some consumers use price comparison apps and others do not. Third, in many markets, including the German retail gasoline market, a combination of ad valorem taxes (e.g., VAT or sales tax) and unit taxes (e.g., excise taxes) are utilized. Finally, in response to the COVID-19 pandemic, a VAT cut was implemented, namely from 19% to 16%.

Our paper proceeds as follows. We first document high level facts concerning the German market. We use the *value of information* (VOI), measuring the difference between the *average* and the *minimum* price at a given time t in a geographically well-defined market m, thus capturing both price dispersion, and the potential savings of an informed consumer relative to an uninformed consumer buying at a random retail outlet. We show that VOI is higher in high-income markets. Linking our price data with car registry

[1] In 2022, OECD countries faced inflation rates of 30% for energy while food and prices for other products increased by 7% and 13% respectively (OECD, 2024).

data and Google Trends search data, we find that high-income regions are associated with (i) larger cars for which the gains from search are higher and (ii) stronger search intensity for gasoline-related keywords on Google's search engine. These findings suggest that consumers in different regions might be differentially affected by tax changes due to their access and returns to information.

Indeed, exploiting the aforementioned VAT reduction, we split the sample of gasoline stations at the median income per capita of the county in which the station is located. In a difference-in-differences setting, we find that prices in above-median income counties decrease *more* relative to below-median income counties after the VAT cut went into effect, suggesting that consumers in above-median income counties benefit about 12% more than those in below median income counties.

Motivated by these reduced-form findings, we then aim to quantify different underlying channels through the lens of a structural model with consumer information heterogeneity (Armstrong et al., 2009, Lach and Moraga-González, 2017), allowing for vertical differentiation of gasoline stations (Wildenbeest, 2011). In particular, consumers differ in the number of price quotes they obtain before the purchasing decision. This heterogeneity in fixed-sample search stems from differences in the costs of obtaining quotes, which vary across consumers and markets.[2]

To estimate this model, we propose a two-stage estimation procedure, extending the approach from Wildenbeest (2011). In the first stage, we obtain a non-parametric estimate of the price distribution, conditional on market characteristics, from which we can then directly infer the cutoff points in the distribution of search costs. This determines the number of price quotes obtained for different consumer types. In the second stage, we match the sample moments of the price distribution with those generated by the model to estimate the parameters of the firms' cost function and the distribution of search costs (Hong and Shum, 2006, Moraga-González and Wildenbeest, 2008). We find that estimated search costs are lower in high-income areas, and decrease over time. Both are consistent with the evidence mentioned above.

We then compute a range of counterfactual tax scenarios, motivated by recent tax policy changes in Germany. We perform out-of-sample simulations with a reduced VAT rate of 16% and find that posted prices decrease by 1.92%, corresponding to an average pass-through rate of 77%. Although we estimate our model on pre-pandemic data, this is very much in line with the reduced-form findings from a complementary study by Montag et al. (2023). They find prices in Germany to fall by 2.06% after the VAT cut.

Our structural model allows us to disentangle this pass-through effect into two channels. First, holding consumer search behavior fixed, the lower tax rate reduces the minimum price and increases dispersion as well as firm profits. Prices fall on average. Second,

[2] Fixed-sample search likely models consumer search behavior well (Moraga-González et al., 2017, Santos et al., 2012).

consumers respond by intensifying their search as increased price dispersion rewards price comparisons. This allows them to obtain a larger share of the increase to surplus due to lower taxes. Hence, the price falls further. Both channels explain around half of the overall pass-through each. We also show that prices decrease more strongly in high-income markets where consumers search more. In markets in the top decile of the income distribution, the price decrease is 18% stronger than in the bottom decile.

Finally, we investigate how the form of consumption taxation affects outcomes. In particular, we compute the effects of an excise tax reduction such that the total tax revenue equals the revenue obtained under the VAT reduction, i.e. it yields the same outcome from the point of view of the tax authority. We show that, relative to a VAT reduction, prices decreases even stronger when the excise tax is reduced, i.e., when a given tax revenue is financed primarily through VAT. This is akin to known results in the public finance literature (e.g., Anderson et al., 2001a), although there typically perfect information and elastic demand is assumed. In our setting, in contrast, the preference of ad valorem taxes over unit taxes (from a consumer welfare point of view) emerges despite imperfect information, equilibrium price dispersion, and no aggregate surplus effect due to inelastic demand. In Appendix D, we show that this is a general feature of taxation in homogeneous goods search models.

Our results have important implications. First, we provide an information mechanism through which tax policy heterogeneously affects consumers. We show that differences in search behavior result in considerable heterogeneity in effective pass-through faced. Second, we unveil that search effort is related to consumers' income. This can inform policymakers about the effective direction and distributional implications of tax changes. Finally, we show that by the stated objective of supporting consumers, and specifically, low-income consumers, reducing the excise tax would have been a more suitable tool than the VAT reduction.

Our paper also contributes methodologically by employing a non-parametric first-stage estimator. Additionally, we demonstrate that characterizing the firm's price distribution (utility) in terms of quantiles allows for estimation of a dataset that would otherwise exceed computational capacities, as these quantile expressions directly result in one-dimensional integrals at the market level.

The remainder of the paper is organized as follows. Below we discuss the related literature. Section 2 describes the institutional setting and our data. We present descriptive and reduced-form evidence in Section 3. Section 4 introduces the model and characterizes equilibrium pricing and search behavior. In Section 5, we describe our estimation method, and in Section 6 the estimation results. In Section 7, we conduct and analyze several counterfactual tax experiments, and we conclude in Section 8.

Related Literature. Thematically, our paper relates to the vast literature on taxation and tax incidence, going back to Ramsey (1927), see Mirrlees and Adam (2010) for a comprehensive overview.[3] Common themes in this literature include the efficiency of different tax types, as well as overall pass-through rates (Weyl and Fabinger, 2013, Miller et al., 2017, Adachi and Fabinger, 2022, Anderson et al., 2001b, Ritz, 2024). We contribute to this literature by showing that imperfect price information, modulated through endogenous search, has important consequences with respect to pass-through faced by different consumer types. From an efficiency point of view, the public finance literature has shown that ad valorem taxation is welfare-superior to unit taxes (Delipalla and Keen, 1992, Anderson et al., 2001a). We find that also in our setting with imperfect information and unit demand, ad valorem taxes are consumer-surplus optimal despite the lack of output expansion under perfectly inelastic aggregate demand, because the revenue-sharing internalization channel of firms is still effective. In contrast to several studies with a macro perspective on pass-through (Bonnet et al., 2024, Gautier et al., 2023, Gelman et al., 2023, Kilian, 2022), we take a closer look into local markets and different consumer types, using methods well established in industrial organization. This allows us to quantify several channels arising at the micro level only.

In terms of the industry studied, our paper also contributes to the literature on gasoline markets, surveyed in Eckert (2013) and Noel (2016). Our paper is closely related to Montag et al. (2023) and Genakos and Pagliero (2022) who also investigate pass-through in Germany and Greece, respectively, but do not focus on heterogeneous effects across consumer types.[4]

Methodologically, we contribute to the literature on estimating search costs (Hortaçsu and Syverson, 2004, Hong and Shum, 2006, Moraga-González and Wildenbeest, 2008, Moraga-González et al., 2013, Wildenbeest, 2011, Honka, 2014, Honka et al., 2019), and, more broadly, on markets with imperfect price information and consumer search (Varian, 1980, Burdett and Judd, 1983, Armstrong et al., 2009). Building on the approach introduced by Wildenbeest (2011) and extended by Nishida and Remer (2018), we propose a novel two-stage estimation routine relying on a non-parametric first-step estimator (Li and Racine, 2008). Additionally, we show that characterizing the firm's price (utility) distribution in terms of quantiles, as in Lach and Moraga-González (2017), has attractive computational features because it allows for the usage of vectorized Newton's method at the market level. This facilitates the estimation and computation of equilibrium in a

[3]Markets studied empirically include among others liquor (Miravete et al., 2018, 2020), soda drinks (Dubois et al., 2020), restaurants (Benzarti and Carloni, 2019), hairdressing (Benzarti et al., 2020) and grocery stores (Chetty et al., 2009).

[4]Besides the German market (see e.g., Assad et al., 2023, Fischer, 2024, Fischer et al., 2024, Montag et al., 2021 and Martin, 2024), there are also several other countries studied, e.g., Australia (Byrne and De Roos, 2019, 2022, Byrne et al., 2023), Canada (Clark and Houde, 2013, Carranza et al., 2015), Chile (Lemus and Luco, 2021, Luco, 2019), Italy (Rossi and Chintagunta, 2018, Pavan et al., 2020, Alderighi and Nicolini, 2022) and the US (Hastings, 2004, Noel, 2007, Chandra and Tappata, 2011, Lewis, 2011, Lewis and Noel, 2011, Nishida and Remer, 2018).

model where such calculations would otherwise be computationally infeasible.

2 Industry background and data

We study heterogeneity in pass-through by different degrees of consumer information in the German gasoline market. Gasoline markets are locally narrowly defined (Bundeskartellamt, 2011, Chandra and Tappata, 2011, Fischer, 2024, Fischer et al., 2024, Martin, 2024, Pennerstorfer et al., 2020). This implies that firms' pricing and pass-through behavior likely is a function of local demographics and socio-economic circumstances as well as consumer behavior. The small market size in this industry further allows for cross-market comparison, enabling us to analyze and compare markets with varying characteristics such as income levels or consumer information.

We gather data from various sources. First, we use the diesel prices of the universe of German gasoline stations. For our reduced-form analysis, we make use of 2020 data around the VAT cut. For our structural model and counterfactual analysis, we utilize data from the pre-COVID and pre-energy crisis period spanning 2015 to 2019. This approach ensures that our results are not distorted by the shocks in 2020. Stations fall under an obligation to report all price changes in real-time to the Market Transparency Unit for Fuel (MTU) of the German competition authority, the Bundeskartellamt. We access this price data through the online portal `tankerkoenig.de`. We focus on prices at 5pm on working days when most people fuel (Bundesministerium für Wirtschaft und Energie, 2018). To keep our structural analysis later on tractable, we restrict our analysis to 10% of the working days between 2015 and 2019.[5]

The MTU data also includes detailed information on the gasoline stations' characteristics. Coordinates of all stations allow us to specify stations' exact location and to define geographical markets. Information on brand affiliation gives insights into 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 slightly less than 50% of all stations.

Following the literature (Bundeskartellamt, 2011, Fischer, 2024, Fischer et al., 2024, Martin, 2024), we drop all highway stations from the dataset. Even when highway stations are nearby street stations, they typically belong to separate markets (Bundeskartellamt, 2011). We follow Fischer et al. (2024) in their procedure to identify highway stations in the data.

Second, we collect data on daily wholesale prices for diesel provided by a private company, Argus Media.[6] Wholesale price data are constructed based on interviews with

[5] We show robustness of our main results to different times of the day in the Appendix. We also use out-of-sample data for the reduced-form evidence in Section 3.3, i.e. data from 2020 and 2021 when the tax changes took place, but do not include this data in our main structural analysis.

[6] The same data is also used in, for example, Assad et al. (2023) and Fischer et al. (2024).

industry experts and agents who share their wholesale market transaction prices. This wholesale price data already include the energy tax (47.04 Eurocent per litre, ct/l) but not the VAT of 19%. To understand pass-through in the gasoline industry, we are interested in how changes in wholesale prices map into gasoline retail prices. Comparing the time series of average gasoline prices and the wholesale price data shows they are highly correlated with each other (see Figure E.1 in the Appendix).

We also make use of detailed administrative information on demographic and socio-economic differences across regions in Germany. We obtain data on the income per capita (p.c.) and the share of large cars (cylinder capacity of at least 2000ccm) 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.

Finally, we use data on Google search queries on several fueling-related keywords (e.g., diesel, fuel prices, gas station, etc.) at the city level. Aggregating this data to the county level, we later document regional differences in income to differences in search intensity.

We delineate markets using a hierarchical clustering algorithm (Carranza et al., 2015, Lemus and Luco, 2021, Martin, 2024), which generates non-overlapping markets that are required for our estimation later on. 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), market definition does not account for local station density patterns. Moreover, it would not be computationally feasible for structural estimation and counterfactual equilibrium computation.[7]

In total, we obtain 2,328 unique markets including more than 14,000 stations. Table 1 presents summary statistics for the key market characteristics. On average, there are around six stations per market, out of which around 40% are classified as “major” stations, and 7% belong to an integrated brand. Figure E.3 in the Appendix shows the distribution of market size. The average 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 compute the centroid 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.

[7]Figure E.2 in the Appendix displays the market distribution in and around the cities of Aachen and Wuppertal in Germany. The circles' radii indicate the distance from the market's centroid, which is the geographical center of a market, to the station farthest away. For our main specification, we parameterize the clustering algorithm with an upper bound of ten stations per market, and a maximal distance of ten kilometers between stations, which appears reasonable in our setting.

