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The Heterogeneous Effects of Entry on Prices

Abstract

We study the effect of entry on the price distribution in the German retail gasoline market. Exploiting more than 700 entries over five years in an event study design, we find that entry causes a persistent first-order stochastic shift in the price distribution. Prices at the top of the distribution change moderately only, but prices at the left tail decrease by up to 12% of stations' gross margins. Consumers with easy access to information on prices gain the most from entry. The reduction in transaction prices is 32-44% stronger for fully informed consumers than for uninformed consumers.

JEL-Codes: D220, L110, D830, L810, R320.

Keywords: entry, information frictions, price distribution, (unconditional) quantile treatment effects.

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1 Introduction

How changes in market structure affect competitive outcomes and consumer rents is a long-standing question in economics. The overall welfare effect of an increase in the number of firms, i.e. entry, in oligopoly settings is ambiguous as entry involves fixed costs but generally lowers prices and improves product quality (Mankiw and Whinston, 1986). Therefore consumers benefit, on average, from entry.

However, when not all consumers are equally informed about prices in the market, their gains of entry are potentially heterogeneous. To illustrate this idea, suppose that there are two types of consumers in a homogeneous product market (Varian, 1980). *Uninformed* consumers do not compare prices and simply purchase from a firm at random. For these consumers, the expected transaction price equals the average price in the market. *Informed* consumers, in contrast, observe all prices. The average transaction price of such a consumer corresponds to the expected *minimum* price in the market instead. In the presence of price dispersion, the effect of entry for these two groups depends on how entry affects the price distribution.[1]

Price dispersion is ubiquitous in markets for physically homogeneous goods to an extent that cannot be explained by differences in location, cost or services. Thus, it is important to understand how entry affects the distribution of prices and subsequently, how consumers holding different information about prices are heterogeneously affected. As consumer information and search behavior are strongly correlated with market-specific socio-economic variables such as income (Byrne and Martin, 2021, Nishida and Remer, 2018), heterogeneous effects along the information distribution imply distributional effects across socio-economic backgrounds.

In this paper, we empirically investigate how information about prices mediates the effect of entry on consumers in the retail gasoline market. Using real-time price data for the universe of German gasoline stations over five years and exploiting over 700 time- and geo-coded station entries, we identify the effect of entry on the entire price distribution.

The retail gasoline market provides an ideal setting to tackle the question at hand. First, despite an arguably fairly homogeneous product, gasoline markets exhibit substantial price dispersion. In our sample, the average price range is 2.7 ct/l (Eurocents per liter), corresponding to almost 40% of an average station's margin. Second, stations primarily compete on the price dimension where menu costs are effectively zero. Third, the retail gasoline industry consists of numerous small markets, in which entry by one more station is likely to have non-negligible effects. The spatial nature of competition

[1] In the model of sales introduced by Varian (1980), average prices even increase upon entry, so that uninformed consumers are hurt by entry and only informed consumers benefit. Lach and Moraga-González (2017) show that this result does not extend to richer heterogeneity in consumer information. In Appendix C, we present a stylized model based on Armstrong et al. (2009) and Lach and Moraga-González (2017) that illustrates the main channel through which entry differentially affects consumers, depending on their access to information.

in combination with a lack of nation-wide pricing also provides suitable control markets. Last, the fact that we observe several hundreds of entry events into narrow, isolated markets allows us to study heterogeneous effects of entry depending on station and market characteristics.

Exploiting the staggered nature of entry events in a difference-in-differences event study design, we first quantify the effect of entry on incumbent stations' average prices. Although this is only the first step in our paper, we do believe that this is an important contribution relative to the existing literature in its own right, since we get a very clean identification of average treatment effects on the treated of entry due to the large number of fairly comparable entry events. Most of the existing literature, in contrast, relies on cross-industry comparisons or draws conclusions from a relatively small number of observations.

Next, we estimate the effect of entry on the price distribution at different quantiles by implementing both the recentered influence function (RIF) regression approach of Firpo et al. (2009). To infer the counterfactual price distribution we employ the distribution regression approach by Chernozhukov et al. (2013). When consumers are differentially informed (i.e., they observe a different number of price draws before making a purchase decision), their expected *transaction prices* differ, even when they face the same *posted prices*. Thus, we also quantify the effect of entry on different consumer types, depending on how well-informed these consumers are, by simulating transaction prices before and after entry.

Our main findings are as follows. The estimated average effect of entry is a price reduction of around 0.5 ct/l which corresponds to 7% of stations' gross margins. Entry reduces incumbents' prices at all quantiles of the price distribution. The post-entry price distribution is first-order stochastically dominated by the counterfactual distribution of prices absent entry. Hence, all consumers benefit from an increase in competition. However, entry affects the price distribution in an asymmetric fashion: The price decrease from entry is most pronounced at the left tail of the distribution where prices decrease by around 0.9 ct/l or 12% of stations' gross margins. At the top of the distribution, price changes due to entry are not significantly different from zero.

Simulations of consumer transaction prices allow us to exactly quantify how the value of information is affected by competition: better-informed consumers, who observe more prices, benefit significantly more from entry. Fully informed consumers experience a reduction in transaction prices 32-44% larger in absolute terms than the benefits of entry for uninformed consumers. As entry might additionally facilitate price comparisons for consumers due to more stations in the direct vicinity, our estimates are a conservative estimate of the gains from entry.

The estimated effects are robust to a variety of sensitivity checks. We show that entry persistently increases the number of firms in the treated markets. Entry neither fosters nor anticipates exit, i.e. it does not take place in response to exit. This allows us to determine long-run effects of a competition change that is unique to the industry. Using hourly traffic data from almost 2,000 traffic counting stations in Germany, we also show that entry does not take place in response to a demand shift, i.e. an increase in traffic. Our estimates further show no effect of entry on incumbents' opening hours. Entry also neither affects pass-through nor consumer frictions in the market. This suggests that adjusted pricing is incumbents' primary response to entry. Lastly, our findings are robust to various specifications of fixed effects, inclusion of region-time specific controls, different approaches to inference and using data from different times of the day.

By uncovering the distributional implications of entry, our paper also contributes to the debates on how policymakers should affect consumer information. In the national gasoline markets of, for example, Germany, France, Austria or Western Australia, policymakers have introduced price comparison tools for consumers to reduce search costs. While most academic research focuses on the question of whether transparency policies foster firm coordination more than consumers' ability to find the lowest price (Ivaldi et al., 2003, Küehn and Vives, 1995, Luco, 2019, Rossi and Chintaguanta, 2016), our paper unveils a positive effect of such transparency policies: consumers who become better informed due to such tools benefit more from an increase in competition.

This paper relates to several strands of the literature. First, we contribute to research studying the effect of firm entry on prices. While the earlier literature employing cross-industry analyses has found only modest effects of entry on price-cost margins (e.g., Geroski, 1995), more recent papers studying specific industries have found more pronounced effects (e.g., Arcidiacono et al., 2020). The largest body of research studies retail grocery. Basker (2005) and Basker and Noel (2009) show that Walmart entry reduces competitor prices as well as market-level average prices. Arcidiacono et al. (2020) find that Walmart entry substantially reduces revenues by incumbent grocery stores, but they do not identify a significant price response. Bauner and Wang (2019) and Oschmann (2022) show that incumbents instead react to Walmart or Costco entry by reducing product variety and adapting their pricing strategies to more fluctuating prices. Atkin et al. (2018) and Busso and Galiani (2019) study retail markets in Mexico and find price effects of entry in the range of 2-6%.

For the airline industry, Whinston and Collins (1992) show that incumbent airlines' market value drops significantly when a low-cost carrier enters a route served by the incumbent and that the incumbent lowers prices on these routes accordingly. Goolsbee and Syverson (2008) establish that incumbents lower prices already in response to the mere threat of entry by a discount carrier. Prince and Simon (2015) show that this response is accompanied by a reduction in service quality as measured by on-time performance of incumbents. Reiffen and Ward (2005) employ the timing of FDA approval as exogenous in the pharmaceutical industry to establish how generic entry competes away price-cost margins. We provide new insights into the effects of entry by looking at the heterogeneous effects through an information channel in a homogeneous goods market. Additionally, we can estimate average price effects very precisely due to our large sample and clean identification.

We also contribute to the literature on the interaction of competition and informational frictions, especially in gasoline markets, such as Chandra and Tappata (2011) or Lach and Moraga-González (2017). Rather than relying on cross-sectional variation in the number of competitors between markets, the event study design allows us to look at within-firm and within-market price variation. This allows us to keep any firm- or market-specific characteristics constant to isolate the effect of a marginal increase in competition (entry). Moreover, the setting enables us to study how consumers are differently affected by entry, depending on how informed they are about prices. Our results are in line with Lach and Moraga-González (2017) who also find more informed consumers to profit the most from competition. However, we find stronger effects of changes in competition.

Finally, our paper complements the few papers which examine the effect of competition on the price distribution. Allen et al. (2014) study a bank merger and its heterogeneous effect on mortgage prices across local markets. In contrast to us, they can only exploit the ownership structure in the market and not changes in the number of outlets. Moreover, the entry of different types of stations into various kinds of markets allows us to study how entrant and incumbent characteristics affect the change of the price distribution.

The remainder of the paper proceeds as follows: In Section 2, we discuss the institutional setting of our research as well as the data we use. We then proceed with discussing the empirical strategy in Section 3. In Section 4, we present our results on the effect of entry on the price distribution and to which degree a consumer's informedness affects the benefits of entry. We discuss our results and conclude in Section 5.

2 Industry Background and Data

We study the effect of entries into the German gasoline market from 2015 to 2020 by combining data from various sources.[2]

We obtain the universe of prices and detailed information for all gasoline stations (brand affiliation, address, exact location) over the entire sample period from Tankerkönig[3].

[2]Our sample ends in early 2020, the beginning of the COVID-19 pandemic. We drop the period due to substantial demand shocks as well as a temporary VAT reduction in 2020.

[3]`http://tankerkoenig.de/`. The same data source is also used e.g. in Montag et al. (2023), Montag et al. (2021) and Martin (2023). This database uses real-time data provided by the German Market Transparency Unit (MTU, in German Markttransparenzstelle für Kraftstoffe MTS-K), which is a sub-unit of the German competition authority (Bundeskartellamt). By regulation, gasoline stations are required to submit all price changes to the MTU 'instantanenously' since December 2013. The introduction of this regulation sufficiently predates our sample period and should therefore be inconsequential for our subsequent analysis.

The market is dominated by five major brands: Aral (BP), Shell, Total, Esso, and JET, which together operate almost half of all stations in Germany (see Figure D.1 in the Appendix for a detailed overview). Around 25% of stations are not affiliated with any brand and are therefore considered independent.

Gasoline stations on highways are arguably competing for a different set of consumers (Bundeskartellamt, 2011, Martin, 2023, Montag et al., 2021). We follow the literature and omit these stations from our analysis entirely.[4] Throughout, we focus on diesel prices at 5 pm, which is when most consumers fuel their cars (Deutscher Bundestag, 2018). Later we also provide results for E5 gasoline and other times of the day (see Section 4.5).

Table 1 provides summary statistics on the stations in our sample, 15,437 in total, where approximately 40% are open 24/7. Across all stations, the average posted price over the sample period is 117 ct/l. Prices at major brands (Total, Shell, Esso, Aral) tend to be higher, with an average brand premium of around 1 ct/l relative to unbranded stations, and even around 2 ct/l relative to budget stations such as JET stations.[5]

Gross margins account for about slightly more than 6% of the retail price. Similar to Assad et al. (2023), we use daily, diesel wholesale price data for nine price regions in Germany as published in the Oil Market Report by 'Argus Media' to calculate gross margins.[6] We match the closest, available regional wholesale price to each station on a daily basis. The average margin of slightly more than seven ct/l fits industry survey evidence of slightly around ten ct/l (Scope Investor Services, 2021).

Using stations' address information and location data, we compute the number of competitors within a given radius (Pennerstorfer et al., 2020). The average station has 0.9 (2.6) competitors within a 1 km (2 km) radius, respectively. The implied market structure is illustrated in Figure D.2 in the Appendix. According to a market delineation based on a 1 km (2 km) radius, 47% (25%) of markets are local monopolists, and 29% (21%) are duopolies respectively. Consequently, the majority of stations face local competition, even within fairly small radii.