A prominent feature of retail gasoline markets is price dispersion. We calculate three measures of price dispersion, evaluated per market m at a certain time t (5pm on a specific date), given by

$$VOI_{m,t} = E(p_{m,t}) - E_{min}(p_{m,t})$$
$$Range_{m,t} = E_{max}(p_{m,t}) - E_{min}(p_{m,t})$$
$$SD_{m,t} = \sqrt{E(p_{m,t}^2) - E(p_{m,t})^2}$$

where $VOI_{m,t}$ denotes the *value of information*, i.e., how much a consumer can gain by purchasing at the cheapest (minimum) price $E_{min}(p_{m,t})$ as opposed to the expected price $E(p_{m,t})$ in market m at time t. The price range $Range_{m,t}$ gives the difference between the expected maximum $E_{max}(p_{m,t})$ and minimum price $E_{min}(p_{m,t})$. $SD_{m,t}$ is the market-date-specific standard deviation.

In Table 1, we also report aggregate statistics on price data. Over our sample period, the average price is 116 ct/l. However, there is considerable price dispersion in most markets. On average, consumers can gain 1.6 ct/l when buying at the minimum price instead of the mean price, which is approximately 25% of the margin of a gasoline station in our sample and model. The maximum price in a market, on average, is 3.4 ct/l higher than the minimum price ($Range_{m,t}$). As approximately 7% 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 Fischer et al. (2024) or Pennerstorfer et al. (2020).

Table 1: Summary statistics, markets

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
# stations	6.07	2.95	1	10
Frac. Major	0.42	0.27	0	1
Frac. Integrated	0.07	0.14	0	1
Frac. Other	0.51	0.28	0	1
Max(dist)	4.01	2.36	0	10.89
Area	67.91	64.2	0	372.6
Pop.dens.	0.55	0.86	0.04	4.72
GDP/cap.	35.7	14.22	15.85	167.21
Mean(price)	116.33	1.85	109.52	131.14
Min(price)	114.71	2.06	108.72	131.14
Max(price)	118.13	2.11	109.52	133.06
S.d.(price)	1.37	0.69	0	7.17
VOI	1.62	1.01	0	6.13
Range	3.43	1.96	0	15.97

Note: This table shows descriptive statistics on characteristics at the market level.

3 Descriptive results

3.1 Value of Information (VOI)

In this section, we provide first descriptive evidence on how regional differences in socio-economic variables, here measured by income per capita, affect market-level price dispersion. To this avail, we categorize markets into deciles in the income p.c. distribution. In Figure 1, we show the distribution of price dispersion, measured by the value of information $VOI_{m,t}$, for the markets in the lowest and highest income decile, respectively. Compared to low-income markets, the distribution of price dispersion is shifted to the right in high-income markets and hence tends to be higher in markets with higher income 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. The left panel in Figure 2 shows that $VOI_{m,t}$ increases with the wholesale price, the right panel shows that $VOI_{m,t}$ remains substantially higher for markets in the top decile of the distribution throughout the sample period.

Naturally, markets which differ in income p.c. might also differ in other dimensions such as the station density or population density. Hence, we also provide simple linear regressions of market-level price dispersion measures on income per capita and other control variables such as competition proxies (see Table 2). They support a significant conditional correlation between price dispersion and income per capita. A 100% increase in income per capita implies an increase in $VOI_{m,t}$ by 0.36 ct/l or more than 20% of the mean respectively. Hence, the gains from being informed are economically relevant higher in high-income markets. We obtain qualitatively similar results for alternative dispersion measures, e.g. the range and standard deviation of market-level prices. Also, the significant relationship between income per capita and the minimum as well as the mean price indicates that income per capita likely has an effect along the entire price distribution and not just for very low prices.

Explanations for the heterogeneity in price dispersion for different income levels are multi-fold. Price dispersion can be higher when more consumers search (but also not too many, see Pennerstorfer et al., 2020). Hence, this might be a consequence of different search cost distributions across markets of different income levels. Also, gains from search might be higher in high-income markets as people fuel more (often). We explore some of these possible explanations next.

Table 2: Baseline price regressions, market level

	(1) Mean(price)	(2) Min(price)	(3) S.d.(price)	(4) VOI	(5) Range
Argus	1.12***	1.07***	0.02***	0.04***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(inc.)	4.05***	3.70***	0.13***	0.36***	0.41***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)
# stations	-0.07***	-0.24***	0.05***	0.17***	0.37***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Log(# stations / sqkm)	-0.07***	-0.00	-0.07***	-0.07***	-0.15***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Pop.dens.	-0.28***	-0.31***	0.04***	0.02***	0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Constant	2.31***	7.24***	-1.17***	-4.93***	-5.21***
	(0.07)	(0.07)	(0.03)	(0.04)	(0.06)
Observations	2633692	2633692	2633692	2633692	2633692
R^2	0.900	0.875	0.150	0.177	0.222

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

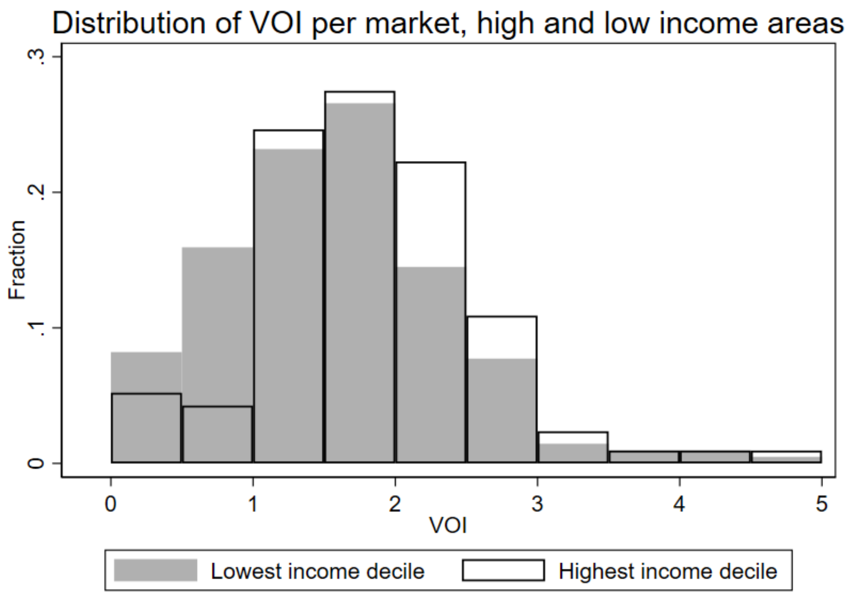

Figure 1: Distribution of $VOI_{m,t}$ per market in low and high income p.c. areas

Note: This figure plots the distribution of market-level $VOI_{m,t}$ for the bottom and top decile of the income per capita distribution of markets. $VOI_{m,t}$ is given in ct/l.

3.2 Larger cars, larger tanks, and search intensity

In this section, we establish that higher income regions are associated with (i) larger cars for which gains from search are higher and (ii) stronger search intensity for gasoline-related

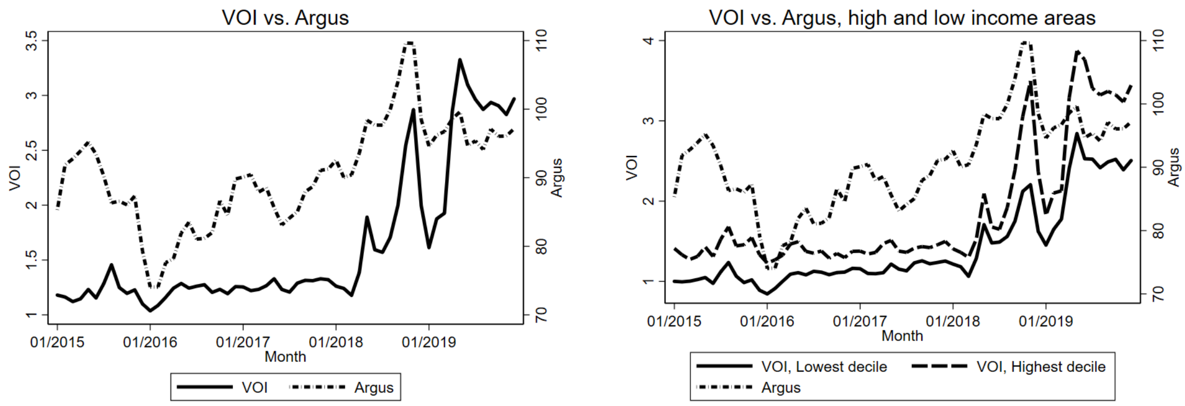

Figure 2: $VOI_{m,t}$ and Wholesale Price, including high vs. low income p.c. areas

Note: The left panel plots the time series of Argus wholesale prices and average $VOI_{m,t}$ across markets. The right panel plots the time series of Argus wholesale prices and average $VOI_{m,t}$ for the bottom and top decile of the income p.c. distribution.

words on Google's search engine. This explains that indeed search intensity is higher in high-income regions, contributing to the fact that price dispersion there is higher.

First, in the left panel of Figure 3, we correlate logged income with a county-level measure of car size, the share of cars with a cylinder capacity of above 2000ccm.[8] As larger cars consume more fuel, the gains from search are larger in counties with a higher share of such cars. The left panel of Figure 3 shows a strong correlation between income and the share of large cars.

Second, the right panel of Figure 3 shows that higher income is associated with a higher search intensity for gasoline-related keywords such as Fueling, Gasoline Prices or Gasoline Station on *Google Trends*. Google reports the relative search frequency for keywords, i.e. the share of searches for a keyword instead of the absolute number of searches for a keyword within a region, and standardizes the values to a measure between 0 and 100 to permit a comparison of search intensity across regions or keywords. We construct an index of search, which is the mean search intensity reported for cities within a county across all keywords. The figure shows a significant relation between logged income and the standardized search intensity index. We take this as suggestive evidence for more search in high income counties.

[8]Approximately 15% of all cars have a cylinder capacity of above 2000ccm. Our results also hold when including the category of cars with 1400ccm to 1999ccm to the group of large cars (64% of all cars have a cylinder capacity of at least 1400ccm).

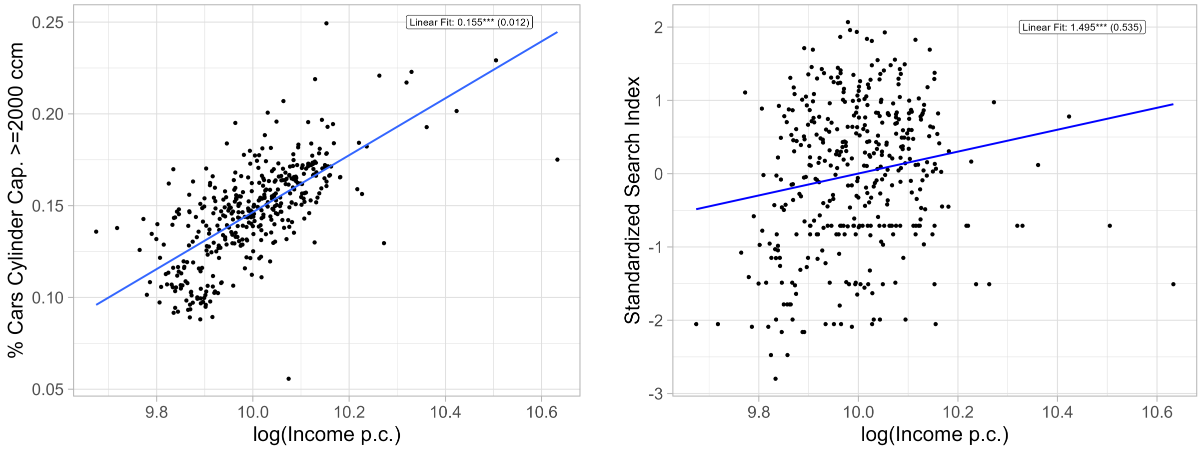

Figure 3: Mechanism - Income, Car Type and Search Intensity

Note: This figure correlates logged income per capita at the county level with the share of large cars (cylinder capacity $\geq$ 2000 ccm) and a search intensity index based on Google Trends search data. The Google Trends index provides the average search intensity for the following seven words in all cities within a county for which Google Trends reports search intensity data: Tanken (Fueling), Diesel (Diesel), Spritpreise (Fuel Prices), Tankstelle (Gas Station), clever tanken (clever tanken), Benzin (Gasoline), Benzinpreise (Gasoline Prices). If there is not a single city with sufficient search intensity to be reported by Google Trends, we set the search intensity to zero. We also residualize the variable for state fixed effects as Google Trends does not allow for direct comparisons of cities across state borders. Finally, we standardize the residualized variable. Linear fits, i.e. the coefficient of an OLS regression of the respective outcome on logged income per capita, are reported in the top right corner. Heteroskedasticity-robust standard errors are reported.

3.3 Reduced form evidence from tax changes

In view of the COVID-19 pandemic, Germany implemented a VAT reduction from 19% to 16% (i.e., a reduction by around 16.6%) from July to December 2020. Due to several lockdowns, disrupted supply chains, and aggregate uncertainty, the economy was off equilibrium altogether, shocking both the demand side and supply side. Under full pass-through[9], prices should adjust by -2.52%. Montag et al. (2023) analyze this VAT reduction by using France as a control group, and find that average posted diesel prices decrease by 2.06%, which implies a pass-through rate of 82%. Note that since the VAT 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.

Instead of only focusing on the average price effect on *all* prices, we are interested in the *heterogeneous* effects of the VAT reduction across markets with different search intensities and income levels. We, therefore, split the sample of gasoline stations at the median income per capita of the county in which the station is located. We then compare prices of stations in counties with above and below median income and the prices before and after the tax change in a dynamic difference-in-differences estimation.[10]

[9]The pass-through rate of this tax change is readily obtained by Montag et al. (2023): $\rho_\tau = \frac{\partial p}{\partial \tau}\frac{1+\tau}{p}$.

[10]Note that for this analysis, we also use data outside of our main sample. The post-pandemic time period is omitted from the main analysis for reasons explained in Section 2.

We estimate the following regression:

$$Price_{it} = \alpha_i + \lambda_{st} + \sum_{\tau=-\underline{\tau},\tau\neq-1}^{\bar{\tau}} \mathbb{1}[(Time = \tau)_t] \times \mathbb{1}[Above\ Median_i] + \varepsilon_{it} \tag{1}$$

where $Price_{it}$ is station i's diesel price on date t, α_i and λ_{st} are station and state-date fixed effects, respectively, and ε_{it} is the error term. The binary variable $\mathbb{1}[Above\ Median_i]$ indicates a station located in an above-median county. We interact this station identifier with weekly bin dummies $1[(Time = \tau)_t]$ to estimate the leads and lags of the treatment effect. We focus on an effect window $(\underline{\tau}, \bar{\tau})$ of about ten weeks before/after the change.

This regression setup allows us to identify effects of tax changes under the parallel trends assumption and the stable unit treatment variable assumption (SUTVA). The former assumption requires that stations in high- and low-income markets would have evolved on similar trends absent treatment. Flat pre-trends will serve as suggestive evidence that this assumption is not violated in our setting. The latter assumption implies that there should not be any spillovers in the treatment status across stations. Note that treatment is determined by the local income distribution that remains mostly unaffected in the very short effect windows. Also, stations are not able to self-select, i.e. relocate to markets of different income levels, in response to the policy.

The results are shown in Figure 4. Station prices in above-median income counties decrease by 0.25 ct/l relative to below-median income counties. This difference corresponds to about one-tenth of the overall effect to be expected under full pass-through (2.52 ct/l, see Montag et al., 2023). The effect materializes quickly and is persistent over time.

Summarizing our findings so far, we have established that, comparing high-income with low-income regions, (i) price dispersion is higher, (ii) consumers tend to search more, and (iii) reduced-form evidence suggests that tax pass-through rate to posted prices is higher.

We will now provide a micro-foundation through a structural model with optimal consumer search. This allows us to disentangle different channels through which tax adjustments operate.

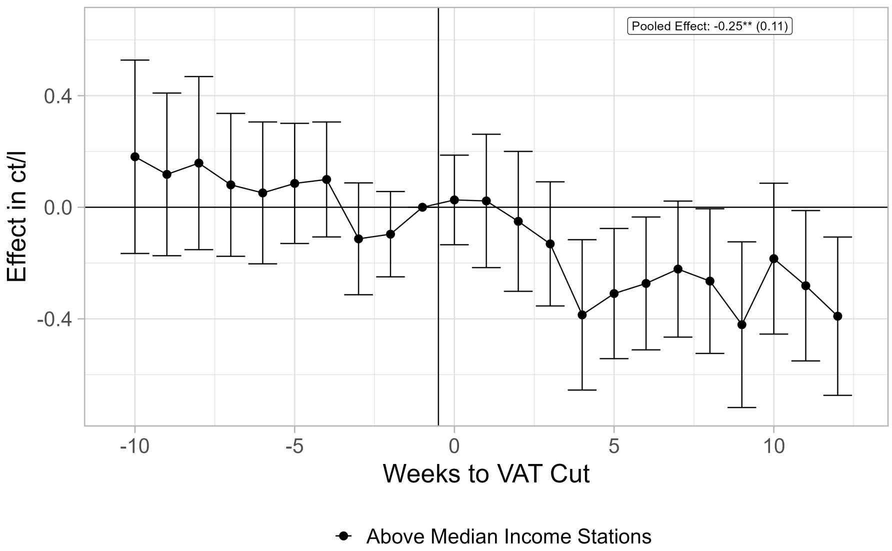

Figure 4: Price Effect of VAT Cut on High- Relative to Low-Income Stations

Note: This figure shows the results of a simple difference-in-differences regression of prices on leads and lags of the VAT cut timing interacted with a dummy for stations which are located in counties with an above-median income. We bin leads and lags to weekly bins and use station as well as state-date fixed effects. Standard errors are clustered at the municipality level. 95% confidence intervals are reported. The number in the top-right corner is the simple difference-in-differences estimate (pooled effect).

4 Model

We consider the setting with vertical differentiation as in Wildenbeest (2011), adjusted for observable input prices and taxes. N firms, indexed by i, compete by simultaneously setting prices p_i. There is a continuum of consumers with mass one and unit demand.[11] Firms are vertically differentiated through an observable quality component q_i, which is additively separable from a common quality component q_0, so that the gross utility to consumers is given by $v_i(q_i) = q_0 + q_i$ and the net utility by

$$u_i = v_i(q_i) - p_i = q_0 + q_i - p_i. \tag{2}$$

Marginal cost consists of two components: The wholesale price for diesel c and the cost of quality provision $r(q_i)$. Assuming perfectly competitive input markets and constant returns to scale in the production of quality production function, we have $r(q_i) = q_i$. There is a per-unit tax τ_0, and an ad valorem tax τ_1, levied both on the final product and input

[11] This assumption on demand is supported by several studies, which find a very low elasticity of demand (Bento et al., 2009, Coglianese et al., 2017, Davis and Kilian, 2011, Levin et al., 2017, Li et al., 2014, Kilian and Zhou, 2024, Knittel and Tanaka, 2021). To provide further support for this assumption, we also show that both traffic and car-related accidents barely respond to the VAT cut in early 2020 (see Figure E.4 and Figure E.5 in the Appendix).

costs for quality provision. Taken together, the net revenue per consumer becomes

$$R_i(p_i) = \frac{p_i}{1+\tau_1} - c - \frac{r(q_i)}{1+\tau_1} - \tau_0,$$

which we can conveniently rewrite in utility space as in Armstrong and Vickers (2001) as

$$\begin{aligned} R_i(p_i) = R_i(u_i) &= \frac{q_0 + q_i - u_i}{1+\tau_1} - c - \frac{q_i}{1+\tau_1} - \tau_0 \\ &= \frac{q_0 - u_i}{1+\tau_1} - c - \tau_0. \end{aligned}$$

The key insight here is that despite the firms being offering asymmetric qualities, we can consider symmetric competition in utility space.

Consumers are heterogeneous in their information endowment, i.e., the number of prices k (utilities) they observe. A share μ_k observes k prices. The corresponding distribution of information is given by $\{\mu_k\}_{k=1}^N$ and we assume $\mu_1 \in (0,1)$. Before providing a micro-foundation for this heterogeneity below, we characterize equilibrium behavior on the supply side.

As $\mu_1 \in (0,1)$, standard arguments (Varian, 1980, Lach and Moraga-González, 2017) imply that a pure strategy equilibrium does not exist. Denote the distribution from which utilities are drawn by $L(u)$, which will be symmetric due to the firms' symmetry in utility space. A firm offering utility u_i makes expected profit

$$\pi_i(u_i) = \underbrace{\left(\frac{q_0 - u_i}{1+\tau_1} - c - \tau_0\right)}_{\text{net revenue per consumer}} \underbrace{\sum_{k=1}^{N} \left(\frac{k\mu_k}{N} L(u_i)^{k-1}\right)}_{\text{expected demand}}. \tag{3}$$

The equilibrium profit is determined by the minimum profit a firm can, namely by offering $\underline{u} = 0$, in which case it sells to consumers who observe one price only and it sells quantity $\frac{\mu_1}{N}$:

$$\pi_i^* = \pi^* = \pi_i(0) = \left(\frac{q_0}{1+\tau_1} - c - \tau_0\right)\frac{\mu_1}{N}.$$

The equilibrium utility distribution $L(u)$ is then implicitly characterized by the following indifference conditions:

$$\begin{aligned} \pi(u) &= \pi^* \\ \left(\frac{q_0 - u}{1+\tau_1} - c - \tau_0\right)\sum_{k=1}^{N}\left(\frac{k\mu_k}{N}L(u)^{k-1}\right) &= \left(\frac{q_0}{1+\tau_1} - c - \tau_0\right)\frac{\mu_1}{N} \end{aligned} \tag{4}$$

Since (4) does not admit a closed-form solution, it is convenient to rewrite it in terms of quantiles ξ of L (Lach and Moraga-González, 2017). Let $\xi(\phi) = L^{-1}(\phi) = u$ and we readily obtain

$$\xi(\phi) = q_0 - \left(\frac{\mu_1 \left(\frac{q_0}{1+\tau_1} - c - \tau_0 \right)}{\sum_{k=1}^{N} k\mu_k \phi^{k-1}} + c + \tau_0 \right) (1 + \tau_1) . \tag{5}$$

In order to find the upper bound $\overline{u}$ of the utility distribution, we evaluate (5) for $\phi = 1$ and obtain

$$\overline{u} = q_0 - \left(\frac{\mu_1 \left(\frac{q_0}{1+\tau_1} - c - \tau_0 \right)}{\sum_{k=1}^{N} k\mu_k} + c + \tau_0 \right) (1 + \tau_1)$$

which we can solve for q_0 given the other parameters:

$$q_0 = \bar{u} \frac{\sum_{k=1}^{N} k\mu_k}{\sum_{k=2}^{N} k\mu_k} + (c + \tau_0)(1 + \tau_1).$$

As in Wildenbeest (2011), we obtain the firm-specific price distribution $F_i(p)$ through $u_i = v_i - p_i$, and hence

$$F_i(p) = Pr(p_i \leq p) = Pr(v_i - u_i \leq p) = Pr(u_i \geq v_i - p) = 1 - L(v_i - p).$$

In the following, it will be convenient to define as $E_k(u)$ the expected maximum out of k draws from $L(u)$ with associated distribution and density:

$$\begin{aligned} L_k(u) &= L(u)^k \\ l_k(u) &= kL(u)^{k-1} l(u) \end{aligned}$$

As $\underline{u} = 0$, we an write $E_k(u)$ as

$$\begin{aligned} E_k(u) &= \int_0^{\overline{u}} u l_k(u) du = \int_0^{\overline{u}} ukL(u)^{k-1} l(u) du \\ &= \overline{u} - \int_0^{\overline{u}} L(u)^k du. \end{aligned} \tag{6}$$

On the demand side, we rationalize heterogeneity in terms of information through optimal non-sequential search and heterogeneous search costs.

Specifically, we start with the premise that 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, 2024), i.e., consumers decide upfront how many prices (utilities) to sample, and subsequently purchase from the firm providing the highest utility 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 and strictly monotone distribution $G(s)$ on $(0, \infty)$. In equilibrium, consumer choices are optimal given their search cost s and given the equilibrium utility distribution $L(u)$. Thus, a consumer searching k times (weakly) prefers the expected outcome to searching $k' \neq k$ times, i.e.

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

Since s has full 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:

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

and hence

$$s_k = E_{k+1}(u) - E_k(u) \tag{7}$$

and $s_N = 0$. Therefore, in equilibrium all consumers with $s \in [s_k, s_{k-1}]$ search k times, resulting in shares

$$\mu_k = G(s_{k-1}) - G(s_k), \; k = 2, 3, \ldots, N-1 \tag{8}$$

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

The average effective search costs of type-k consumers are given by

$$E_k(s) = (k-1) \frac{\int_{s_k}^{s_{k-1}} sg(s)ds}{\mu_k}$$

resulting in total average effective search costs for the information distribution $\{\mu_k\}_{k=1}^{N}$ given by

$$E_\mu(s) = \sum_{k=1}^{N} \mu_k E_k(s) = \sum_{k=2}^{N} (k-1) \int_{s_k}^{s_{k-1}} sg(s)ds. \tag{9}$$

4.1 Equilibrium

In equilibrium, firms take consumer behavior as given (characterized by their information distribution $\{\mu_k\}_{k=1}^{N}$), and draw utilities from $L(u; \{\mu_k\}_{k=1}^{N})$ in (4) (or alternatively, the quantile expression in (5)).

Consumers, in turn, take firm behavior as given (characterized by $L(u; \{\mu_k\}_{k=1}^{N})$), and search according to the cutoff rule $\{s_k\}_{k=1}^{N-1}$ in (7), resulting in $\{\mu_k\}_{k=1}^{N}$ according to (8).

For computing the equilibrium, it is useful to rewrite expressions as in Wildenbeest (2011) to obtain

$$s_k = E_{k+1}(u) - E_k(u) = \int_0^1 u(y)((k+1)y - k)y^{k-1}dy. \tag{10}$$

By using $u(y) = \xi(\phi)$ (see equation (5)) we can eliminate the dependency on $L(u)$ and write

$$s_k(\{\mu_k\}_{k=1}^N) = \int_0^1 \left[q_0 - \left(\frac{\mu_1 \left(\frac{q_0}{1+\tau_1} - c - \tau_0 \right)}{\sum_{k=1}^N k\mu_k y^{k-1}} + c + \tau_0 \right) (1+\tau_1) \right] ((k+1)y - k)y^{k-1}dy$$

and we obtain the equilibrium conditions:

$$\begin{aligned} \mu_1 &= 1 - G(s_1(\{\mu_k\}_{k=1}^N)) \\ \mu_k &= G(s_{k-1}(\{\mu_k\}_{k=1}^N)) - G(s_k(\{\mu_k\}_{k=1}^N)),\ k = 2, 3, \ldots, N-1 \\ \mu_N &= G(s_{N-1}(\{\mu_k\}_{k=1}^N)) \end{aligned} \tag{11}$$

Given that $\mu_N = 1 - \sum_{k=1}^{N-1} \mu_k$, this is a $N-1$-dimensional fixed point problem.