We also collected traffic flow data from almost 2,000 traffic counting stations in Germany operated by BASt (Bundesanstalt für Straßenwesen - Federal Highway Research Institute). Finally, we complement our data with annual, county-level variables from the

[4]We identify highway stations in a two-step procedure: First, we check stations on the website `https://www.raststaetten.de/alle-standorte` and `https://serways.de/standorte`, which together list all highway stations let out to tenants by *Tank & Rast*, the company in charge of all highway roadhouses (Bundeskartellamt, 2011), in a cross-section of February 2023. We get the exact coordinates of these roadhouses and their stations and calculate distances to stations in our dataset. Stations with a distance of below 500 metres to a roadhouse are coded as highway stations. In the second step, we manually check our results for errors. We examine the address list of all German stations to identify stations ID's which were not yet coded as highway stations or falsely coded as such. We classify almost 500 station IDs as highway gas stations and drop them.

[5]See Figure S.11 in the Appendix for a more detailed distribution of brand premia.

[6]The gross margin is given by: $margin_{it} = price_{it}/(1+VAT) - wholesaleprice_{it}$, where the wholesale price already includes the diesel excise tax.

	Station Cross-Section			Station×Date Panel		
	N	Mean	S.D.	N	Mean	S.D.
Station Choices						
Price (ct/l)	15,437	117.05	3.098	26,029,786	116.85	10.288
TOTAL	849	117.72	2.834	1,510,239	117.45	10.316
SHELL	1,714	117.65	2.442	3,076,811	117.58	10.228
ESSO	1,069	117.14	2.333	1,925,844	117.16	10.449
ARAL	2,255	118.21	2.316	4,053,112	118.21	10.536
JET	692	115.86	2.480	1,204,020	115.58	10.040
Others	8,858	116.60	3.404	14,259,760	116.30	10.171
Gross Margin (ct/l)	15,437	7.465	1.656	26,029,786	7.416	3.111
1[Open 24/7]	14,876	0.398	0.481	6,311,536	0.396	0.489
Station Characteristics						
# Competitors 1 km Radius	15,437	0.892	1.091	26,029,786	0.893	1.100
# Competitors 2 km Radius	15,437	2.540	2.615	26,029,786	2.582	2.649
1[Big Four]	15,437	0.381	0.486	26,029,786	0.406	0.491
1[JET]	15,437	0.047	0.211	26,029,786	0.048	0.213
1[Entrant]	15,437	0.047	0.212	26,029,786	0.026	0.158
1[Incumbent - 1 km Radius]	15,437	0.035	0.185	26,029,786	0.035	0.183
1[Incumbent - 2 km Radius]	15,437	0.087	0.282	26,029,786	0.088	0.283

Table 1: Station-Level Information

Note: To obtain station-level, cross-sectional variables, we averaged over the respective observations at the station level. Using daily data from early 2015 to early 2020, we observe approximately 1,850 dates in our sample.

German Statistical Office. This data allows us to control for different local trends in GDP per capita, income, unemployment, population and other socio-economic measures over time. We also obtained data on the number of vehicles and commuters at the same level of aggregation.

2.1 Price Dispersion

An important characteristic of retail gasoline markets is cross-sectional price dispersion, even though gasoline is a fairly homogeneous good. We report several measures of price dispersion at the market level, namely the sample standard deviation of prices ($S.D.$), the range of prices (*Range*), and the value of information (VOI), i.e., the difference between the *average price* and the *minimum price*, in Table 2.

We define markets as circles of 1 km and 2 km radius around each station. This is identical to Moraga-González et al. (2017) and similar to, for example, Chandra and Tappata (2011) who use 1 and 2 miles markets or Cabral et al. (2019) defining station neighborhoods as 1.25 miles circles. Pennerstorfer et al. (2020) use 2 miles driving distance as a critical threshold for market delineation. In our analyses, we will drop markets with entrants in the centroid, as we naturally do not observe these markets before entry events.

Within a 2 km radius, the average price range is around 3 ct/l, i.e., 2.5% of the sample average price or around 40% of stations' average gross margin (Scope Investor Services, 2021).[7] The average value of information is 1.3 ct/l. This implies that consumers could gain considerably, depending on how well they are informed about the price distribution. Moreover, this illustrates that we should not only investigate the effect of entry on average prices, but also on the price distribution, since consumers with different access to information will be heterogeneously affected by entry and profit from changes at different points of the price distribution.

1 km Radius		p10	p25	Mean	p75	p90	S.D.
S.D.	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(p_{it}-\bar{p}_{mt})^2}$	0.000	0.500	1.134	1.414	2.828	1.303
Range	$p_{mt}^{max}-p_{mt}^{min}$	0.000	1.000	1.930	3.000	5.000	2.236
VOI	$\bar{p}_{mt}-p_{mt}^{min}$	0.000	0.250	0.933	1.333	2.250	1.078
2 km Radius		p10	p25	Mean	p75	p90	S.D.
S.D.	$\sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(p_{it}-\bar{p}_{mt})^2}$	0.000	0.577	1.286	1.732	2.828	1.209
Range	$p_{mt}^{max}-p_{mt}^{min}$	0.000	1.000	2.748	4.000	6.000	2.679
VOI	$\bar{p}_{mt}-p_{mt}^{min}$	0.000	0.500	1.276	1.714	2.857	1.244

Table 2: Descriptives on Price Dispersion

Note: Dispersion measures are only calculated for market-date combinations with at least two firms. All values in ct/l. p_{it} denotes a station's i price on date t. p_{mt}^{min}, p_{mt}^{max} and $\bar{p}_{mt}$ denote the minimum, maximum and mean price in market m on date t respectively.

Importantly, the price differences between stations cannot be fully explained by time-invariant differences in station characteristics such as service quality or other measures of vertical differentiation. We show this by documenting how the price ranking between stations changes over time. We implement the rank reversal test proposed by Chandra and Tappata (2011). For any pair of stations A and B, forming a couple c, the test calculates the likelihood that the station which is the cheaper on most days sets the higher price. If station A usually is the cheaper station, then

$$rr_c = \frac{1}{T_c}\sum_{t=1}^{T_c} 1[p_{A,t} > p_{B,t}], \tag{1}$$

where T_c is the number of days, on which both stations operate simultaneously and $p_{A,t}$ and $p_{B,t}$ are both stations' prices on day t.

[7]In some markets, dispersion is 0 ct/l (see values at first decile). This is due to the fact that most markets in our sample are duopolies or triopolies, where firms may also set the same price.

The average rank reversal of pairs with a maximum distance of 1 km (2 km) is 0.118 (0.123). Also, rank reversals increase with the distance between stations. Figure D.3 and Table E.3 in the Appendix show that reversals are lowest for station pairs up to 250 metres distance between the stations, i.e. the likelihood of rank reversal decreases by 5.1 percentage points relative to station pairs between 0.25 and 5km distance. Hence, there is substantial temporal price dispersion at the station-pair level, which cannot be explained by time-invariant differences between stations. Information frictions can explain the observed changes in price rankings.

2.2 Market Entry

We define entry as the first time a station posts a price, which should be very accurate given the mandatory price reporting regulation.[8] Based on these entry dates, we allocate treatment to all stations in a 1 km (2 km) radius at the weekly level.

We record over 700 unique entry events in our sample period. Overall, 1400 stations (i.e., more than 10% of all the stations in our sample) experienced at least one entry event within a 2km radius over our sample period. 550 stations experienced entry even within a 1 km radius. In Figure 1, we illustrate the geographic and temporal distribution of entry events. Entry occurred all over the country and is fairly evenly distributed over time. Slightly fewer entries in later years might reflect the progressing consolidation of the industry as the number of stations in Germany has been slightly falling over the last years (Scope Investor Services, 2021).

3 Empirical Strategy

We estimate the causal relationship between market entry in the German gasoline industry and station- and market-level outcomes by exploiting the high number of market entries documented above. In the following, we first explain the estimation setup. Second, we discuss how our identification strategy addresses standard endogeneity concerns when studying market entry. Lastly, we explicitly outline the estimation procedure, which allows us to study the heterogeneous effects of competition on consumer types, depending on their information about prices.

We study the effect of the staggered 'rollout' of entries in a two-way fixed effect difference-in-differences model, which compares prices of treated *incumbents* before and

[8]Stations which changed their brand affiliation are also listed with a new identifier. We do not count these as 'entry events'. For that purpose, we ensure that there is no station of (almost) identical address. Specifically, we check for each 'potential entrant' with a formerly existing station within 400 metres distance whether this station nearby might be the same station under a different affiliation. We check all these cases manually to arrive at a final list of entries. Despite all efforts, we might erroneously classify incumbent stations as entrants. In that case, we are likely to underestimate the price effect of entry in absolute terms.

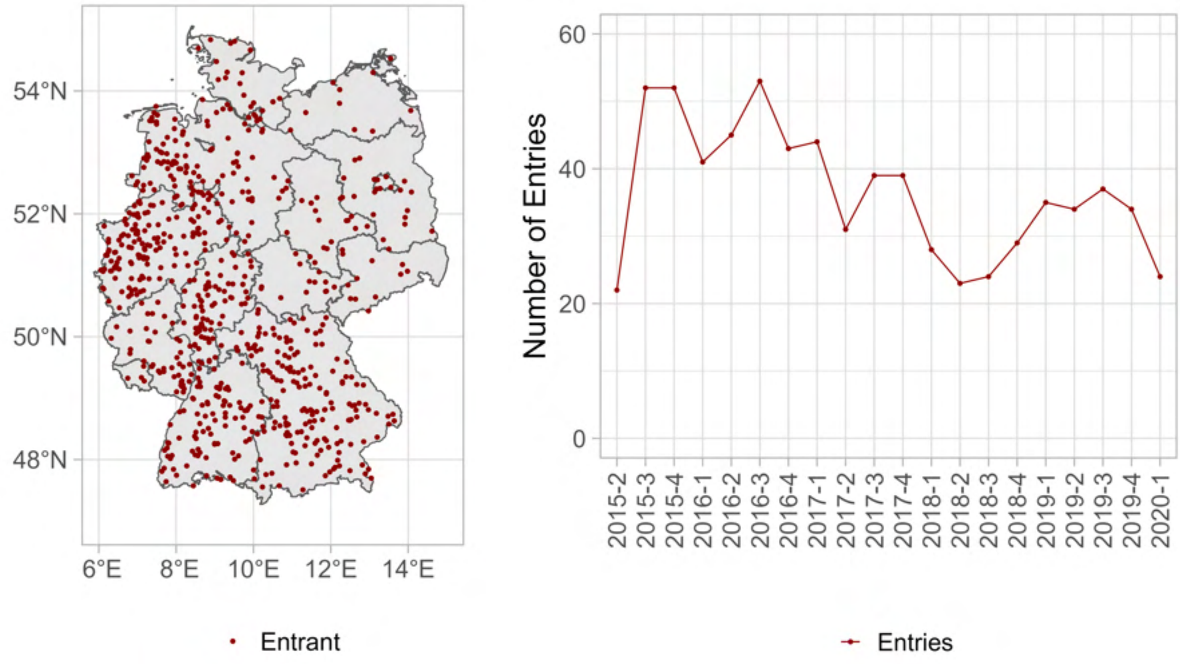


Figure 1: Geographical and Temporal Distribution of Entry

Note: The left figure documents the exact locations of all entry events in our sample. The borders represent the administrative federal state borders ($N = 16$ states). The right figure plots the distribution of entry events over time aggregated at the quarterly level.

after entry with non-treated control stations. The baseline regression is as follows:

$$Y_{it} = \alpha_i + \lambda_{st} + \beta \times 1[Post - Entry]_{it} + \gamma' X_{ct} + \epsilon_{it}. \tag{2}$$

Here Y_{it} is station or market i's outcome (e.g., station price or market mean price) on day t. Individual station (or market) and state-times-day fixed effects ($N = 16$ states) are denoted by α_i and λ_{st} respectively. The vector X_{ct}, with c denoting a county, consists of socio-economic variables at the county-year level (e.g., population, unemployment rate, income), which we include as control variables. Most importantly, $1[Post - Entry]_{it}$ is the binary treatment indicator. It will turn one if an incumbent experiences entry (within 1 km or 2 km radius, respectively) in period t or earlier. The error term is denoted by ϵ_{it}.