4.2 Tax Revenue and Welfare

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

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

and therefore $TR_1 = \frac{\tau_1}{1+\tau_1} E_{trans}(p)$ where the $E_{trans}(p)$ is defined as the weighted expected transaction price:

$$E_{trans}(p) = \sum_{k=1}^N \mu_k E_k(p).$$

This results in total tax revenue

$$TR = TR_0 + TR_1 = \tau_0 + \frac{\tau_1}{1+\tau_1} E_{trans}(p).$$

Total welfare is given by

$$W = CS + N\pi^* + TR = q_0 - c$$

so we can obtain expected transaction prices through

$$E_{trans}(p) = \frac{N\pi^* + \tau_0 + c}{1 - \tau_1/(1+\tau_1)}.$$

5 Estimation

Our estimation is based on aggregation at the market-period level. At a high level, we form market-period moments, matching 'observed' $E(u_{m,t})$, $sd(u_{m,t}) = E(u_{m,t}^2) - E(u_{m,t})^2$ and $E(u_{max,m,t})$, as well as a fourth moment regarding inter-temporal dispersion. We observe market-level objects upfront and perform all calculations at the market-period level. An overview of our estimation routine is shown in Figure 5, and additional details for each step are laid out in the following.

Stage 1:

- **Step 1.** Obtain utilities u_{it} through the fixed-effects regression (12).
- **Step 2.** Non-parametric estimation of the market-m-specific utility distribution in period t conditional on the wholesale price c, $\hat{L}_{m,t}(u|c)$.
- **Step 3.** Compute estimated type-k specific expected utilities $\hat{E}_{k,m,t}$, and then cutoff points $\hat{s}_{k,m,t}$ in the search costs in (7).

Stage 2:

- **Step 4.** For each parameter guess θ, compute the distribution of consumer information types $\{\mu_k\}_{k=1}^n$ by using $G(\hat{s}_{k,m,t};\theta)$ in (8), and subsequently quantiles of the utility distribution through (5).
- **Step 5.** GMM estimation: Compute the market-period moments in (13). Repeat Steps 4 and 5 until convergence.

Figure 5: Estimation routine overview

As in Wildenbeest (2011), our starting point is the relationship $u_{it} = v_i - p_{it}$, which can be mapped into the fixed-effects regression

$$p_{it} = \underbrace{\alpha + \delta_i}_{v_i} + \underbrace{\varepsilon_{it}}_{-u_{it}} \tag{12}$$

to obtain period-t utility estimates $u_{it} = -\varepsilon_{it}$, which due to the symmetry in utility space can simply be pooled.

We then use a multi-step estimation approach that does not require solving the fairly involved equilibrium fixed-point problem 11 at every evaluation of the objective function. Similar to approaches in the auctions literature and in dynamic games, we first estimate (conditional) utility distributions, which can subsequently be used as equilibrium beliefs about firm behavior from the consumers' point of view.

More specifically, we estimate the market-m-specific utility distribution in period t conditional on the wholesale price c, $\hat{L}_{m,t}(u|c)$ non-parametrically, using the method by Li and Racine (2008).[12] We plug this estimated distribution into (6) to compute estimated type-k specific expected utilities $\hat{E}_{k,m,t}$. These estimated expected utilities serve as input in the estimated equilibrium cutoff points $\hat{s}_{k,m,t}$ in the search costs in (7). We therefore can treat the cutoff points $\hat{s}_{k,m,t}$ as "data" when estimating the parameters governing search.

We parameterize the search cost distribution as follows, allowing for an annual trend and dependency on market-level observables such as income per capita and the number of stations.[13] Search costs s in market m in year y are assumed to follow a log-normal distribution $s \sim Lognormal(\beta_{y,m}, \sigma_{y,m})$, where

$$\begin{aligned}
\beta_{y,m} &= \beta_0 + \beta_1(y - 2014) + \beta_2 \log(inc./cap_m) + \beta_3 \log(n_m/sqkm) \\
\sigma_{y,m} &= \sigma_0 + \sigma_1(y - 2014) + \sigma_2 \log(inc./cap_m) + \sigma_3 \log(n_m/sqkm)
\end{aligned}$$

Thus, we are interested in estimating a parameter vector $\theta = (\{\beta_i, \sigma_i\}_{i=0}^3)$. For each parameter guess θ, we immediately obtain the respective fractions of consumers searching k times using equation (8). Then the model-implied objects like $\overline{u}$ and quantiles of the utility distribution are obtained from (5). The respective moments are simple one-dimensional integrals at the market-period level, which we can readily compute using the trapezoid method. Computational details are provided in Appendix A.

[12] We use the R package "np" for estimation of the conditional price distributions, see Hayfield and Racine (2008).

[13] The semi-parametric approach by Moraga-González et al. (2013) is not directly applicable in our setting due to the additional dependency of search costs on market-level characteristics.

Our moments are given by

$$m(\theta) = \frac{1}{T} \begin{pmatrix} z'[E(\hat{u}_{m,t}) - E(\tilde{u}_{m,t};\theta)] \\ z'[sd(\hat{u}_{m,t}) - sd(\tilde{u}_{m,t};\theta)] \\ z'[\hat{u}_{max,m,t} - E(\tilde{u}_{max,m,t};\theta)] \\ z'\left[\left(E(\hat{u}_{m,t}) - E(\widehat{\hat{u}_{m,t}})\right)^2 - \left(E(\tilde{u}_{m,t};\theta) - E(\widehat{\tilde{u}_{m,t}};\theta)\right)^2\right] \end{pmatrix} \tag{13}$$

where $\hat{x}$ denotes the (empirical) mean of x, $\tilde{x}$ denotes the model-implied object x, and the z is an instrument matrix for each of our market-period observations. We use the wholesale price, the number of stations, day-of-the-week dummies, yearly dummies, and market-level demographics as instruments. Our GMM estimator is given by the solution to

$$\underset{\theta}{\operatorname{argmin}}\, m(\theta)'Wm(\theta)$$

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

6 Estimation results

We proceed with the estimation as described in the previous section. Our main estimation results are shown in Table 3.[14] 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 the incremental cost of obtaining one additional price quote, including the opportunity costs of time, relative to the costs of filling up an entire tank. We find that μ decreases over time, and also in the markets' income per capita and station density. Thus, search costs tend to be lower in higher income areas (although the variance is higher). For instance, in the median market, this implies that the median search costs were 1.10 in 2015, and 1.00 in 2017. Relative to filling up an entire tank of 50l, this implies that the relative costs of obtaining one additional price quote is $1.10 \times 50 \approx 55$ Eurocent, which appears reasonable.

[14]Standard errors are obtained from the variance-covariance matrix evaluated at the optimum θ, numerically approximated with finite differences ($h = 10^{-12}$). Thus, the reported standard errors do not consider negligible noise stemming from the first-stage estimation.

Table 3: Estimation results

Variable	Const.	Trend	log(inc./cap.)	# stations
Search cost μ	1.23 (0.10)	-0.05 (0.00)	-0.10 (0.01)	-0.05 (0.00)
Search cost σ	0.90 (0.09)	-0.01 (0.00)	-0.05 (0.01)	0.01 (0.00)
Med(s), 2015	1.10			
Med(s), 2017	1.00			
Med(s), Low inc./cap.	1.01			
Med(s), High inc./cap.	0.99			
Med(s), Low stat.dens.	1.05			
Med(s), High stat.dens	0.98			
Mean(margin)	6.53			

Note: This table shows our baseline estimation results (standard errors in parentheses).

Although we do not match an aggregate margin moment, the estimated margins, with an average of 6.5 ct/l, are close to those provided in industry reports (Scope Investor Services, 2021) and other papers on the German gasoline market (Assad et al., 2023, Fischer, 2024, Fischer et al., 2024).

The estimated search cost distributions are primitives of the model. We now discuss how search costs translate into the equilibrium distribution consumer information, which is a key determinant of firm pricing. The left panel of Figure 6, depicts the distribution (across market-date observations) of the mean number of stations k observed per consumer. Most consumers observe one or two prices only.

The right panel of Figure 6, depicts the distribution of consumer types μ_k, for the case of markets with six stations, i.e. the average market size in our sample, for better comparability. On average, around 70% of consumers observe only one station. These consumers purchase at the expected utility $E_1(u_{m,t})$. Due to their relatively high search costs, they still prefer that outcome to searching for cheaper offers (or higher utility). Around 30% of consumers are inclined to compare offers and sample at least two stations, i.e., $k \geq 2$. The magnitude of the amount of search is comparable to the numbers reported in the survey conducted by the German Federal Ministry of Economics and Technology (Bundesministerium für Wirtschaft und Energie, 2018) and the estimates in Martin (2024).

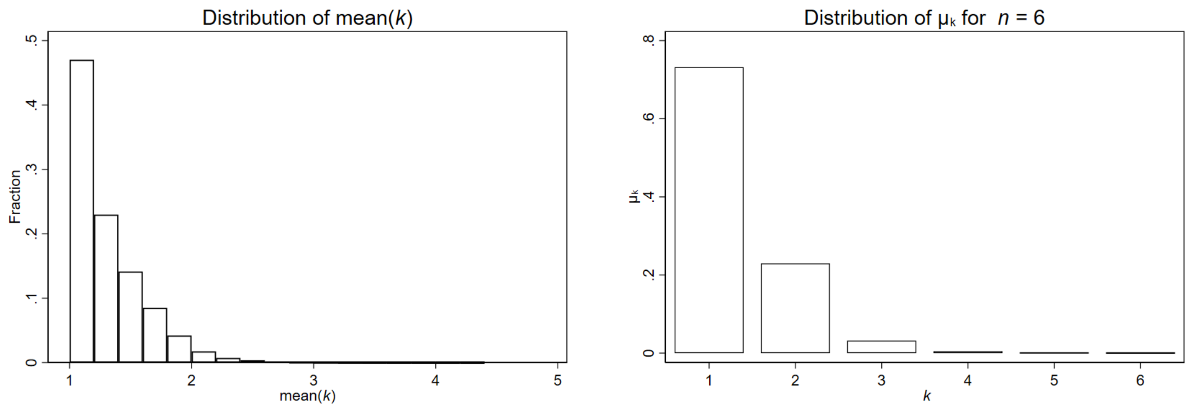

Figure 6: Number of stations observed

Note: The figure gives the distribution the number of stations of which consumers observe prices. The left panel gives the distribution of $\bar{\mu}_k$, which is the average number of prices observed in a market. The right panel gives the distribution of the number of prices consumers observe in markets with $N = 6$ firms.

7 Counterfactual analysis

Having obtained estimates of the model primitives, we can now evaluate the distributional implications of public policies, modulated through an endogenous information mechanism. Motivated by recent tax changes that were actually implemented in Germany recently, as described in Section 3.3, we compute counterfactual effects of several tax policies. We subsequently show how consumer information influences the impact of these taxes on different groups of consumers. Furthermore, we demonstrate how total alternative revenue-neutral policies have differential effects depending on whether taxes are levied ad valorem or per unit.

In the following, it will be useful to introduce a measure of much *more* consumers in the highest income decile benefit, relative to those in the lowest income decile. Denote by $\Delta E^{inc}(p)$ the relative price change faced by consumers in income decile inc where $inc \in \{low, high\}$. We then define

$$\gamma = 100\frac{\Delta E^{high}(p)}{\Delta E^{low}(p)} - 100$$

as how much *more* high-income consumers benefit, relative to low-income consumers.

For our counterfactual, we proceed as follows. Based on our estimates of the structural parameters, we compare the status-quo to counterfactual equilibria (see Section 4.1). Computing counterfactual equilibria is a relatively involved $N-1$-dimensional fixed-point problem at the market level (searching for the distribution of consumer types $\{\mu_k\}$), which is facilitated by the fact that it can be parallelized at the market-period level.

7.1 VAT reduction

Consider the VAT reduction from 19% to 16%, where Montag et al. (2023) find an average price effect of −2.06%.

To first illustrate the importance of information frictions and endogenous search behavior, we separately consider 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 while holding the distribution of consumer types $\{\mu_k\}_{k=1}^{N}$ fixed, according to 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 allow consumers to adjust their search behavior in an optimal way, such that consumers and firms are again both acting optimally vis-á-vis each other.

In Table 4, we depict several outcomes of interest, taking the average across all our markets. Δ_{short} and Δ_{long} denote the relative percentage change over the short (only firms react) and long run (firms and consumers react), 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 1.92% in the long run. This implies a pass-through rate of 77%. 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 firms 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 Π increases by 32%, mostly because firms effectively face lower marginal costs and consumer search behavior remains unchanged. This is also highlighted in respective consumer information measure: μ_x and the resulting mean number of stations k observed are, by construction of the short-run equilibrium, 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 by 23%) instead of one price quote only (μ_1 decreases by 16%). This puts additional competitive pressure on the firms since consumers are effectively more price elastic, leading to lower prices than in the short run.

The remarkable differences between short- and long-run effects also highlight the importance of considering information frictions. Not allowing the optimal response of consumers underestimates the true effects of policy changes.

Table 4: Counterfactual results, short and long run

	$\Delta_{short}\%$	$\Delta_{long}\%$
$E(p)$	-0.98	-1.92
$s.d.(p)$	21.06	23.52
VOI	22.28	14.06
$E_{trans}(p)$	-1.10	-2.07
Π	32.79	10.30
μ_1	0.00	-15.93
μ_2	0.00	22.74
mean(k)	0.00	2.05

Note: This table shows results for the VAT reduction counterfactual, separately for the short run (where no consumer search adjustment takes place) and the long run (allowing for consumer reoptimization).

We now turn to heterogeneous long-run effects across markets. In Table 5, we a breakdown by separately considering only markets in the top (x^{high}) and the lowest decile (x^{low}) in terms of income per capita. Markets with high income per capita experience a stronger price effect, owing to lower search costs, which leads to better-informed consumers.

Although consumers in low-income markets increase the search effort more (the effect on $mean(k)$ is stronger), high-income areas benefit more from the tax reduction due to the higher baseline levels of searching consumers: The price decrease in high-income areas is around 18% stronger than in low-income areas. Our analysis hence 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).

The reduced-form estimated effect of 0.25 ct/l (Section 3.3) is slightly larger in absolute terms but comparable to our counterfactual results. Note that when the actual tax change was implemented, both the supply and demand were disrupted due to the pandemic, possibly leading to further channels not fully picked up by our counterfactual analysis. Nevertheless, the reduced-form estimates and then counterfactual results consistently suggest that high-income areas benefit more from the VAT cut. This is further supported by the evidence shown in Figure 7, where we depict the relative price effects for all income deciles, instead of the highest and lowest decile only. Throughout, a consistent pattern of a stronger price effect in high-income areas is evident.

Table 5: Counterfactual results, low- and high-income areas

	$\Delta^{low}\%$	$\Delta^{high}\%$
$E(p)$	-1.77	-2.09
$s.d.(p)$	25.85	20.38
VOI	16.94	9.85
$E_{trans}(p)$	-1.92	-2.24
Π	13.24	6.77
μ_1	-14.56	-17.49
μ_2	24.73	20.03
mean(k)	2.83	0.59

Note: This table shows results for the VAT reduction counterfactual, separately for low- and high-income areas.

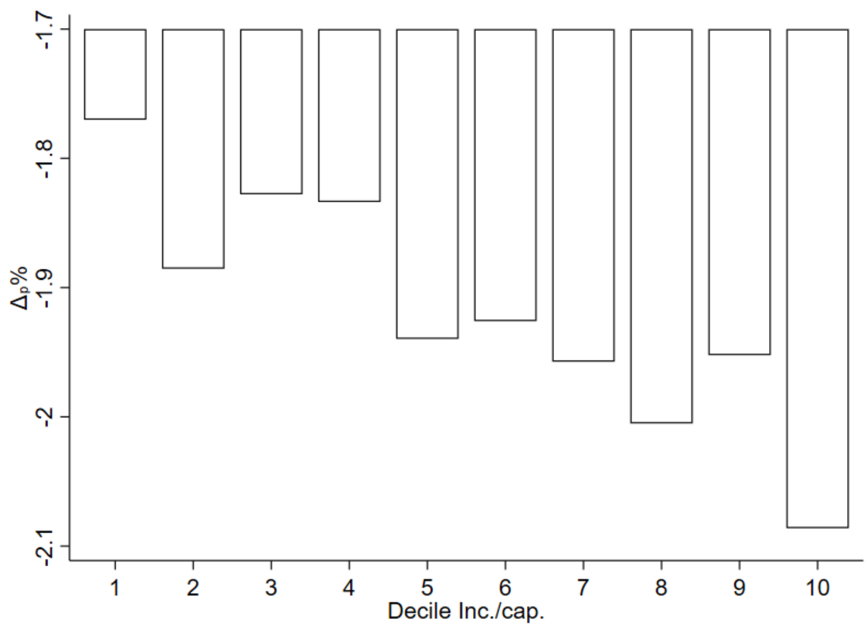

Figure 7: VAT change: Long-run price effects per income group

Note: This figure presents the results of the counterfactual analysis when the VAT is lowered from 19% to 16%. The figure shows the percent price change due to the policy for markets from different income deciles.

So far, we have shown that consumers benefit from the tax decrease (albeit to a differential degree), and so do firms. We now also turn to the third player who has stakes in this environment, namely the government or tax authority. Clearly, total tax revenue (TR) decreases with a VAT decrease. This is shown in the counterfactual results overview in Table 6, for the counterfactual with VAT -16% in the short and long run. In the short run, tax revenue decreases by around 4%. In the long run, tax revenues decrease even more (-4.2%), since also the tax base, expected transaction prices, decreases stronger through the additional consumer search response described above.

Since we are considering a unit-demand model, prices and taxes are total welfare-neutral transfers between consumers, firms, and the government only. Also, quality production is welfare-neutral under the assumptions above. The only total-welfare relevant quantity is effective search costs $E_\mu(s)$, which, from an efficiency point of view, are purely wasteful. In the long run (VAT -16%), consumers search more, leading to an increase of effective search costs $E_{e.}(s)$ by 36.5%. Since search costs are only a negligible fraction of total welfare, total welfare decreases by 0.18%.

Table 6: Counterfactual results overview

Spec.	Δ $E(p)$	Δ $E_{tr.}(p)$	$\Delta\Pi$	Δ TR	Δ $E(k)$	Δ $E_\mu(s)$	Δ $W_{inc.}$	γ
VAT -16%, short	-0.98	-1.10	32.80	-4.01	0.00	0.00	0.00	29.43
VAT -16%	-1.92	-2.07	10.30	-4.24	2.04	36.47	-0.18	17.85
Excise -2.4 ct/l	-2.00	-2.16	7.74	-4.23	2.02	35.28	-0.18	17.04
$C0_2$ tax	4.53	5.07	-56.56	12.39	-31.10	-62.05	0.31	24.33

Note: This table shows results for several counterfactuals (in % relative to the baseline), as explained in the main text. For the VAT reduction of 16%, both short and long term results are shown.

7.2 Excise tax reduction

In the presence of two tax types, as is the case here, either one can be adjusted in order to obtain a certain level of total tax revenue. We now analyze what would happen if excise taxes were reduced instead of the VAT cut, such that the same reduction of total tax revenue materializes.

An identical tax revenue reduction is achieved when the excise tax is reduced from 47.04 ct/l to 44.68 ct/l, i.e., by 2.36 ct/l or around 5%. The main results are shown in the last row of Table 6. Compared to the -16% VAT reduction, the excise tax reduction leads to an even stronger decrease in both posted prices (by 2%) and transaction prices (by 2.2%). Thus, consumers are, on average, even better off under the excise tax reduction than under the VAT reduction. Moreover, the excise tax reduction leads to more equal outcomes, as is evident in the measure γ - the relative advantage of high-income consumers is only 17% instead of almost 18% under the VAT change. Thus, if the main objective of the tax reduction is promoting consumer welfare, and specifically, welfare of low-income consumers, than reducing excise taxes is the clearly superior tool. These results are in line with the findings of Delipalla and Keen (1992) and Anderson et al. (2001a) for markets with perfectly informed consumers. The intuition from these papers carries over in the following way. While firms fully internalize the reduction in revenue from a price decrease under a unit tax regime, the loss in revenue is shared with the government under an ad valorem tax. In Appendix D, we demonstrate that this effect is not unique to our empirical application but rather, it is a general feature of markets with imperfectly informed consumers.

7.3 Other counterfactuals

In Appendix C, we also demonstrate that all our results remain robust when examining different times of the day. Across various specifications and income deciles, the reduction in VAT is predicted to result in a price decrease ranging between 1.7% and 2.1%. Moreover, the effect size consistently appears to be higher in high-income markets, and a reduction in excise tax would have been preferable from the consumer's perspective.

Our model can also be used to examine other counterfactual policies and their distributional impact across heterogeneously informed consumers and income groups. In Appendix B, we analyze another policy change. Specifically, on January 1st, 2021, the temporary VAT reduction from 19% to 16% expired, coinciding with an increase in the CO_2 price. We investigate this natural experiment using both the reduced-form and structural methods outlined previously in Appendix B. Once again, we find qualitatively similar patterns and results to those observed for the tax counterfactuals explored earlier. For a theoretical and comprehensive treatment of taxation in markets with imperfect consumer information, we direct readers to Appendix D.

8 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 by consumers.

Specifically, we apply 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, search costs are lower in the markets with very high-income per capita than in markets with very low income per capita. These results are very well in line with reduced-form evidence.

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 the *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 higher.

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 0.98% in the short run and by 1.92% in the long run, which implies an average pass-through rate of 77%. The long-run effect is stronger due to an adjustment in the endogenous information acquisition by consumers: searching for cheap offers becomes more attractive, putting additional competitive pressure on the firms.

Separately analyzing markets with high and low incomes per capita, respectively, we find that the price reduction following the VAT change is stronger in markets with high per capita income. 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 policymakers.

We also show that an excise tax reduction would have been preferable from a consumer welfare point of view. Thus, our findings extend existing results from the public finance literature to a setting with imperfect information, and in which otherwise relevant total demand effects are inactive due to very low aggregate demand elasticity.

As a final note, we mention a limitation that our comparison of different tax types shares the public finance literature, namely considering the tax revenue obtained through different tax types as identical from the tax authority's point of view. This stands in contrast to the legislation in many jurisdictions, according to which for example VAT is part of a different revenue stream than excise taxes levied through gasoline sales. Some of these revenue streams are earmarked for certain expenditures and hence the authority cannot simply transfer tax revenue obtained through different channels, as assumed in our study. We nevertheless believe that our paper is informative about optimal tax design and leave these considerations for future research.

Appendix

A Computational details

For computation, it is convenient to calculate model-implied objects using integration by parts as follows:

$$
\begin{aligned}
E(\tilde{u};\theta) &= \int_{\underline{u}}^{\overline{u}} ul(u)du = \overline{u} - \int_{\underline{u}}^{\overline{u}} L(u)du \\
E(\tilde{u}^2;\theta) &= \int_{\underline{u}}^{\overline{u}} u^2 l(u)du = \overline{u}^2 - 2\int_{\underline{u}}^{\overline{u}} uL(u)du \\
sd(\tilde{u};\theta) &= \sqrt{E(\tilde{u}^2;\theta) - E(\tilde{u};\theta)^2} \\
E(\tilde{u}_{max};\theta) &= \int_{\underline{u}}^{\overline{u}} ul_{max}(p)du = \overline{u} - \int_{\underline{u}}^{\overline{u}} L(u)^N du
\end{aligned}
$$

with respective sample analogues:

$$
\begin{aligned}
E(\hat{u}_{m,t}) &= \frac{1}{N}\sum_{i=1}^{N_{m,t}} u_{i,m,t} \\
sd(\hat{u}_{m,t}) &= \sqrt{\frac{1}{N}\sum_{i=1}^{N_{m,t}} u_{i,m,t}^2 - E(\hat{u}_{m,t})^2} \\
\hat{u}_{max,m,t} &= \max\left(\{u_{i,m,t}\}_{i=1}^{N_{m,t}}\right)
\end{aligned}
$$

Additionally, we construct a moment capturing inter-temporal and cross-sectional variation based on long-term average objects, i.e.,

$$
\begin{aligned}
\widehat{E(\hat{u}_{m,t})} &= \frac{1}{T}\sum_{i=1}^{T} E(\hat{u}_{m,t}) \\
\widehat{E(\tilde{u};\theta)} &= \frac{1}{T}\sum_{i=1}^{T} E(\tilde{u};\theta)
\end{aligned}
$$

B Carbon price (CO_2) tax

Following up on the reduced form evidence described in Section 3.3, the second tax change we observe took place on January 1st 2021, when the VAT rate decrease was undone (i.e., increased back from 16% to the initial 19%), and simultaneously a carbon tax was introduced. The carbon price is 25 Euro per tonne of CO_2, which implies a per-unit tax of 6.69 ct/l for diesel (7.14 including VAT, see Montag et al., 2023). Using again France as control group, Montag et al. (2023) estimate a *joint* pass-through rate of both tax changes of 86% for diesel. Under full pass-through, prices should increase by 9.96% or 10.75 ct/l. We repeat our difference-in-differences estimation for high-and low-income stations using the regression (1), where we analyze the income heterogeneity in a reduced-form difference-in-differences setting, comparing above-median income to below-median income stations. The results are shown in Figure B.1. Again, we find a significantly stronger and persistent response in high-income areas. Posted prices in above-median income counties increase by 0.41 ct/l relative to below-median income counties. Though, note that this is the joint, reduced-form effect of the simultaneous VAT increase and the CO_2 cut. However, the absolute effect size exceeds the effect of the VAT cut as shown above.