We only consider the first entry event for each incumbent and drop observations as soon as a second entry event occur. By this, we avoid pooling the likely structurally different entry effects of a first and second entry. Further, this allows us to estimate the simple difference-in-differences coefficients β, which gives us the effect of entry on outcome Y_{it}.[9] We account for correlation in the residuals of the regression by clustering standard errors at the municipality level.

[9]Note that only 1.7% (1 km) and 3.8% (2 km) of all incumbents experience more than one entry event in our sample period. Only looking at the first four months after entry, no station in our sample experiences a second competitor entry.

3.1 Identification

Analyzing firm entry is empirically challenging as the econometrician might not observe all market characteristics which determine entry incentives. This is illustrated in Table E.1, where we show that entrants typically have significantly fewer competitors in a 1 km or 2 km radius than the treated incumbents. As profitability and prices are the main driver of entry, a reverse causality bias is a concern. We address this problem by holding such unobserved characteristics of stations and markets fixed over time by including the respective fixed effects.

An additional challenge to identification may be that market-level profitability could change over time. This will be a problem if profitability does not change at the same time and in the same fashion in the treatment and control group, i.e., if treatment and control stations are not on the same trend. To alleviate this concern, we provide event studies for our difference-in-differences analyses estimated based on the following regression form:

$$Y_{it} = \alpha_i + \lambda_{st} + \sum_{\tau=-\underline{\tau},\neq-1}^{\bar{\tau}} \beta_\tau 1[Entry]_{it,\tau} + \epsilon_{it}, \tag{3}$$

where $\sum_{\tau=-\underline{\tau},\neq-1}^{\bar{\tau}} 1[Entry]_{it,\tau}$ are leads and lags of the treatment. In our baseline regressions, we bin leads and lags to six-month bins with an effect window of four bins before and five bins after the treatment ($\underline{\tau} = \bar{\tau} = 4$). Endpoints are binned, i.e., the most left and right bins include all observations lying outside the effect window.

If the pre-trends of the event studies are flat, this will be indicative of treated and control stations being on parallel trends. Simultaneously, it will alleviate concerns of a reverse causality bias. In the case of reverse causality, diverging pre-trends should be observable, too. We find that pre-trends are rather flat in all of our event studies later on. In the appendix, we even show that treated incumbent stations are very similar in observable characteristics compared to the universe of other outside stations in our sample before the treatment (see Table E.2). Incumbents do not differ in their price or margin level as well as county-level observables. If anything, treated markets already have a slightly larger number of competitors prior to the entry event. This is suggestive of the estimated effects likely being representative of the overall population of stations in our sample, too.

Another concern is that we might pick up unrelated price shocks, which occur at the same time and in the same markets as the entry events. To invalidate our identification strategy, two conditions would have to be satisfied. First, such shocks have to be highly dispersed over space and have to affect stations heterogeneously within a state. Second, such shocks need to chronologically coincide with our entry events. Both seem unlikely. We support this claim by showing that entry is not driven by structural changes on the demand side, proxied by traffic flow data from almost 2,000 traffic counters all over

Germany. Figure D.4 in the Appendix shows that traffic at counters near entrants does not change around the time of entry.

It is also unlikely that entry is triggered by, for example, local policy shocks at the time of the shock, since a gasoline station cannot simply be opened at arbitrary locations, and certainly not within a short period of time. Similarly, entry in response to local changes in search behavior, e.g. due to heterogeneous trends in the use of price comparison apps across markets and over time, would be visible in the pre-trends as search behavior affects observed prices.

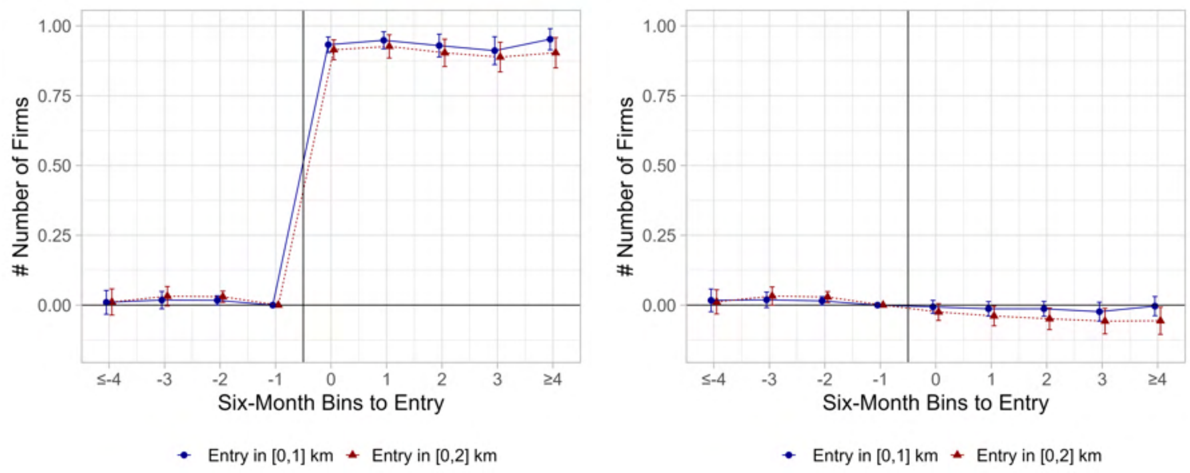
Moreover, for our difference-in-differences regressions to uncover the causal relationship requires the stable unit treatment variable assumption (SUTVA) is not violated. This implies that spillovers of the treatment of incumbents should not affect control stations. As identification stems from comparing prices within federal states and given the typically very narrow markets in the gasoline industry, it seems unlikely that control stations are strongly affected by entry. If at all, the strategic complementarity in incumbent and control station prices would result in underestimating of the effect in absolute terms.

Furthermore, a natural concern is that the studied local shock on competition might not be persistent over time. For example, entry could occur in markets where exit has recently happened or is anticipated. However, we provide evidence that the shock on the number of firms is persistent. Figure 2 shows in its left panel that entry increases the number of stations in the short and long run. At the same time, we do not find that a substantial number of stations are triggered to exit the market in response to entry. Flat pre-trends also show that entry does not happen in markets that experienced a declining number of firms in advance.

Finally, the recent literature on two-way fixed effects difference-in-differences estimations with a staggered rollout of treatment shows that estimated effects might be biased (Borusyak et al., 2022, Callaway and Sant'Anna, 2021, De Chaisemartin and d'Haultfoeuille, 2020, Sun and Abraham, 2021). This will be the case if treatment effects are heterogeneous for incumbents who experience entry at different points in time. For example, changes in the search behavior of consumers over time, e.g. due to the adoption of more price comparison apps, effects sizes might vary over time. Our results are unlikely to be qualitatively affected by this problem as the vast majority of stations in our sample are never-treated control stations (Borusyak et al., 2022). Nevertheless, we provide robustness checks with the proposed estimator of Sun and Abraham (2021) later on.

3.2 Quantile Treatment Effects and Counterfactual Distribution

We want to study how consumers, who hold different information about prices, are heterogeneously affected by station entry. Better-informed consumers purchase at different



(a) Including Entrant

(b) Excluding Entrant

Figure 2: Market-Level Number of Firms

Note: This figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. The outcome variable is the number of firms in a market on a certain date. In the left plot, entrants are included. In the right plot, only incumbents are considered. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.

prices than less-informed consumers. We, therefore, examine how the price distribution changes over its entire range instead of just at the (conditional) mean. As we need to observe pre-entry prices to construct the counterfactual, this analysis focuses on the incumbent prices and not yet includes entrants' prices. We will consider them later on. First, we estimate the quantile treatment effects of entry. Formally, denoting the distribution of incumbents' observed post-entry prices by $F_{entry}(p_{it})$ and the counterfactual distribution of incumbents' prices absent entry by $F_{no\ entry}(p_{it})$, the quantile treatment effect at quantile q is defined by $F^{-1}_{entry}(q) - F^{-1}_{no\ entry}(q)$.

Note that, in our setting, we are especially interested in the *unconditional* quantile treatment effect instead of the *conditional* quantile treatment effect from standard quantile regressions. The latter gives the distributional effects conditional on covariates. For example, the conditional quantile treatment effect at the 90th percentile quantifies the effect on stations with relatively high prices (given their characteristics), but not on stations that are at the 90th percentile of the unconditional price distribution. We, however, care about the general effects along the price distribution - also across stations of different characteristics as consumers likely compare such within a market - and hence are interested in the unconditional quantile treatment effects.

While the formal expression for the quantile treatment effect is rather simple, the econometrician's challenge is to obtain the unobserved counterfactual price distribution $F_{no\ entry}(p_{it})$. We implement two approaches which construct the counterfactual price distribution: first, we estimate quantile treatment effects by applying the 'recentered influence function (RIF)' by Firpo et al. (2009). This method uses a local linear approximation of the counterfactual distribution based on observed prices to implicitly derive counterfactual prices. The approximation allows us to estimate quantile treatment effects with OLS regressions. While this provides valuable insights about the change at a chosen quantile of the distribution, it does not allow us to draw conclusions about the global shift of the price distribution. For example, testing whether the distribution of observed prices is first-order stochastically dominated by counterfactual (non-entry) prices is desirable, as this is a sufficient condition for all consumers to profit from entry in a homogeneous goods market. In a second step, we, therefore, elicit the *complete* counterfactual distribution of prices absent entry by adopting the 'distribution regression' approach suggested by Chernozhukov et al. (2013).[10]

Firpo et al. (2009) relies on a local linear approximation of the counterfactual price distribution. The intuition behind the approach is as follows: upon construction of a binary indicator of whether a price observation is above a price threshold p, a simple regression as in (2) yields the estimated vertical distance $F_{entry}(\hat{p}) - F_{no\ entry}(\hat{p})$ between the distribution of actual and counterfactual prices at a given price $\hat{p}$. The larger the empirical density at price $\hat{p}$, $f_{entry}(\hat{p})$, the smaller the change in prices (horizontal distance) needed to reach the found vertical distance. This horizontal price distance between the two distributions defines the quantile treatment effect. Formally, this is implemented by transforming the outcome variable to the 'recentered influence function (RIF)':

$$Y_{it}(\hat{q}) = p(\hat{q}) + \frac{\hat{q}}{f(p(\hat{q}))} - \frac{1[p_{it} < p(\hat{q})]}{f(p(\hat{q}))}. \tag{4}$$

Here $Y_{it}(\hat{q})$ is the RIF and $p(\hat{q})$ the price at the $\hat{q}^{th}$ quantile. The function $f(p(\hat{q}))$ denotes the empirical density function of observed prices evaluated at $\hat{q}$. We estimate $f(p)$ using an Epanechnikov kernel with a bandwidth following Silverman's rule of thumb as in, for example, Dube (2019). Given $\hat{q}$, $p(\hat{q}) + \frac{\hat{q}}{f(p(\hat{q}))}$ is constant, so the main variation in the new outcome variable stems from whether the price is below or above $p(\hat{q})$. Estimating (3) with the RIF as the dependent variable allows us to obtain the quantile treatment effect at a certain quantile in only one regression. Applying this approach for different quantiles $\hat{q}$ allows us to estimate the shift at several discrete points of the entire price distribution.

Note that, as we insert (4) as the dependent variable in the regression equation (2), we identify changes in the empirical distribution due to entry within state-date cells. Hence, the estimation of quantile treatment effects relies on within-day price comparisons.

Chernozhukov et al. (2013) propose to construct the counterfactual price distribution by estimating how entry affects the likelihood of prices being below a certain threshold.

[10] The estimation of distributional effects of public policies is especially common in the field of public and labour economics. For example, see Havnes and Mogstad (2015) and Huebener et al. (2017) for applications of Firpo et al. (2009). Dube (2019) and Hernæs (2020), among others, use the method introduced by Chernozhukov et al. (2013).

In our context, the respective regression equation is:

$$1[p_{it} \leq \hat{p}] = \alpha_i + \lambda_{st} + \beta \times 1[Post - Entry]_{it} + \gamma' X_{ct} + \epsilon_{it}. \tag{5}$$

The outcome variable is a dummy which will be one if $p_{it} \leq \hat{p}$. The coefficient β corresponds to the estimated vertical difference between the two distribution functions, $F_{entry}(\hat{p})$ and $F_{no\ entry}(\hat{p})$ at price. Estimating one regression for each unique price value in the dataset constructs the counterfactual empirical price distribution $\hat{F}_{no\ entry}(p_{it})$. Hence, this approach is computationally more intense but explicitly models the counterfactual distribution instead of a local linear approximation.