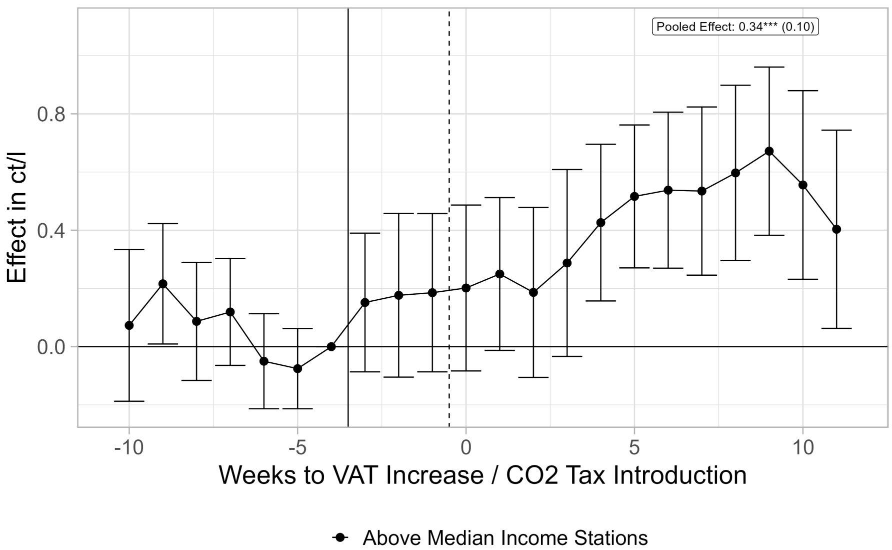

Figure B.1: Price Effect of VAT Increase/CO_2 Tax Introduction on High- Relative to Low-Income Stations

Note: This figure gives the results of a simple difference-in-differences regression of prices on leads and lags of the VAT cut timing interacted with a dummy for stations which are located in counties with an above-median income. We bin leads and lags to weekly bins and use station as well as state-date fixed effects. Standard errors are clustered at the municipality level. 95% confidence intervals are reported. The pooled effect in the top-right corner gives the simple difference-in-differences coefficient where we use the solid vertical line as the effective treatment timing as in Montag et al. (2023) since anticipatory effects were observable.

Analogous to the counterfactual analysis we conducted in Section 7, we now simulate a CO_2 tax in a counterfactual manner in our estimated model. In contrast to the VAT, the carbon tax is a non-proportional tax and mathematically is equivalent to an increase of the excise tax. As described above, the carbon price is 6.69 ct/l.

An overview of the counterfactual results is shown in Table 6. Posted prices increase by about 4.5%. This seems reasonable in view of the estimates of Montag et al. (2023), who investigate a simultaneous VAT increase. As price dispersion decreases under the CO_2 tax, the incentives to search are reduced, leading to fewer searches in equilibrium. This dampens the otherwise even stronger price effect.

Figure B.2 displays the differences in pass-through depending on the market-level income p.c. Again, pass-through increases with income. Pass-through is about 25% stronger in markets from the tenth income decile in comparison to the markets from the lowest income decile.

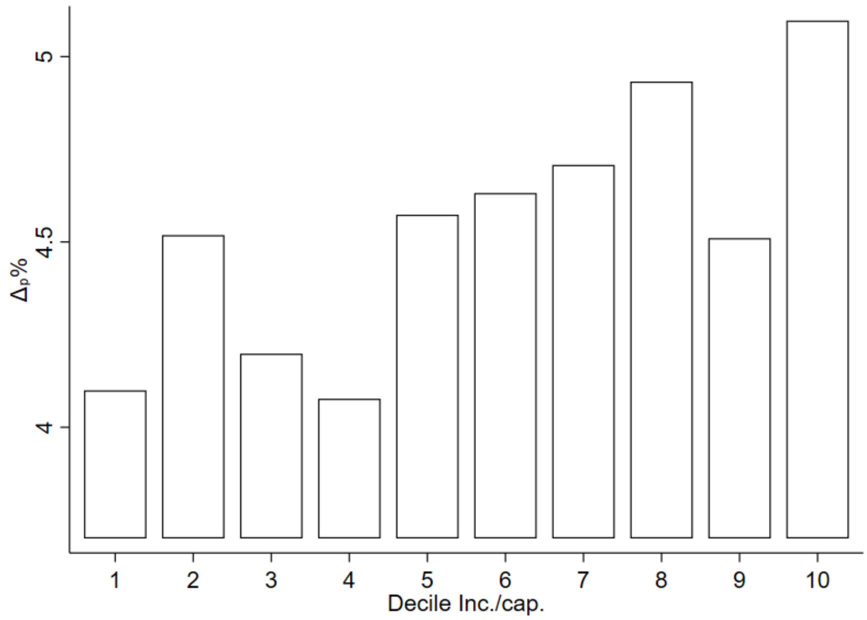

Figure B.2: CO_2 tax change: Long-run price effects per income group

Note: This figure gives the results of the counterfactual analysis when the CO_2 tax of 25 Euro per tonne is introduced. The figure gives the percent price change due to the policy for markets from different income deciles.

C Robustness checks

C.1 Different time of the day: 9am

Table C.1: Estimation results (9am)

Variable	Const.	Trend	log(inc./cap.)	# stations
Search cost μ	1.24 (0.09)	-0.04 (0.00)	-0.06 (0.01)	-0.05 (0.00)
Search cost σ	0.90 (0.09)	-0.01 (0.00)	-0.05 (0.01)	0.01 (0.00)
Med(s), 2015	1.65			
Med(s), 2017	1.51			
Med(s), Low inc./cap.	1.52			
Med(s), High inc./cap.	1.49			
Med(s), Low stat.dens.	1.57			
Med(s), High stat.dens	1.48			
Mean(margin)	9.88			

Note: This table shows our baseline estimation results (standard errors in parentheses).

Table C.2: Counterfactual results overview (9am)

Spec.	$\Delta\ E(p)$	$\Delta\ E_{tr.}(p)$	$\Delta\Pi$	$\Delta\ TR$	$\Delta\ E(k)$	$\Delta\ E_{\mu}(s)$	$\Delta\ W_{inc.}$	γ
VAT -16%, short	-0.86	-0.97	22.45	-4.05	0.00	0.00	0.00	22.91
VAT -16%	-1.83	-1.98	7.76	-4.30	-0.50	53.69	-0.28	11.95
Excise -2.4 ct/l	-1.90	-2.06	5.49	-4.19	-0.65	52.30	-0.27	12.40
$C0_2$ tax	5.14	5.79	-22.71	12.55	-29.80	-56.82	0.30	19.92

Note: This table shows results for several counterfactuals (in % relative to the baseline), as explained in the main text. For the VAT reduction of 16%, both short and long term results are shown.

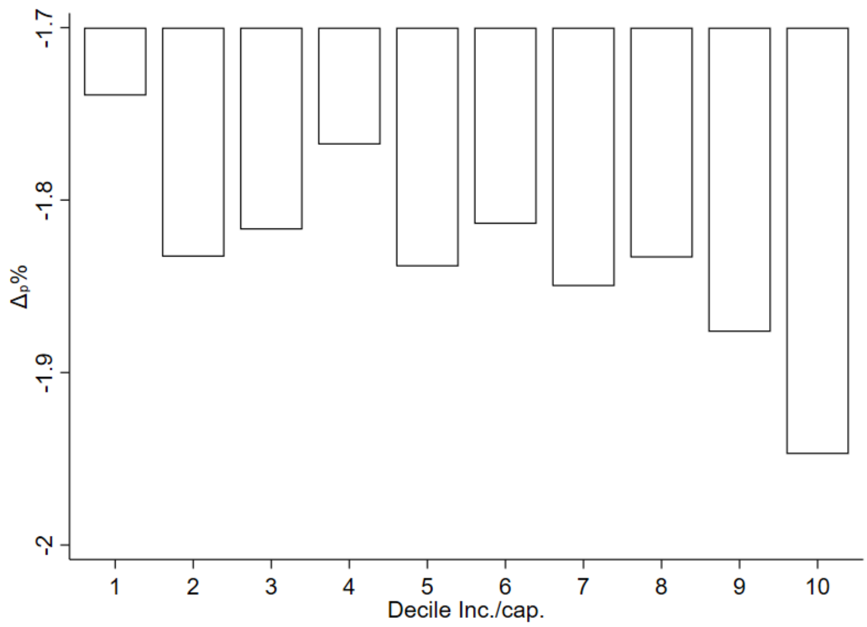

Figure C.1: VAT change: Long-run price effects per income group (9 am)

Note: This figure gives the results of the counterfactual analysis when the VAT is lowered from 19% to 16%. The figure gives the percent price change due to the policy for markets from different income deciles.

C.2 Different time of the day: noon

Table C.3: Estimation results (noon)

Variable	Const.	Trend	log(inc./cap.)	# stations
Search cost μ	1.23 (0.09)	-0.05 (0.00)	-0.08 (0.01)	-0.05 (0.00)
Search cost σ	0.90 (0.09)	-0.01 (0.00)	-0.05 (0.01)	0.01 (0.00)
Med(s), 2015	1.29			
Med(s), 2017	1.17			
Med(s), Low inc./cap.	1.19			
Med(s), High inc./cap.	1.16			
Med(s), Low stat.dens.	1.23			
Med(s), High stat.dens	1.15			
Mean(margin)	7.63			

Note: This table shows our baseline estimation results (standard errors in parentheses).

Table C.4: Counterfactual results overview (noon)

Spec.	$\Delta\ E(p)$	$\Delta\ E_{tr.}(p)$	$\Delta\Pi$	$\Delta\ TR$	$\Delta\ E(k)$	$\Delta\ E_{\mu}(s)$	$\Delta\ W_{inc.}$	γ
VAT -16%, short	-0.95	-1.07	28.01	-4.02	0.00	0.00	0.00	26.09
VAT -16%	-1.89	-2.05	9.13	-4.25	0.77	38.32	-0.21	15.62
Excise -2.4 ct/l	-1.98	-2.14	6.66	-4.22	0.71	37.02	-0.20	14.23
$C0_2$ tax	4.89	5.49	-38.69	12.50	-31.06	-64.17	0.34	22.63

Note: This table shows results for several counterfactuals (in % relative to the baseline), as explained in the main text. For the VAT reduction of 16%, both short and long term results are shown.

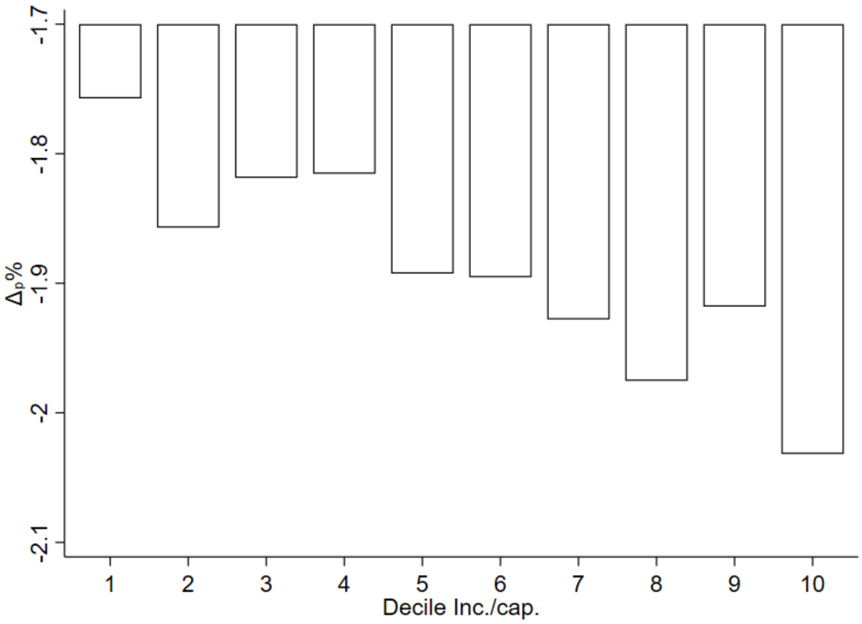

Figure C.2: VAT change: Long-run price effects per income group (noon)

Note: This figure gives the results of the counterfactual analysis when the VAT is lowered from 19% to 16%. The figure gives the percent price change due to the policy for markets from different income deciles.

D Taxes in homogeneous goods search models

For expositional clarity, consider a standard homogeneous goods search model in the spirit of Varian (1980). There are n firms, offering a homogeneous good for which all consumers have willingness to pay $v > 0$. As in Lach and Moraga-González (2017) and our main model, we generalize the distribution of consumer information types, and we assume an exogeneously given distribution $\{\mu\}_{k=1}^{n}$, with the interpretation that μ_k consumers observe k prices. Denote common marginal costs by $c \geq 0$, (per-unit) excise taxes τ_0 and a VAT rate τ_1. For $\mu_1 \in (0,1)$, a pure strategy equilibrium does not exist, but a mixed strategy equilibrium always exists.

In the mixed-strategy equilibrium, firms' profit is determined by selling to loyal consumers only, so

$$\pi = \left(\frac{v}{1+\tau_1} - c - \tau_0\right)\frac{\mu_1}{n}$$

resulting in total-industry profit Π given by

$$\Pi = n\pi = \left(\frac{v}{1+\tau_1} - c - \tau_0\right)\mu_1$$

Consumer surplus is simply

$$CS = v - E_{trans}(p)$$

and total tax revenue is

$$TR = \tau_0 + E_{trans}(p)\frac{\tau_1}{1+\tau_1}$$

Total welfare is defined through

$$W = v - c = \Pi + CS + TR$$

which we can solve for $E_{trans}(p)$ and obtain

$$\begin{aligned}
v - c &= \Pi + CS + TR \\
v - c &= \Pi + v - E_{trans}(p) + \tau_0 + E_{trans}(p)\frac{\tau_1}{1+\tau_1} \\
E_{trans}(p) &= \frac{\Pi + c + \tau_0}{1 - \frac{\tau_1}{1+\tau_1}} \\
E_{trans}(p) &= \frac{\left(\frac{v}{1+\tau_1} - c - \tau_0\right)\mu_1 + c + \tau_0}{1 - \frac{\tau_1}{1+\tau_1}} = \left(\left(\frac{v}{1+\tau_1} - c - \tau_0\right)\mu_1 + c + \tau_0\right)(1+\tau_1)
\end{aligned}$$

We can use this expression and solve for τ_0 such that total tax revenue TR is constant, i.e., for τ_0 as a function of TR, τ_1, and the other primitives of the model:

$$
\begin{aligned}
TR &= \tau_0 + \tau_1 \left(\left(\frac{v}{1+\tau_1} - c - \tau_0 \right) \mu_1 + c + \tau_0 \right) \\
&= \tau_0(1 + \tau_1(1 - \mu_)) + \frac{v\mu_1\tau_1}{1+\tau_1} + c\tau_1(1-\mu_1) \\
\tau_0(TR, \tau_1) &= \frac{TR - c\tau_1(1-\mu_1) - \frac{v\mu_1\tau_1}{1+\tau_1}}{1+\tau_1(1-\mu_1)}
\end{aligned}
$$

Similarly, we can then write and simplify $E_{trans}(p; TR, \tau_1)$ as

$$
E_{trans}(p; TR, \tau_1) = \frac{v\mu_1 + (1-\mu_1)(1+\tau_1)(c+TR)}{1+(1-\mu_1)\tau_1}
$$

and taking the derivative w.r.t. τ_1, we obtain

$$
\frac{\partial E_{trans}(p; TR, \tau_1)}{\partial \tau_1} = -\frac{(v-c-TR)(1-\mu_1)\mu_1}{(1+(1-\mu_1)\tau_1)^2} < 0
$$

Thus, holding total tax revenue TR constant, increasing τ_1 (which decreases τ_0 to ensure total tax revenue neutrality) lowers transaction prices. This implies that consumers are better off when a certain level of total tax revenue is financed through high VAT and low excise taxes.

Similarly, we can investigate the equilibrium profits π as a function of TR and τ_1

$$
\pi(TR, \tau_1) = \frac{v-c-TR}{1+(1-\mu_1)\tau_1}\frac{\mu_1}{n}
$$

which is also decreasing in τ_1. The same is true for the lower bound $\underline{p}$ of the price distribution, which also decreases in τ_1.

E Additional figures

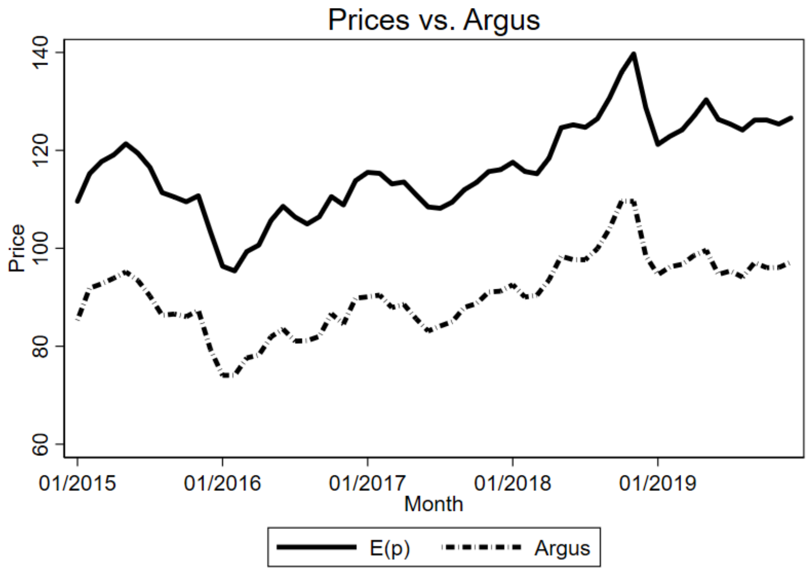

Figure E.1: Retail prices and brent

Note: The figure plots the time series of retail prices across markets and Argus wholesale prices.

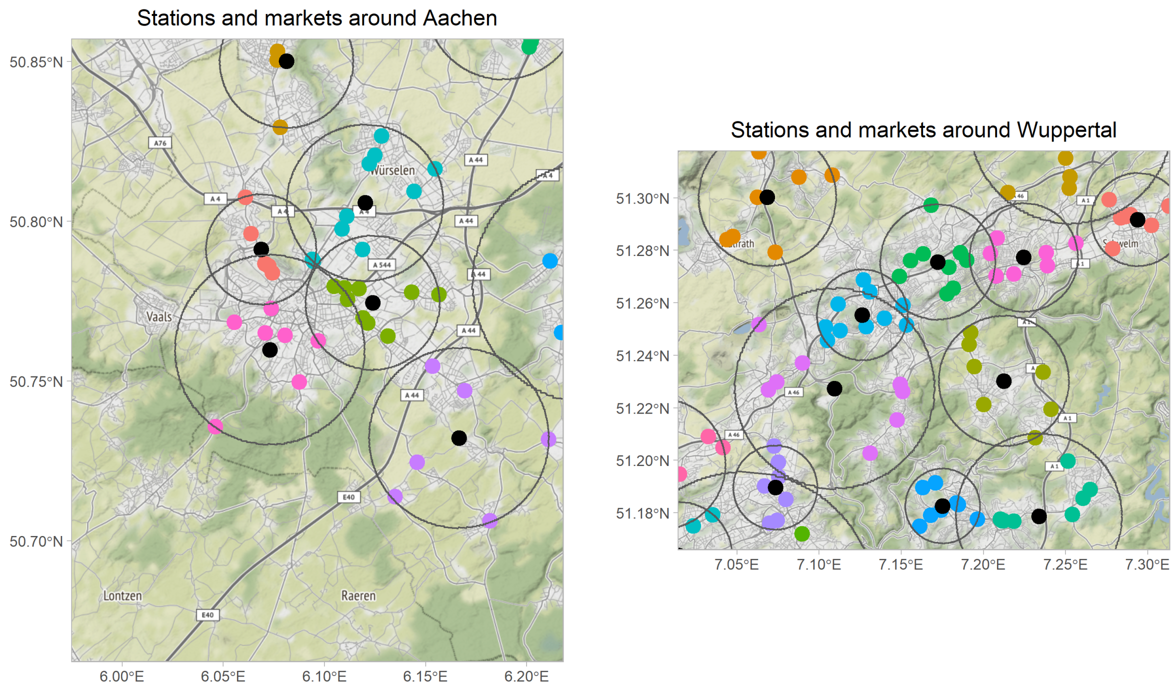

Figure E.2: Illustration of market delineation

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.

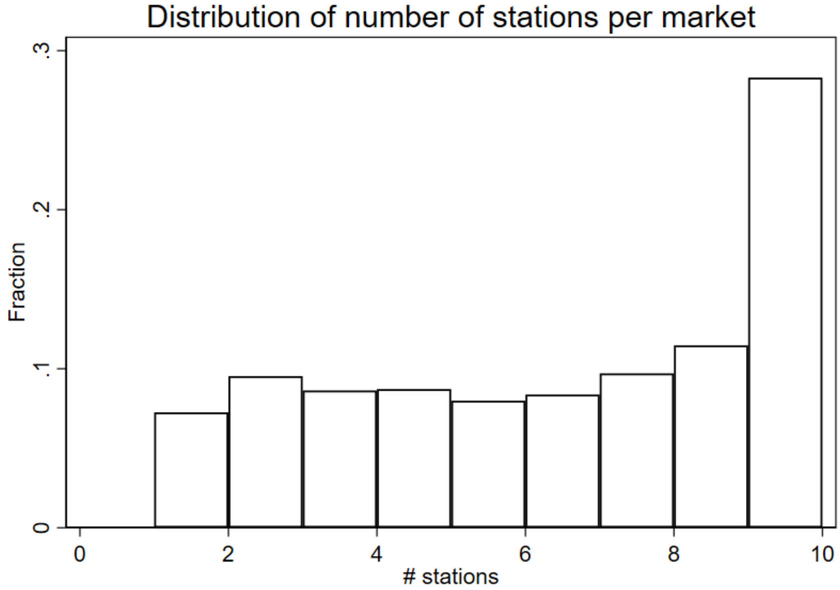

Figure E.3: Distribution of number of stations per market

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

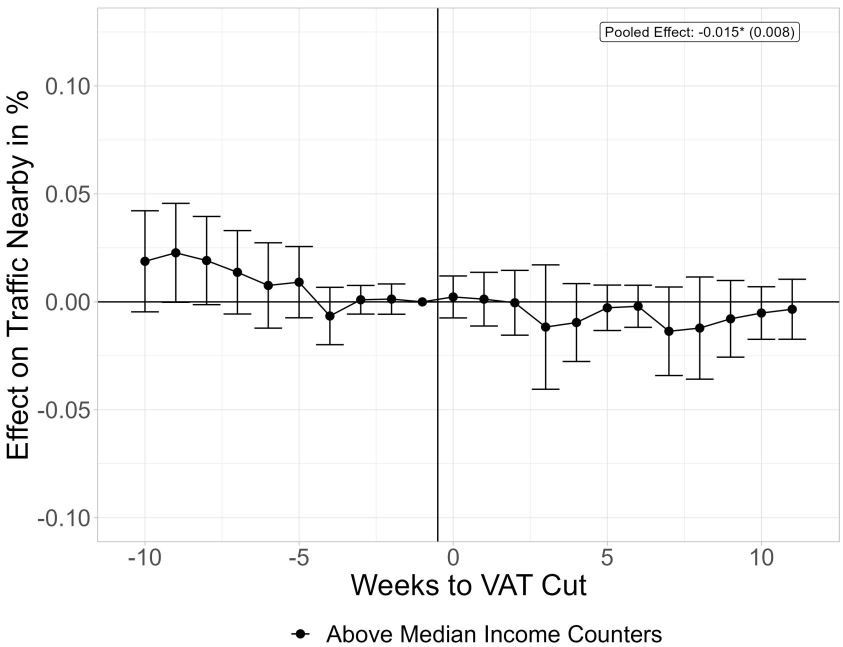

Figure E.4: Traffic Effect of VAT Cut on High- Relative to Low-Income Regions

Note: This figure gives the results of a simple difference-in-differences regression of traffic-counter-level daily traffic on leads and lags of the VAT cut timing interacted with a dummy for counters which are located in counties with an above-median income. We bin leads and lags to weekly bins and use counter as well as state-date fixed effects. There are about 1,500 counters in the sample and only counters which are active over the complete period of the difference-in-differences analysis are included in the estimation. Standard errors are clustered at the municipality level. 95% confidence intervals are reported. The number in the top-right corner is the simple difference-in-differences estimate (pooled effect).

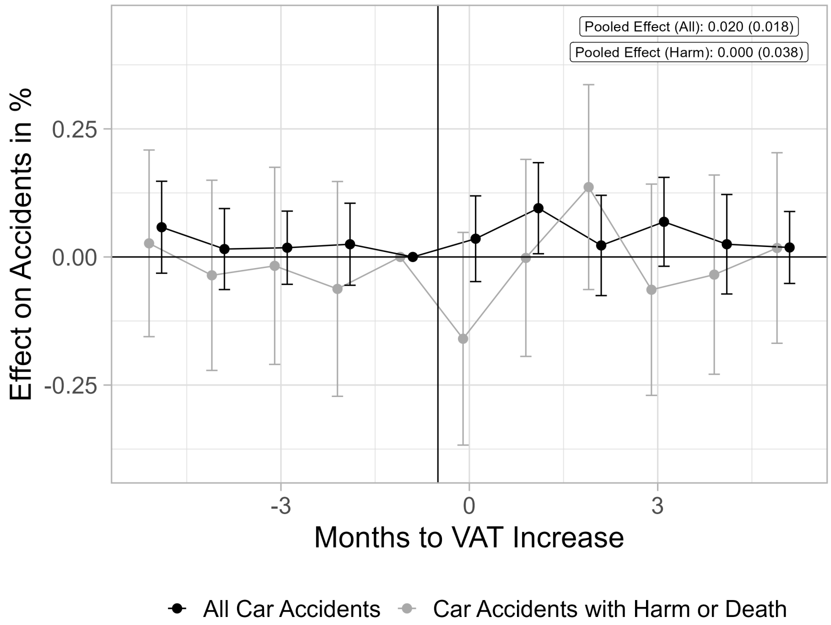

Figure E.5: Accident Effect of VAT Cut on High- Relative to Low-Income Regions

Note: This figure gives the results of a simple difference-in-differences regression of county-level monthly police-reported accidents with personal damage and cars involved on leads and lags of the VAT cut timing interacted with a dummy for counters which are located in counties with an above-median income. We bin leads and lags to weekly bins and use county as well as state-date fixed effects. Standard errors are clustered at the county level. 95% confidence intervals are reported. The number in the top-right corner is the simple difference-in-differences estimate (pooled effect).