In our empirical analysis in Section 4, we implement both methods laid out here. We build on the approach by Firpo et al. (2009) to estimate quantile treatment effects. Additionally, we estimate the price counterfactual distribution using Chernozhukov et al. (2013) to then test for a global shift of the price distribution in a first-order stochastic manner. The outcome from Chernozhukov et al. (2013) also serves as an input to cross-validate our results when using the method of Firpo et al. (2009) instead, by comparing the empirical price distribution and the counterfactual price distribution.

3.3 First-order Stochastic Dominance

The quantile treatment effects are, by design, informative about the effect of entry at certain points of the price distribution *in isolation*. However, we are also interested in how entry shifts the entire price distribution. For example, only if the price distribution is first-order stochastically dominated by the counterfactual (no entry) price distribution, we can be sure that both uninformed and well-informed consumers benefit from entry. This requires to *jointly* test for the difference between the distribution of observed and counterfactual prices at multiple prices.

We, therefore, implement three statistical tests to examine whether observed prices are jointly first-order stochastically dominated by counterfactual prices. The one-sided Kolmogorov-Smirnov test is based on the maximum vertical distance between two distributions. In contrast, the stochastic-dominance tests proposed by Barrett and Donald (2003) and Davidson and Duclos (2000) are based on the minimum vertical distance between two distributions and therefore more conservative. To compute those distances, the test by Davidson and Duclos (2000) takes a pre-specified set of points on the price grid as an input. Barrett and Donald (2003) integrate over the entire support of prices, which eliminates the necessity to fix a set of points upfront.

To examine the robustness of our findings, we present the results for all three tests. We compare observed post-entry prices with the counterfactual no-entry prices, elicited through the distribution regressions as in Chernozhukov et al. (2013) as explained above.[11] Note that the elicited counterfactual distribution, given by the point estimates of the distribution regressions, may not be monotonically increasing at all prices. The distribution regressions at all prices do not condition on a positive density function across distribution regressions. However, this does not affect the test results, as the tests compare the observed price distribution and the counterfactual price distribution at certain prices only. As we take the point estimates of the estimated counterfactual distribution, we abstract from its confidence interval. Admittedly, this facilitates confirming strict first-order stochastic dominance. Though the test results are very much in line with a visual inspection of the compared distribution functions.

Note that a shift of the price distribution due to entry in a first-order stochastic dominance manner cannot be rationalized by, for example, the standard model as in Varian (1980). The intuition is that stronger competition induces firms to lay more probability mass on high prices in the price distribution. In Appendix C we present a model based on Armstrong et al. (2009) and Moraga-González et al. (2017) which rationalizes such a shift.

3.4 Heterogeneous Effects on Consumers

The methods above allow us to estimate the changes along the price distribution. Importantly, this reflects only *posted prices*, which are different from the prices consumers actually pay (*expected transaction prices*). Therefore, shifts in the price distribution are not fully informative about to which extent consumers of different information levels benefit from entry. For example, a shift at the left tail of the price distribution affects consumers differentially, depending on whether they buy at the cheapest price, or whether they buy at a random price. We present a stylized model based on Armstrong et al. (2009) and Lach and Moraga-González (2017) in Appendix C.

To fully understand which kind of consumers benefits how much, we need not only to analyze changes in the price distribution, but consumers' actual transactions, depending on their information endowment. This also includes entrants' prices and not just incumbents' prices. Since a matching of transaction data to consumers' unobserved degree of informativeness at the consumer level is naturally not possible, we simulate different consumer types and analyze the respective effects of entry (Lach and Moraga-González, 2017).

More specifically, we simulate consumers with heterogeneous information endowments. A type-k consumer is aware of a random sample of k out of n prices in a given market, and purchases at the station with the cheapest out of these k prices. At the extreme, some

[11] An alternative would be to compare observed pre-entry and post-entry distributions. Since several additional determinants of prices, e.g., input prices, might have changed meanwhile as well, this would be a potentially misleading comparison though.

consumers might only observe one random price for 'uninformed consumers' (i.e., $k = 1$) or all prices for 'fully informed' consumers (i.e., $k = n$, the number of firms in the market). We simulate consumers who are able to observe $k = 1, 2, \ldots, 5$ prices in a market as well as the benchmark consumer who is perfectly informed ($k = n$). These k prices are drawn randomly from the observed price in a market. For each market-date cell, we calculate the transaction price per consumer type, repeat the simulation 100 times and take the mean of the drawn transaction prices as the outcome variable. Finally, we regress the simulated transaction prices on the post-entry dummy in the standard difference-in-differences setup as described in equation (2) above.

4 Results

In this section, we first show that, indeed, prices *on average* decrease in response to entry. Building on this result, we then study the heterogeneous effects of entry along the price distribution and implications for consumer welfare through expected *transaction prices* .

4.1 Average Effect on Prices

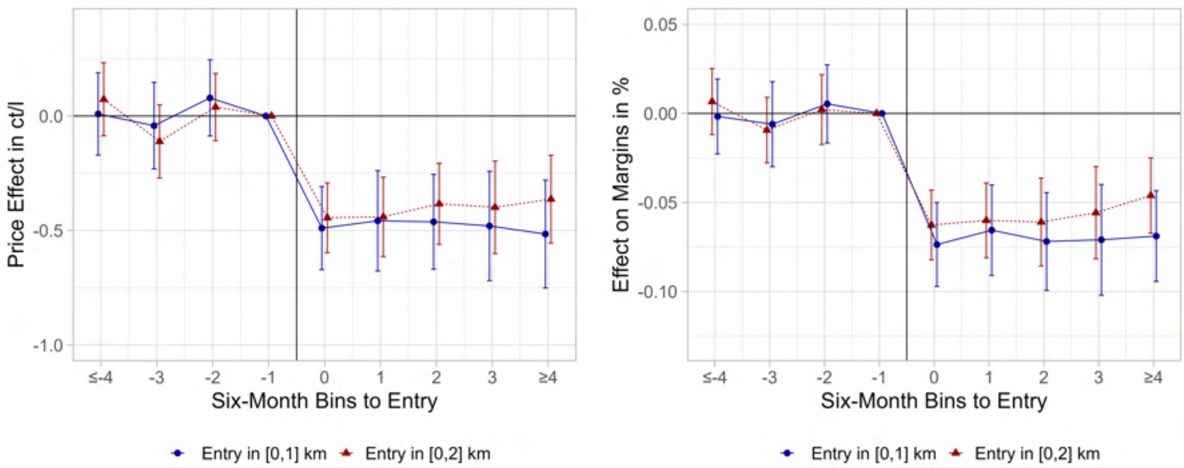
In the first step, we estimate the dynamic effect of entry events on posted prices at stations nearby as outlined in equation (3). We estimate the event studies for entry happening in a linear distance radius of 1 km or 2 km around a station. The left panel of Figure 3 shows that we find a negative effect of entry on prices. Flat pre-trends lend support that we do not violate the parallel trends assumption and, by that, are indicative of a causal relation between entry and prices. They are also suggestive of no anticipatory pricing in the months before entry because incumbents' prices right before entry do not significantly differ from prices more than two years before entry. The price effects are rather persistent over time for entry up to 2 km distance.

When entry occurs close by (i.e., up to 1 km distance between entrant and incumbent), the estimated average effect is a price reduction of around 0.5 ct/l. To put these numbers into perspective, recall that the major brand premium is around 1 ct/l, so only around twice as big as the effect of a single entry. Moreover, a retail price reduction of 0.5 ct/l implies a reduction of around 7% of gasoline stations' gross margins. In the right panel of Figure 3, we provide event-study results on the effect on margins explicitly confirming this. In the cross-sectional study by Lach and Moraga-González (2017), a 10% increase in the number of stations is associated with a 0.06 ct/l price reduction in 1 km-radius markets. Since a single entry event increases the number of stations considerably in relative terms (e.g., by 50% and 20% for markets with two and five incumbent stations, respectively), our implied effects are much stronger than in Lach and Moraga-González (2017).

As expected, the effect of entry is weaker for entry farther away from the incumbent.

When pooling entry events in up to 2 km distance around incumbents, the price effect estimates are slightly smaller in absolute terms.

The respective pooled difference-in-differences estimates coinciding with the event studies can be found in Table E.4 of the Appendix. In the Appendix, we also provide more detailed results on how the entry effect declines with increasing distance between entrant and incumbent (see Figure D.5).



(a) Prices

(b) ln(Margins)

Figure 3: (Average) Effect of Entry on Prices and ln(Margins)

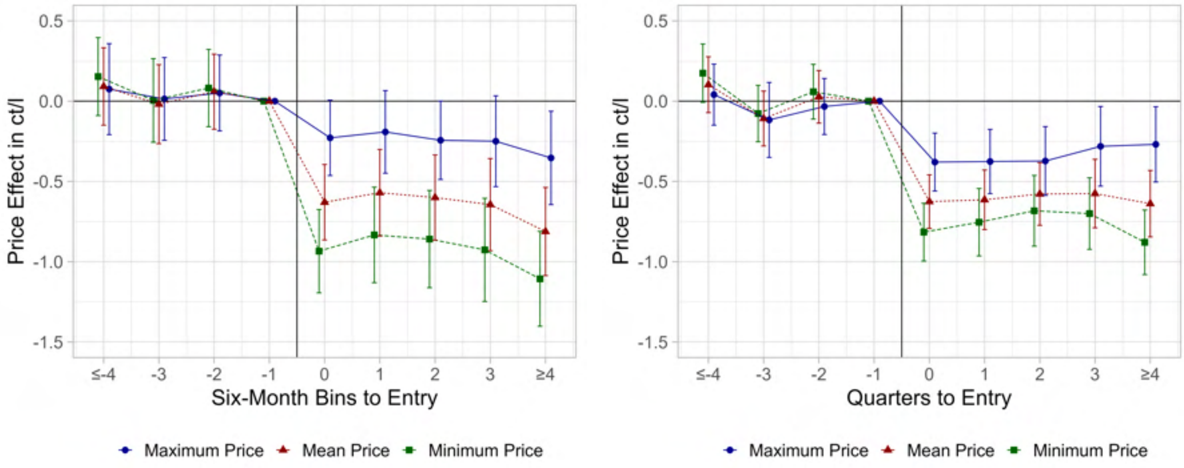
Note: This figure presents the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

4.2 Distributional Effects on Prices

We continue by analyzing the effect along the market-level price distribution. For this, we first show how market-level minimum, mean and maximum prices are affected by the entry events. Subsequently, we investigate the effect of prices at all quantiles of the price distribution and estimate quantile treatment effects.

Figure 4 demonstrates that the minimum, mean, and maximum market prices are impacted differentially by entry. For example, the maximum price decreases by less than half a ct/l in response to entry up to a distance of 1 km. In contrast, the mean price drops by 0.7 ct/l and the minimum price falls by 1.0 ct/l. The same qualitative pattern holds for markets of 2 km radius.

We draw the following conclusions from these findings: First, a decrease in the minimum price is indicative of fully informed consumers likely profiting more from entry. Similarly, a decreasing mean price suggests that uninformed consumers, who buy at a random station in the market, benefit as well - though, less than fully informed consumers. Second, the effect of entry on consumer prices is persistent over time.



(a) Entry in [0,1] km

(b) Entry in [0,2] km

Figure 4: Effect of Entry on Price Distribution

Note: This figure presents the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Outcome variables are the market-level minimum, mean and maximum price for each market-date observation. Only observations with at least two firms in the market included. Entrants' prices are included in the calculation. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

To get an impression of how the price distribution changed at all prices instead of just the minimum, mean or maximum price, we estimate quantile treatment effects as in Firpo et al. (2009). We do this at every 5th percentile between the 10th and 90th percentile. Figure 5 presents the estimation results. While the average price effect of entry in a 1 km radius around a station was approximately 0.5 ct/l, there is substantial variation in the price effect along the price distribution. Quantile treatment effects range from 0.8 ct/l at the left tail of the price distribution to 0.2 ct/l at the right tail of the distribution. For higher quantiles between the 65th and 85th percentile, the effect is less pronounced. A similar pattern is observable for entry in a radius of 2 km, although the distributional heterogeneity is less pronounced.