References

Adachi, Takanori and Michal Fabinger, "Pass-through, welfare, and incidence under imperfect competition," *Journal of Public Economics*, 2022, *211*, 104589.

Alderighi, Marco and Marcella Nicolini, "Strategic information disclosure in vertical markets," *International Journal of Industrial Organization*, 2022, *85*, 102886.

Anderson, Simon P, Andre De Palma, and Brent Kreider, "The efficiency of indirect taxes under imperfect competition," *Journal of Public Economics*, 2001, *81* (2), 231–251.

_ , _ , and _ , "Tax incidence in differentiated product oligopoly," *Journal of Public Economics*, 2001, *81* (2), 173–192.

Armstrong, Mark and John Vickers, "Competitive price discrimination," *RAND Journal of economics*, 2001, pp. 579–605.

_ , _ , and Jidong Zhou, "Consumer protection and the incentive to become informed," *Journal of the European Economic Association*, 2009, *7* (2-3), 399–410.

Assad, Stephanie, Robert Clark, Daniel Ershov, and Lei Xu, "Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market," *Journal of the Political Economy*, 2023. forthcoming.

Bento, Antonio M., Lawrence H. Goulder, Mark. R. Jacobsen, and Roger H. von Haefen, "Distributional and Efficiency Impacts of Increased US Gasoline Taxes," *American Economic Review*, 2009, *99* (3), 667–699.

Benzarti, Youssef and Dorian Carloni, "Who really benefits from consumption tax cuts? Evidence from a large VAT reform in France," *American Economic Journal: Economic Policy*, 2019, *11* (1), 38–63.

_ , _ , Jarkko Harju, and Tuomas Kosonen, "What goes up may not come down: asymmetric incidence of value-added taxes," *Journal of Political Economy*, 2020, *128* (12), 4438–4474.

Bonnet, Odran, Étienne Fize, Tristan Loisel, and Lionel Wilner, "Compensation against Fuel Inflation: Temporary Tax Rebates or Transfers?," 2024.

Bundeskartellamt, "Sektoruntersuchung Kraftstoffe: Abschlussbericht Mai 2011," 2011.

Bundesministerium für Wirtschaft und Energie, "Evaluierungsbericht zur Markttransparenzstelle für Kraftstoffe," 2018.

Burdett, Kenneth and Kenneth L Judd, "Equilibrium price dispersion," *Econometrica: Journal of the Econometric Society*, 1983, pp. 955–969.

Byrne, David P and Nicolas De Roos, "Learning to coordinate: A study in retail gasoline," *American Economic Review*, 2019, *109* (2), 591–619.

_ and _ , "Start-up search costs," *American Economic Journal: Microeconomics*, 2022, *14* (2), 81–112.

— , **Nicolas de Roos, Matthew S Lewis, Leslie M Marx, and Xiaosong Andy Wu**, "Asymmetric Information Sharing in Oligopoly: A Natural Experiment in Retail Gasoline," *Available at SSRN 4513435*, 2023.

Carranza, Juan Esteban, Robert Clark, and Jean-François Houde, "Price controls and market structure: Evidence from gasoline retail markets," *The Journal of Industrial Economics*, 2015, *63* (1), 152–198.

Chandra, Ambarish and Mariano Tappata, "Consumer search and dynamic price dispersion: an application to gasoline markets," *RAND Journal of Economics*, 2011, *42* (4), 681–704.

Chetty, Raj, Adam Looney, and Kory Kroft, "Salience and taxation: Theory and evidence," *American Economic Review*, 2009, *99* (4), 1145–77.

Clark, Robert and Jean-François Houde, "Collusion with asymmetric retailers: Evidence from a gasoline price-fixing case," *American Economic Journal: Microeconomics*, 2013, *5* (3), 97–123.

Coglianese, John, Lucas W. Davis, Lutz Kilian, and James H. Stock, "Anticipation, Tax Avoidance, and the Price Elasticity of Gasoline Demand," *Journal of Applied Econometrics*, 2017, *32*, 1–15.

Davis, Lucas W. and Lutz Kilian, "Estimating the Effect of a Gasoline Tax on Carbon Emissions," *Journal of Applied Econometrics*, 2011, *26*, 1187–1214.

Delipalla, Sofia and Michael Keen, "The comparison between ad valorem and specific taxation under imperfect competition," *Journal of Public Economics*, 1992, *49* (3), 351–367.

Dubois, Pierre, Rachel Griffith, and Martin O'Connell, "How well targeted are soda taxes?," *American Economic Review*, 2020, *110* (11), 3661–3704.

Eckert, Andrew, "Empirical studies of gasoline retailing: A guide to the literature," *Journal of economic surveys*, 2013, *27* (1), 140–166.

Fischer, Kai, "Alcohol prohibition and pricing at the pump," *Journal of Industrial Economics*, 2024, *72*, 548–597.

— , **Simon Martin, and Philipp Schmidt-Dengler**, "The heterogeneous effects of entry on prices," *Working Paper*, 2024.

Gautier, Erwan, Magali Marx, and Paul Vertier, "How do gasoline prices respond to a cost shock?," *Journal of Political Economy Macroeconomics*, 2023, *1* (4), 707–741.

Gelman, Michael, Yuriy Gorodnichenko, Shachar Kariv, Dmitri Koustas, Matthew D Shapiro, Dan Silverman, and Steven Tadelis, "The response of consumer spending to changes in gasoline prices," *American Economic Journal: Macroeconomics*, 2023, *15* (2), 129–160.

Genakos, C. and M. Pagliero, "Competition and Pass-Through: Evidence From Isolated Markets," *American Economic Journal: Applied Economics*, 2022, *14* (4), 35–57.

Hastings, Justine A., "Vertical Relationships and Competition in Retail Gasoline Markets: Empirical Evidence from Contract Changes in Southern California," *American Economic Review*, 2004, *94* (1), 317–328.

Hayfield, Tristen and Jeffrey S Racine, "Nonparametric econometrics: The np package," *Journal of statistical software*, 2008, *27*, 1–32.

Hong, Han and Matthew Shum, "Using price distributions to estimate search costs," *RAND Journal of Economics*, 2006, *37* (2), 257–275.

Honka, Elisabeth, "Quantifying search and switching costs in the US auto insurance industry," *RAND Journal of Economics*, 2014, *45* (4), 847–884.

_ , Ali Hortaçsu, and Matthijs Wildenbeest, "Empirical search and consideration sets," in "Handbook of the Economics of Marketing," Vol. 1, Elsevier, 2019, pp. 193–257.

Hortaçsu, Ali and Chad Syverson, "Product differentiation, search costs, and competition in the mutual fund industry: A case study of S&P 500 index funds," *The Quarterly Journal of Economics*, 2004, *119* (2), 403–456.

Janssen, Maarten CW and José Luis Moraga-González, "Strategic pricing, consumer search and the number of firms," *The Review of Economic Studies*, 2004, *71* (4), 1089–1118.

Kilian, Lutz, "Understanding the estimation of oil demand and oil supply elasticities," *Energy Economics*, 2022, *107*, 105844.

_ and Xiaoqing Zhou, "Heterogeneity in the Pass-Through From Oil to Gasoline Prices: A New Instrument for Estimating the Price Elasticity of Gasoline Demand," *Journal of Public Economics*, 2024, *232*, 105099.

Knittel, C. R. and S. Tanaka, "Fuel Economy and the Price of Gasoline: Evidence From Fueling-Level Micro Data," *Journal of Public Economics*, 2021, *202*, 104496.

Lach, Saul and José L Moraga-González, "Asymmetric price effects of competition," *The Journal of Industrial Economics*, 2017, *65* (4), 767–803.

Lemus, Jorge and Fernando Luco, "Price leadership and uncertainty about future costs," *The Journal of Industrial Economics*, 2021, *69* (2), 305–337.

Levin, L., M. S. Lewis, and F. A. Wolak, "High Frequency Evidence on the Demand for Gasoline," *American Economic Journal: Economic Policy*, 2017, *9* (3), 314–347.

Lewis, M. S., "Asymmetric Price Adjustment and Consumer Search: An Examination of the Retail Gasoline Market," *Journal of Economics and Management Strategy*, 2011, *20*, 409–449.

_ and M. Noel, "The Speed of Gasoline Price Response in Markets With and Without Edgeworth Cycles," *The Review of Economics and Statistics*, 2011, *93*, 672–682.

Li, Qi and Jeffrey S Racine, "Nonparametric estimation of conditional CDF and quantile functions with mixed categorical and continuous data," *Journal of Business & Economic Statistics*, 2008, *26* (4), 423–434.

Li, Shanjun, Joshua Linn, and Erich Muehlegger, "Gasoline Taxes and Consumer Behavior," *American Economic Journal: Economic Policy*, 2014, *6* (4), 302–342.

los Santos, Babur De, Ali Hortaçsu, and Matthijs R Wildenbeest, "Testing models of consumer search using data on web browsing and purchasing behavior," *American Economic Review*, 2012, *102* (6), 2955–2980.

Luco, Fernando, "Who benefits from information disclosure? the case of retail gasoline," *American Economic Journal: Microeconomics*, 2019, *11* (2), 277–305.

Martin, Simon, "Market transparency and consumer search-Evidence from the German retail gasoline market," *RAND Journal of Economics*, 2024. forthcoming.

Miller, Nathan H, Matthew Osborne, and Gloria Sheu, "Pass-through in a concentrated industry: empirical evidence and regulatory implications," *RAND Journal of Economics*, 2017, *48* (1), 69–93.

Miravete, Eugenio J, Katja Seim, and Jeff Thurk, "Market power and the Laffer curve," *Econometrica*, 2018, *86* (5), 1651–1687.

_ , _ , and _ , "One markup to rule them all: Taxation by liquor pricing regulation," *American Economic Journal: Microeconomics*, 2020, *12* (1), 1–41.

Mirrlees, James A, "Optimal tax theory: A synthesis," *Journal of Public Economics*, 1976, *6* (4), 327–358.

_ and Stuart Adam, *Dimensions of tax design: the Mirrlees review*, Oxford University Press, 2010.

Montag, Felix, Alina Sagimuldina, and Monika Schnitzer, "Does tax policy work when consumers have imperfect price information? Theory and evidence," 2021.

_ , Robin Mamrak, Alina Sagimuldina, and Monika Schnitzer, "Imperfect Price Information, Market Power, and Tax Pass-Through," 2023.

Moraga-González, José Luis and Matthijs R Wildenbeest, "Maximum likelihood estimation of search costs," *European Economic Review*, 2008, *52* (5), 820–848.

_ , Zsolt Sándor, and Matthijs R Wildenbeest, "Semi-nonparametric estimation of consumer search costs," *Journal of Applied Econometrics*, 2013, *28* (7), 1205–1223.

_ , _ , and _ , "Nonsequential search equilibrium with search cost heterogeneity," *International Journal of Industrial Organization*, 2017, *50*, 392–414.

Nishida, Mitsukuni and Marc Remer, "The determinants and consequences of search cost heterogeneity: Evidence from local gasoline markets," *Journal of Marketing Research*, 2018, *55* (3), 305–320.

Noel, Michael D, "Edgeworth price cycles, cost-based pricing, and sticky pricing in retail gasoline markets," *The Review of Economics and Statistics*, 2007, *89* (2), 324–334.

_ , "Retail gasoline markets," in "Handbook on the Economics of Retailing and Distribution," Edward Elgar Publishing, 2016, pp. 392–412.

OECD, "Consumption Tax Trends 2022: VAT/GST and Excise, Core Design Features and Trends," *OECD Publishing*, 2022.

— , "Inflation (CPI) (indicator)," 2024.

Pavan, Giulia, Andrea Pozzi, and Gabriele Rovigatti, "Strategic entry and potential competition: Evidence from compressed gas fuel retail," *International Journal of Industrial Organization*, 2020, *69*, 102566.

Pennerstorfer, Dieter, Philipp Schmidt-Dengler, Nicolas Schutz, Christoph Weiss, and Biliana Yontcheva, "Information and price dispersion: Theory and evidence," *International Economic Review*, 2020, *61* (2), 871–899.

Ramsey, Frank P, "A Contribution to the Theory of Taxation," *The Economic Journal*, 1927, *37* (145), 47–61.

Ritz, Robert A, "Does competition increase pass-through?," *RAND Journal of Economics*, 2024.

Rossi, Federico and Pradeep K Chintagunta, "Price Uncertainty and Market Power in Retail Gasoline: The Case of an Italian Highway," *Marketing Science*, 2018, *37* (5), 753–770.

Scope Investor Services, "Branchenstudie Tankstellenmarkt Deutschland, 2019/2020," 2021.

Varian, Hal R, "A model of sales," *The American economic review*, 1980, *70* (4), 651–659.

Weyl, E Glen and Michal Fabinger, "Pass-through as an economic tool: Principles of incidence under imperfect competition," *Journal of Political Economy*, 2013, *121* (3), 528–583.

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