Hence, prices at the left tail of the distribution respond more strongly to entry. This favors more informed consumers as they are more likely to fuel at a low price. Nevertheless, also uninformed consumers profit from low prices to decrease as the expected price in the market decreases then, too.

We cross-validate our results on heterogeneous price effects along the price distribution by eliciting the counterfactual price distribution as in Chernozhukov et al. (2013). With the full counterfactual distribution at hand, we can inspect the difference between observed and counterfactual post-entry prices over the entire support. Figure 6 supports our findings that entry affects prices especially at the left tail of the distribution. Counterfactual prices (i.e., incumbents' prioces after the timing of entry if entry had not happened) are significantly higher than observed prices at the left tail of the distribution.

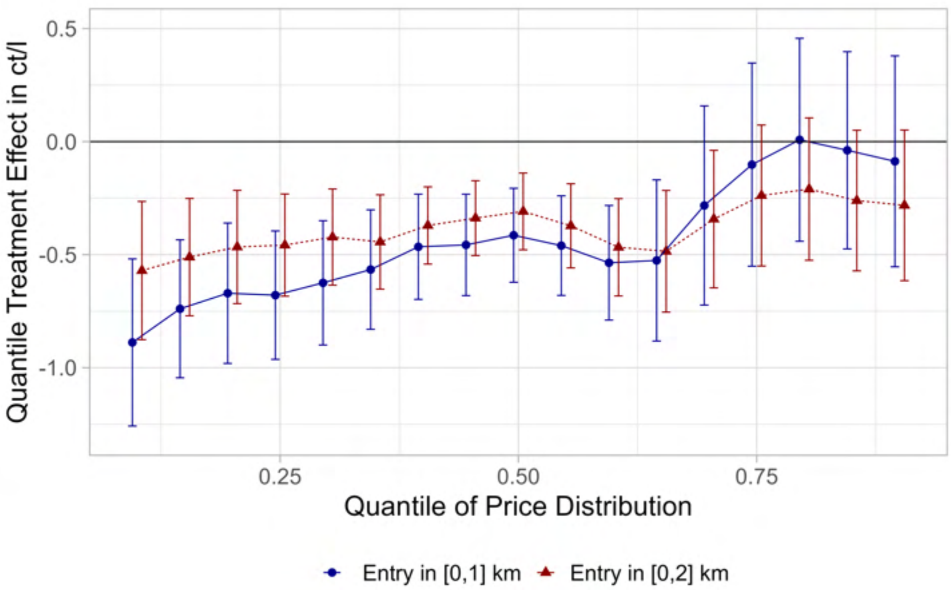
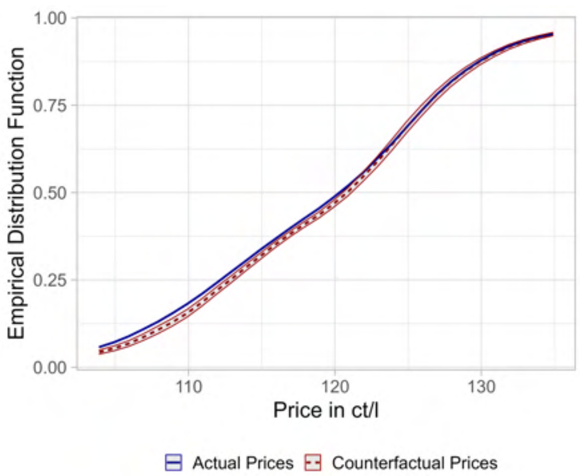
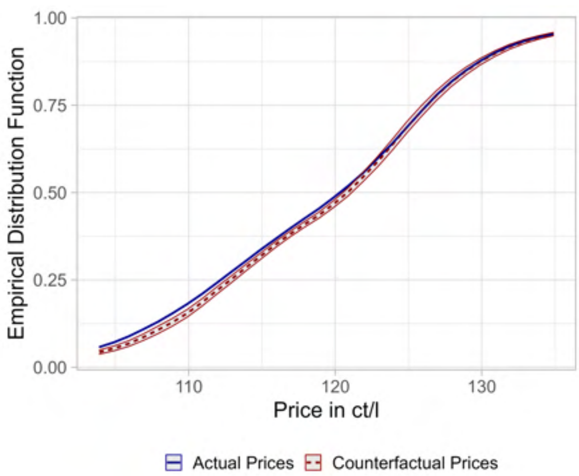


Figure 5: (Unconditional) Quantile Treatment Effects of Entry on Prices

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius (blue) and 2 km radius (red) estimated using the method of Firpo et al. (2009). Estimates for every 5th percentile between the 10th and 90th percentile are provided. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included. Results obtained from regressions in which we also control for daily, region-specific wholesale price variations deliver almost identical estimates (see Figure D.6 in the Appendix).



(a) Entry in [0,1] km



(b) Entry in [0,2] km

Figure 6: Observed Prices and Counterfactual Distribution

Note: The figures plots the actual price distribution of incumbents' prices, which experienced entry (blue) and the estimated counterfactual price distribution (red) of a scenario without (or before) entry. The counterfactual distribution is obtained using distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for price thresholds at each integer ct/l. The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

4.3 First-order Stochastic Dominance

As Figure 6 shows, entry shifts the whole price distribution upwards. If the price distribution is shifted upwards at each percentile, this would be indicative of all consumers, independent of their information about prices, being positively affected by entry. We, hence, test the observation of post-entry prices being first-order stochastically dominated by counterfactual prices in Table 3.

We provide results for three different tests: the one-sided Kolmogorov-Smirnov (KS) Test, as well as the two tests proposed by Davidson and Duclos (2000) and Barrett and Donald (2003). The KS-Test builds on the maximum, one-sided distance between the distribution of observed and counterfactual prices. The tests by Davidson and Duclos (2000) and Barrett and Donald (2003) check whether the counterfactual distribution dominates the empirical distribution function of observed prices at all prices. All three tests report that entry indeed shifts the price distribution in a first-order stochastic manner upwards.[12]

	1 km Radius		2 km Radius	
	Test Statistic	p-value	Test Statistic	p-value
One-Sided KS-Test	0.0267	< 0.01	0.0181	< 0.01
Davidson and Duclos (2000)	$\in [-35.063, 0.314]$	< 0.01	$\in [-38.685, -9.553]$	< 0.01
Barrett and Donald (2003)	-13.192	< 0.01	-13.929	< 0.01

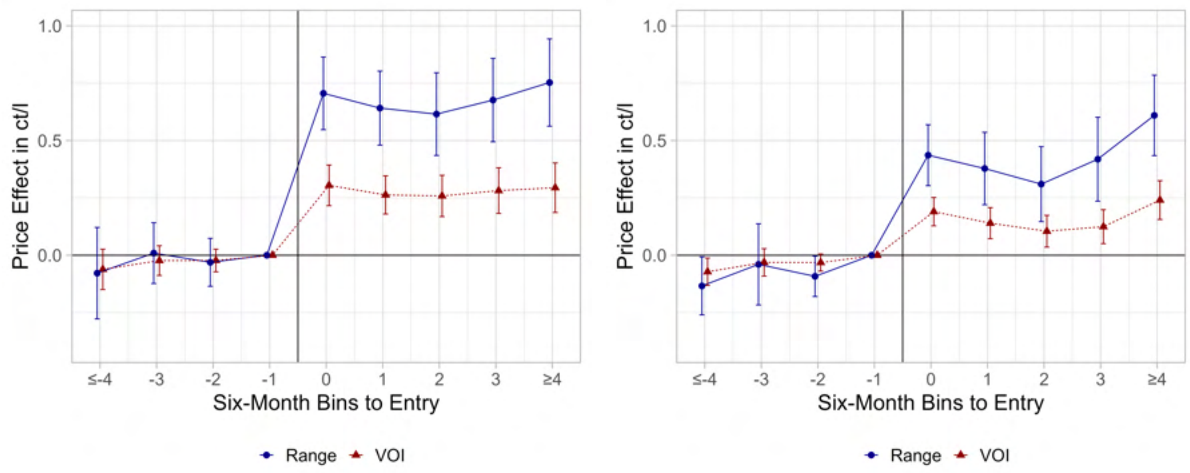
Table 3: First-Order Stochastic Dominance

Note: We implement the FOSD test by Davidson and Duclos (2000) as done in Asplund and Nocke (2006). The tests differ in the assumptions necessary. The one-sided KS-Test only evaluates the maximum distance between actual and counterfactual distribution. Davidson and Duclos (2000) extend the comparison of both distribution to more than the point of maximum distance. Barrett and Donald (2003) smooth out the comparison by integrating over several points. Hence, the comparison can be interpreted as more continuous along the distributions. We evaluate the Davidson and Duclos (2000) approach as well as Barrett and Donald (2003) at all prices in equal distance between 1.039 and 1.349 Euro/l, which represents the 5th and 95th percentile of the distributions. Barrett and Donald (2003) is the most demanding test for FOSD as it takes the minimum distance between the two CDFs independent of how far the CDFs lie apart at all other points.

4.4 Heterogeneous Effects on Consumers

In this subsection, we show how consumers are affected by entry. First, we show how entry changes market-level measures of dispersion, and hence the saving potential for consumers. Second, we simulate consumer decisions to estimate the actual effect of entry on transaction prices. Note that up to now, we looked at how entry shapes the price

[12]Note that the counterfactual CDF, estimated using distribution regressions as in Chernozhukov et al. (2013), may not be monotonically increasing in the price, because separate regressions are run at all price realizations (see Section 3). This does not affect the tests as all test statistics are based on pairwise comparisons of the observed and counterfactual distribution at a certain price.



(a) Entry in [0,1] km

(b) Entry in [0,2] km

Figure 7: Market-Level Dispersion Effects of Entry

Note: This figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Only observations with at least two firms in the market included. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

distribution, i.e., posted prices. *Transaction prices*, however, additionally depend on consumers propensity to search.

We showed that prices in treated markets decrease on average. Besides this general decrease in prices, especially informed consumers could even more profit from entry if entry also causes an increase in price dispersion. Then more cheaper outliers are available. We show in Figure 7 that price dispersion also increases after entry. The value of information (VOI) increases by about 0.2 ct/l after entry in 1 km radius markets, making it more attractive for consumers to become informed. This effect is persistent over time throughout our sample.

Using quantile treatment effects methods as above, we can further show that the increase in dispersion is evident along the complete dispersion distribution (see Figures D.7 and D.8 in the Appendix). Hence, most informed consumers can profit from a higher level of dispersion in all markets. Though, the effect is especially pronounced in formerly less dispersed markets. These findings are different from Moraga-González et al. (2017) who did not find increasing competition to be associated with higher dispersion.

We now simulate how consumers with different knowledge about prices benefit from entry, as described in Section 3.4. The results are shown in Figure 8. Better informed consumers benefit more from entry, which is in line with the finding in Lach and Moraga-González (2017). Highly informed consumers (high k) profit the most from entry with an up to 1.0 ct/l decrease in the simulated purchase price (which compares to about 15% of stations' margins). A similar pattern is evident for the 2 km radius markets. While all consumers benefit significantly from entry, holding more information about prices plays out positively for consumer welfare. Comparing the price decrease due to entry for fully informed ($k = n$) with fully uninformed consumers ($k = 1$), we find that the benefits of entry are 44% (32%) larger for fully informed consumers with 1 km (2 km) markets.

To show that the benefits from competition are *significantly* different across the consumer groups $k \in \{1, ..., 5\}$, we add Table E.5 to the Appendix. There, we jointly estimate the entry effect for all types k in one regression which allows a direct comparison of the estimates.

The simulated price effects are larger than the average price effects in Figure 3 as consumers will purchase at prices in the left tail of the distribution more often if they hold at least some information about prices. Also, note that the simulated price effects are slightly larger than the quantile treatment effects. This is because consumers can choose to buy from the entrant in the simulations while we only look at incumbents' price reactions to entry in the distributional analysis above. Hence, for consumers who hold some form of price information, this gives additional room for savings.

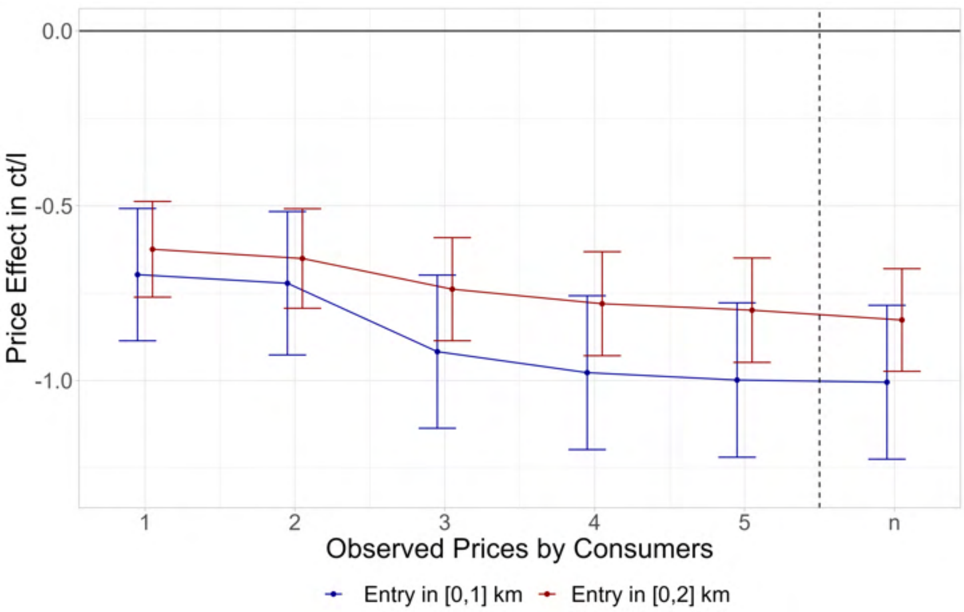


Figure 8: Effect of Entry on Simulated Consumer Prices

Note: This figure provides the β coefficient of the simple difference-in-differences regression (2). The outcome variable is the mean of 100 simulated prices in each market-date observation. Only markets with at least two firms. Markets around entry stations not included. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.

However, note that entry might implicitly affect the number of prices k a consumer is searching for. First, one additional supplier entails the benefit for consumers that they might get easier access to more prices, i.e. that the effective number of prices k that each consumer observes increases due to smaller search costs. Second, the search incentives of consumers change as an additional firm in the market affects price dispersion in the market. Since we showed above that price dispersion and, by that, the incentive to search increases with entry, both of these considerations suggest that the consumer type k might be an increasing function of the number of firms in our case study. However, absent a fully specified model about how the distribution of consumer information materializes, we cannot quantify this effect on transaction prices for different consumer types. We, therefore, take the rather conservative position that the number of price quotes observed by each consumer remains constant. In that sense, we are likely to underestimate the benefits of entry to consumers.

4.5 Alternative Mechanisms & Robustness Checks

In this subsection, we shortly discuss alternative channels via which stations could react to gasoline entry absent from the pure price mechanism modeled above. We then continue in describing a set of sensitivity checks to prove the robustness of our estimation results. All tables and figures for this subsection can be found in the Online Appendix.

Other Strategic Responses. We investigate whether stations react to entry by adapting non-price instruments such as opening hours or whether Edgeworth cycles change in treated markets after entry. If opening hours are not affected, this will indicate that the firm responses to entry mainly channel through prices due to its low menu costs. Figure S.1 studies how entry changes opening hours. Opening hours are measured in a daily, station-level dummy turning one if a station opens 24/7. Incumbents' opening hours are not significantly different after entry in comparison to before entry.

Concerning Edgeworth cycle characteristics, Figure S.2 shows that neither the absolute number of price changes nor the median price change (as a measure of cycling asymmetry) change at the station level in response to entry.[13]

Finally, we examine two channels via which entry could have affected prices beyond the pure price pressure of providing consumers with an additional choice. In Sections A and B of the Appendix, we test how consumer frictions and stations' pass-through behavior changes in response to entry. Decreasing consumer frictions and a quicker pass-through of wholesale prices might also reduce incumbents' prices. We extend the test for consumer frictions proposed by Chandra and Tappata (2011) used in Section 2 to a dynamic setting. We calculate quarterly, station pair rank reversal measures for pairs of incumbent stations. In a similar event study setting compared to equation (3), we examine how rank reversals are affected when entry occurs near one of the stations of the couple. We do not find changes in consumer frictions (see Appendix A). Importantly, this also suggests that the information distribution of consumer types does not change

[13] Other papers like Noel (2007) or Siekmann (2017) show that the existence of Edgeworth cycles or their characteristics depend on the local competitive environment. Though, these papers compare cycles across markets or stations and do not exploit within-station changes in the competitive environment.

significantly with entry.

With regard to pass-through behavior, we analyze how incumbents' average, long-run pass-through changes with entry nearby. For this, we use daily, region-specific wholesale price data from Argus Media. In Appendix B, we lay out our empirical strategy to analyze pass-through. We empirically show that pass-through of prices does not change with entry for all prices as well as simulated transaction prices for the different consumer types k.

Alternative Distributional Analysis. We study the heterogeneous effects of entry along the price distribution by applying an alternative approach to identify heterogeneous effects of a treatment along a distribution of an outcome variable - the method proposed in Cengiz et al. (2019). In separate regressions, we estimate how the treatment affects the likelihood of observing prices in certain price bins of the distribution. Figure S.3 supports our results from above. Entry increases the probability of observing prices in the lowest price bins while reducing the probability of observing very high prices. Observing intermediate price bins is not significantly more likely than absent treatment.

Identification Cells & Inference. We test whether our results are robust to different identification cells, i.e. identification within different layers of (non-)administrative regions. Figure S.4 presents the baseline event studies for including Date, County-Date (401 counties) or ROR-Date (96 'Raumordnungsregionen') fixed effects instead of State-Date (16 states) fixed effects. A narrow identification grid reduces the average price effect of entry. Though, the concern of spillovers within narrow geographical areas of counties might downward-bias the effect size (in absolute terms). The qualitative results hold for both market definitions. Also, the quantile treatment effects are similar for all fixed effects combinations as evident in Figure S.5.

We, moreover, check whether the interpretation of our results changes when standard errors account for correlation in residuals within stations, within counties or RORs instead of within municipalities. Our results are unaffected by this (see Figures S.6 and S.7).

Binning. We show that the average estimated price effects are not sensitive to the choice of the number of leads and lags. Figure S.8 shows that the event studies look very alike for different approaches. We further report an event study (see Figure S.9) which zooms in the weeks and months right around the entry events. This figure also illustrates that the main effect of entry materializes rather quickly, i.e., within a two-weeks time window.

Heterogeneous Treatment Effects. We examine heterogeneity in the average and distributional effects of entry. We exploit the richness in the entry events across incumbent and entrant characteristics, e.g. brand affiliation or exposure to local competition. Figure S.10 shows heterogeneous effects on prices as estimated in equation (2). For entry in 1 km radius markets, prices decrease more strongly in concentrated markets, in markets where low-price stations such as JET enter, for brands that do not belong to the Big Four (ARAL, SHELL, TOTAL, ESSO), for formerly expensive stations and markets in which the entrant brand operated a station before.[14]

We show that these dimensions of heterogeneity do not change the qualitative conclusions regarding the distributional effects, but the magnitude of these effects. Exemplarily, we look at entry by the low-price brand JET.[15] We find that low-price entry substantially decreases prices in the left tail of the price distribution (see Figure S.12). At higher prices, quantile treatment effects are not statistically different from zero. This is also supported by the distributional analysis as in Chernozhukov et al. (2013) (see Figure S.13). Correspondingly, the distributional implications of prices also hold for non-JET entries, but in a less pronounced way (see Figures S.14 and S.15). We, further, show in Figure S.16 that the market concentration determines how strong price reactions are at different quantiles. However, the pattern of stronger price effects at the left tail is robust across markets with a different number of non-entrant stations.

Recent work by Borusyak et al. (2022), Callaway and Sant'Anna (2021), De Chaisemartin and d'Haultfoeuille (2020) and Sun and Abraham (2021) has shown that treatment effect heterogeneity in combination with staggered treatment can bias the estimated treatment effect. In our setting, changes in search behavior over time might change the dynamic treatment effect across stations that are treated at different points in time. We address this concern by exemplarily also running our main regressions with the estimator proposed in Sun and Abraham (2021). The estimates support our qualitative findings. Figure S.17 shows that entry (on average) decreases prices in a similar fashion as in Figure 3. If at all, the pattern becomes more extreme with no price effect at all for the top five deciles. Moreover, the right-hand side of the figure clearly shows that quantile treatment effects are stronger at the left tail of the price distribution. This also is in line with the differences between observed and counterfactual prices as reported in Figure S.18.

Alternative Daytimes & Types of Fuel. It might be that our analysis is sensitive to the time of the day or the type of fuel, e.g. when the composition of consumers changes over the course of the day or demand elasticity varies between fuel types (Montag et al., 2023). Hence, we carry out the analysis also for 7 am and 12 am as well as for E5 gasoline prices instead of diesel. Figures S.19 and S.20 show, on the one hand, that results on diesel fuel are not strongly affected by the time of the day. On the other hand, there is no qualitative difference between our results for diesel and E5 gasoline.

[14]Entrants are of the same brand as incumbents in 2-2.5% of all entry events (depending on whether markets are defined in 1 km or 2 km radii).

[15]Prices by brand are reported in Figure S.11.

5 Conclusion

In this paper, we study station entry in the German gasoline market and its impact on prices and the implications for different consumer types. Owing to our comprehensive data set with a very high number of unique entry events, we thus complement existing findings in the literature regarding the *average* effect of prices. The average effect of entry is a price reduction of around 0.5 ct/l. For the firms operating in that market, this reduction is certainly non-negligible as it corresponds to a reduction in gross margins by 7%. Since entry also affects the gains of search and thus the distribution of consumer information types, this is likely to be a conservative estimate of the effect of entry.

Additionally, we find that entry decreases prices in a first-order stochastic dominance manner. Price effects are stronger at the left tail of the distribution, benefiting both informed and uninformed consumers.

We simulate pre- and post-entry expected transaction prices, depending on how many prices a consumer observes. The effect on fully informed consumers is 32-44% stronger. These results have implications for the distributional effects of competition on different types of consumers in homogeneous goods markets. The findings show that increasing competition in search markets might not benefit uninformed consumers the most.

In this paper, we do not take a position regarding which segments of the population tend to fall into the informed or uninformed consumer category, respectively (Byrne and Martin, 2021). Irrespective of whether high-income consumers have more or less elastic demand, they may be more inclined to search (Nishida and Remer, 2018), rendering them the main beneficiaries of entry. In that case, policies regarding entry barriers and market structure also need to take into account distributional consequences. Through this channel, our findings inform policymakers to understand the relevance of competition for different consumer groups.

A Information Frictions

Price dispersion in homogeneous goods markets can arise from the fact that consumers hold heterogeneous information (Varian, 1980). However, entry could improve consumer information about prices. More firms in a market imply a higher likelihood to observe prices (e.g., for commuters). Hence, entry may decrease consumer frictions. Chandra and Tappata (2011) proposed a static test for consumer frictions based on how often the price ranking of a pair of neighboring stations alters. The intuition is that rank reversals in a homogeneous goods market can hardly be rationalized without consumer frictions. For a detailed explanation of the static test see Section 2.

To examine how price rank reversals (i.e., consumer frictions) change over time and after entry, we extend their environment to a dynamic approach. In detail, we calculate a rank reversal measure for each station pair and quarter. Hence, the outcome variable - the measure of rank reversal between station A and B (couple c) in quarter q where station A sets the lower price on at least half of all days in a quarter - is constructed in the following way:

$$rr_{c,q} = \frac{1}{T_{c,q}} \sum_{t=1}^{T_{c,q}} 1[p_{A,t} > p_{B,t}], \tag{6}$$

where $T_{c,q}$ is the number of days in quarter q on which both stations report a price.

We then take $rr_{c,q}$ as the outcome in the following event-study regression:

$$rr_{c,q} = \alpha_c + \lambda_{sq} + \sum_{\tau=-\underline{\tau},\neq -1}^{\bar{\tau}} \beta_\tau 1[Entry]_{cq,\tau} + \epsilon_{cq} \tag{7}$$

where we include couple fixed effects (α_c) and state-quarter fixed effects (λ_{sq}).[16] $1[Entry]_{cq,\tau}$ gives the leads and lags of entry events. A couple will be treated if at least one station experiences entry in a given radius. Similar to our approach in the main analysis, we only look at the first entry event per couple and drop observations after the date of the first entry.

Ex-ante the effect of entry on rank reversals is ambiguous. Entry might foster rank reversals because, e.g., a new entrant very close to an incumbent might make the price ranking with other stations less important. At the same time, entry might improve consumers knowledge about prices. Then, information frictions and rank reversals could decrease. Figure A.1 provides results of entry effects on rank reversals. We report the effect of entry in a 0.5 km, 1 km and 2 km radius[17]. In all three cases, we cannot identify

[16]Note that for some couples, stations might not be located in the same federal state. Hence, we construct the point in the middle between both stations and match this point to federal states. A similar procedure allows us to match county-level covariates to the regression and allows for clustering at the municipality level.

[17]We add the more narrow entry radius of 0.5 km as Chandra and Tappata (2011) suggest that rank reversal of very close stations is significantly lower than for other station pairs.

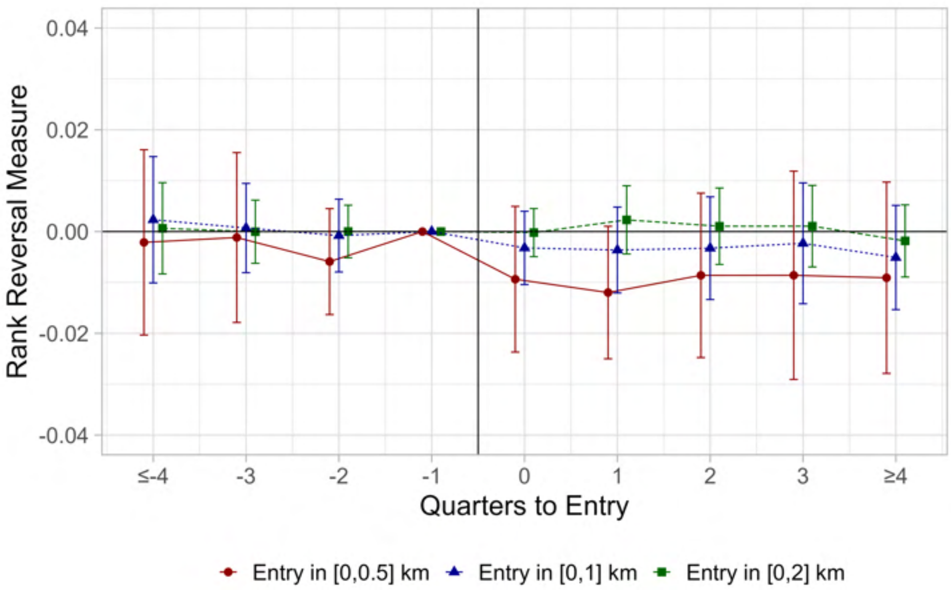


Figure A.1: Entry Effect on Rank Reversal

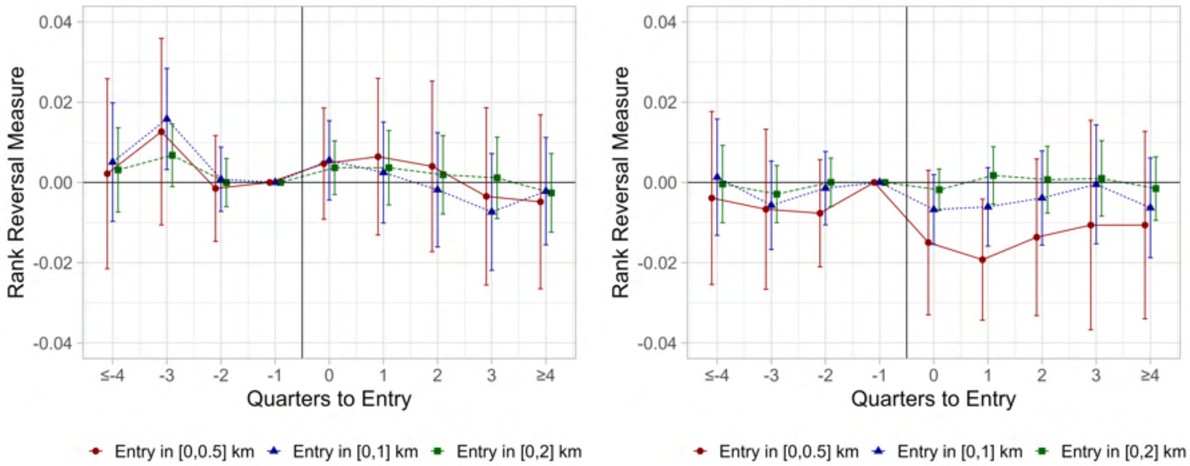
Note: This figure provides the leads and lags of the event study regression (7) with an effect window of four bins before and five bins after the entry event. The outcome variable is the rank reversal measure per couple and quarter constructed as in Chandra and Tappata (2011). The dataset includes all rank reversals of station pairs with a bilateral distance of 2 km maximum. This follows our market definitions from above. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.

a change in the likelihood of rank reversal. Our results are also not sensitive to whether looking at entry's effect on couples with a bilateral distance of up to or above 1 km (see Figure A.2) or only looking at entry events where the entrant is the nearest competitor of at least one of the stations (see Figure A.3). We take this as suggestive for entry not sufficiently affecting consumer frictions to affect prices through this channel.

B Pass-Through

In this section, we study the effect of entry on incumbents' average, long-run pass-through. Similar to Montag et al. (2021) and Genakos and Pagliero (2022), who exploit VAT or excise duty changes as quasi-experimental setting to examine pass-through, we take an entry nearby as shock to the pass-through of incumbents. For this, we obtain daily wholesale price data from the Oil Market Report (O.M.R.) by Argus Media for eleven price regions. For each station and day we match the wholesale price of the nearest region for which wholesale price data is available on this day.

To identify the causal effect of entry on the pass-through rate, we run triple difference-in-differences regressions. To be precise, we interact the wholesale price of station i on day t, C_{it}, with a dummy for incumbent stations and a dummy for post-entry observations of

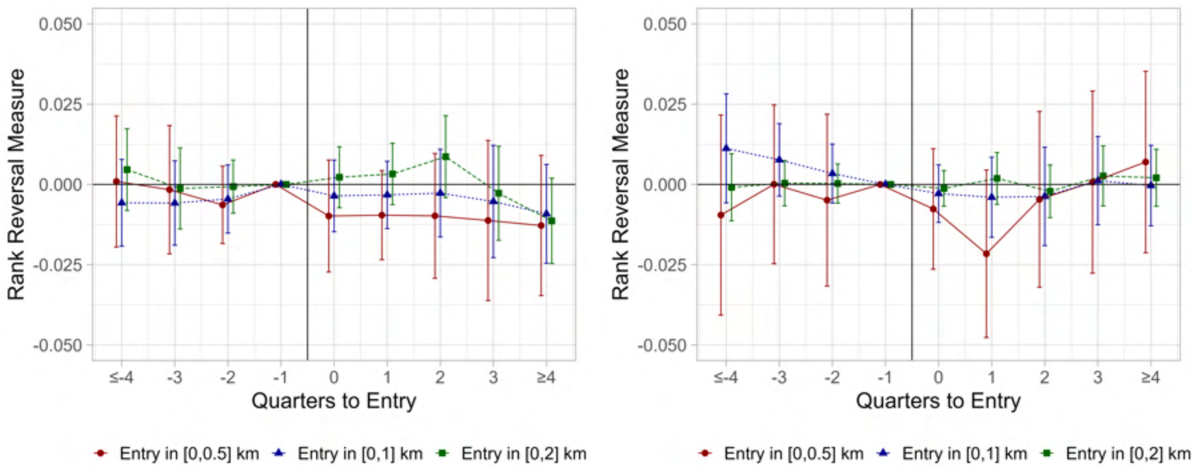


(a) Couple Distance in [0,1] km

(b) Couple Distance in (1,2] km

Figure A.2: Entry Effect on Rank Reversal by Couple Distance

Note: This figure provides the leads and lags of the event study regression (7) with an effect window of four bins before and five bins after the entry event. The outcome variable is the rank reversal measure per couple and quarter constructed as in Chandra and Tappata (2011). The dataset includes all rank reversals of station pairs with a bilateral distance of 2 km maximum. This follows our market definitions from above. The left plot looks at couples with a bilateral distance of 1 km maximum. The right plot looks at couples with a bilateral distance of between 1 km and 2 km. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.



(a) Entrant is Nearest Neighbor

(b) Entrant is not Nearest Neighbor

Figure A.3: Entry Effect on Rank Reversal by Entrant Characteristic

Note: This figure provides the leads and lags of the event study regression (7) with an effect window of four bins before and five bins after the entry event. The outcome variable is the rank reversal measure per couple and quarter constructed as in Chandra and Tappata (2011). The dataset includes all rank reversals of station pairs with a bilateral distance of 2 km maximum. This follows our market definitions from above. The left plot looks at couples where the entrant is the nearest neighbor. The right plot looks at couples for which this is not the case. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.

incumbents. The following regressions reflect the identification strategy:

$$P_{it} = \alpha_i + \lambda_{st} + \rho C_{it} + \beta 1[Post-Entry]_{it} + \gamma 1[Incumbent]_i \times C_{it} + \phi 1[Post-Entry]_{it} \times C_{it} + \epsilon_{it}, \quad (8)$$

The coefficient ϕ gives us the change in pass-through due to entry. If entry changes pass-through rates and through this can explain price changes prices, β should be smaller in absolute terms than in the simple price regressions as in equation (2). $1[Post-Entry]_{it} \times C_t$ would be a 'bad control' then but informative for our purposes.[18] Table B.1 gives the regression results from equation (8). Controlling for entry-induced changes in the pass-through does not explain parts of the observed price effect. Instead, there is no significant effect of entry on the pass-through. This result is robust for all posted prices as well as the simulated transaction price for different consumer types k.

	$Price_{it}$	$Simulated\ Price_{it}$					
Entry in [0,1] km		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=n$
$1[Post-Entry]_{it} \times C_{it}$	0.001	−0.002	−0.003	−0.005	−0.005	−0.005	−0.002
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Observations	25,352,812	13,412,597					
Entry in [0,2] km		$k=1$	$k=2$	$k=3$	$k=4$	$k=5$	$k=n$
$1[Post-Entry]_{it} \times C_{it}$	0.005	0.003	0.002	0.000	−0.000	−0.000	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Station FE	✓	✓	✓	✓	✓	✓	✓
State-Date FE	✓	✓	✓	✓	✓	✓	✓
Observations	25,324,103	19,137,880					

Table B.1: (Average) Effect of Entry on Pass-Through

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the municipality level. County-level controls included. Observation numbers differ across treatment allocation as observations of stations, which experience entry more than once, are dropped from the sample after the date of the second entry. Variables $1[Post-Entry]_{it}$, C_{it} and $1[Incumbent]_{it} \times C_{it}$ suppressed for convenience. Regressions of simulated prices only include markets with more than one station.

[18]Note that MacKay et al. (2014) indicate that reduced-form, linear pass-through regressions might be biased in two ways: First, if the functional form of pass-through is mis-specified and pass-through rates are a function of the cost level. Second, if firms' unobserved and observed costs correlate with each other. In our setting, pass-through rates likely are independent of the cost level as oil and gasoline prices almost perfectly co-move with each other. Further, unobserved labour costs are likely uncorrelated with observed wholesale prices which themselves already encompass almost all variable costs of fuel.

C Stylized Model

In this section, we illustrate the mechanism through which entry affects prices and heterogeneously informed consumers. As our empirical results show, consumers who observe a different amount of prices are heterogeneously affected by entry. Hence, we present a simplified model of heterogeneous consumer information based on Armstrong et al. (2009) and Moraga-González et al. (2017). For ease of exposition, we omit taxes and marginal costs, although these could easily be added without any considerable effect in the current context.

A market is served by $N \geq 2$ symmetric firms, each selling a homogeneous good - such as gasoline - to a unit mass of consumers with a willingness-to-pay $v > 0$. Firms, indexed by $i = 1, \ldots, N$, simultaneously set prices p_i.

Consumers are heterogeneous in their access to information, in particular, in the number of prices they observe. After observing k prices, each consumer purchases from the cheapest firm out of these, as long as this price does not exceed v[19]. Ties are resolved by uniform randomization. We do not allow consumers to engage in additional search beyond the prices already observed. Denote the fraction of consumers observing k prices by μ_k, where $\sum_{k=1}^{n} \mu_k = 1$, and we assume that $\mu_1 \in (0, 1)$.

The final assumption is crucial. $\mu_1 > 0$ implies that for any price $p_i \leq v$, firm i sells at least to μ_1/N firms. $\mu_1 < 1$ implies that there are at least some consumers with $k \geq 2$, so each firm i faces at least one competitor with a positive probability for a subset of consumers. Since consumers always buy from the cheapest firm observed, firm i ends up competing in Bertrand manner in this case.

Using standard arguments (Lach and Moraga-González, 2017, Varian, 1980), it can easily be shown that a pure strategy equilibrium does not exist and hence the equilibrium entails mixing over prices. Denote the symmetric equilibrium price distribution by F (with associated density f), with continuous support on the interval $[\underline{p}, \overline{p}]$, which is determined in equilibrium.

It follows readily (see Moraga-González et al. (2017) for details) that firms never charge a price above v in equilibrium, so $\overline{p} = v$. Thus, in equilibrium, firms could sell to only fully uninformed consumers and earn profits $\pi(\overline{p}) = v\frac{\mu_1}{N}$. An equal-profit-condition for all prices $p_i \in [\underline{p}(N), \overline{p}]$ to manifest the mixed-strategy equilibrium uniquely pins down the equilibrium price distribution $F(p, N)$, although a closed-form solution is not available in general:

$$\pi(p_i) = p_i \sum_{k=1}^{N} \frac{\mu_k}{N} (1 - F(p_i))^{k-1} = \pi(\overline{p})$$

[19]Heterogeneous search efforts by consumers can, for example, be an endogenous outcome of different search costs of consumers (Burdett and Judd, 1983).

and finally $\underline{p}$ is implicitly obtained through $F(\underline{p}) = 0$.

A consumer observing k prices purchases at the cheapest out of k prices. Denote the distribution of the cheapest out of k prices by F_k, which is given by $F_k(p, N) = 1 - (1 - F(p, N))^k$ and implied density $f_k(p, N) = k(1 - F(p, N))^{k-1} f(p, N)$, resulting in expected prices

$$E_k(p, N) = \int_{\underline{p}(N)}^{\overline{p}} p f_k(p, N) dp = \underline{p}(N) + \int_{\underline{p}(N)}^{\overline{p}} (1 - F(p, N))^k dp \tag{9}$$

where the last expression is obtained through integration by parts. The expected consumer surplus for a type-k consumer is given by $CS_k(N) = v - E_k(p, N)$.

From equation (9), it is straightforward that consumer types k are differentially affected by entry, depending on how exactly entry shifts the price distribution. In principle, the effect of a change in competition on $E_k(p, N)$ is mitigated by the degree of information k in two countervailing channels: On the one hand, consumers with a high k observe more prices and hence have more opportunities to find a lower price in a market with $N + 1$ firms. On the other hand, the potential price reduction due to competition per observed price decreases with k. This is because the pre-entry price of consumers with a high k has been quite low before.

Note that the sketched model can rationalize the estimated shift of the price distribution in a first-order stochastic dominance shift (Lach and Moraga-González, 2017). In contrast to the clearinghouse model by Varian (1980), the more dispersed information structure causes stations to not become more likely to set relatively high prices with rising competition.

Lastly, it is relevant to mention that the number of prices observed by a consumer type k might be a function of market concentration, $k(N)$. Search costs could be affected by entry (e.g., travel costs between stations) and search incentives dependent on the equilibrium price dispersion in the market. The latter is a function of the number of firms. In particular, an increase in the average information level $\bar{k} = \sum_k \mu_k k$ as well as a decrease in the share of uninformed consumers μ_1 is even necessary to justify a first-order stochastic shift of the price distribution. We discuss the empirical implications of this observation for our results in Section 4.4.

D Additional Figures

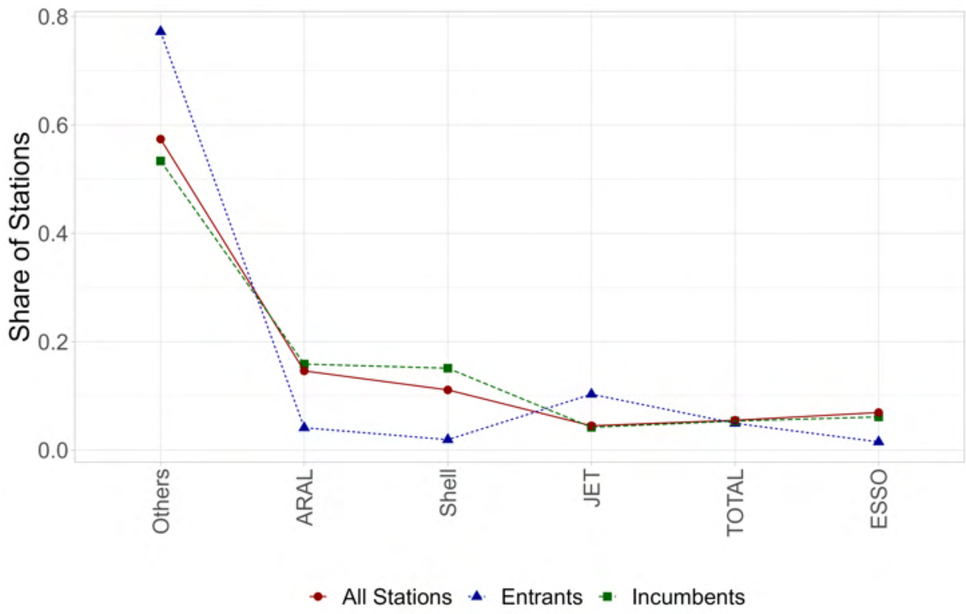


Figure D.1: Brand Distribution

Note: This figure shows the share of stations per brand among all German gasoline stations; for entrants only; and for incumbents only. Incumbents refer to stations in a 1km radius around entrants. Other brands are pooled in 'Others'.

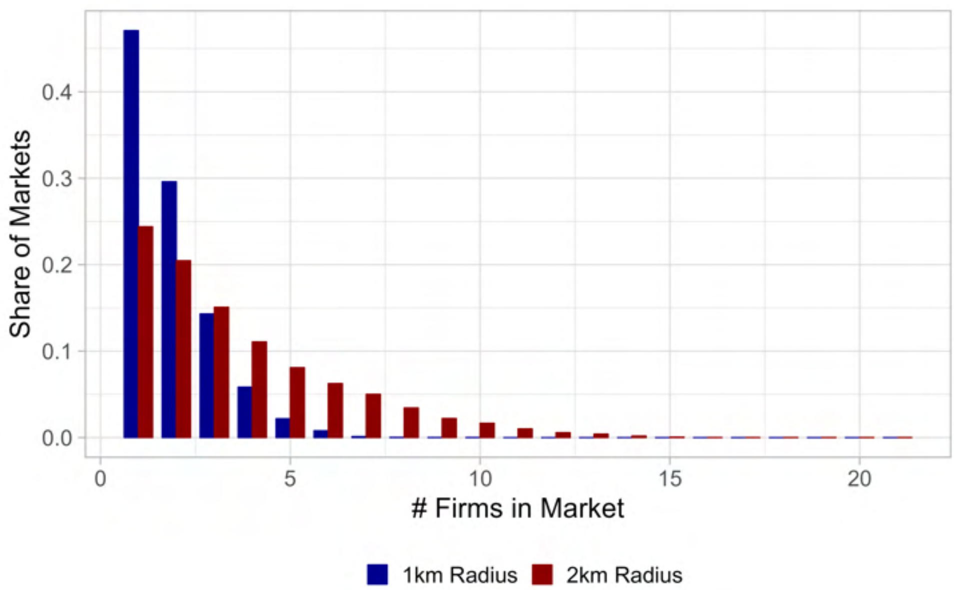


Figure D.2: Market Size Distribution - 1 km and 2 km Radius

Note: The histogram plots the distribution of the number firms in a market using our baseline market definitions: Circles of 1 km or 2 km linear distance around each station. Markets around entrants are not included. Market size is defined at the market-date level.

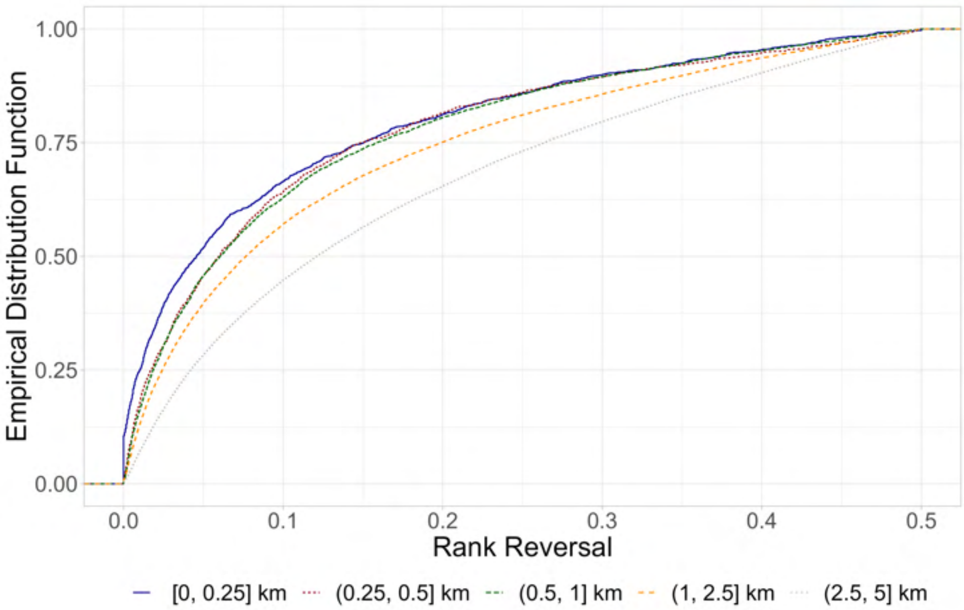


Figure D.3: Rank Reversals - Chandra and Tappata (2011)

Note: Empirical distribution functions of station couples with heterogeneous distances between stations. The rank reversal measure follows the definition in Chandra and Tappata (2011): The share of observations, in which the mostly cheaper station, is the more expensive one.

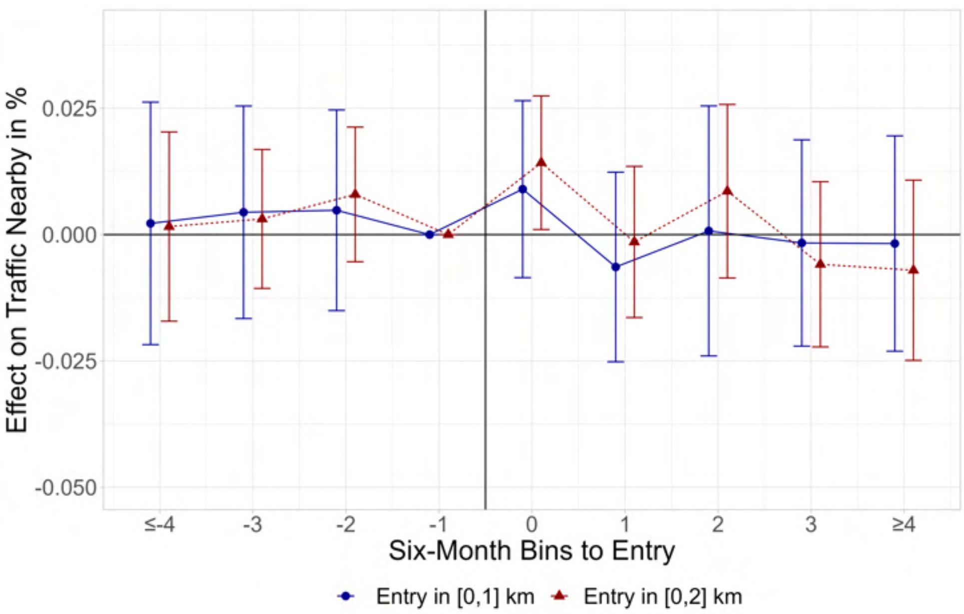


Figure D.4: Effect of Entry on Traffic

Note: This plot shows the effect of station entry on traffic flows between 4 pm and 6 pm at traffic counters in Germany. Traffic counters in less than 1 km or 2 km to entry are treated in this analysis. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included. Observations after a second entry are not included.

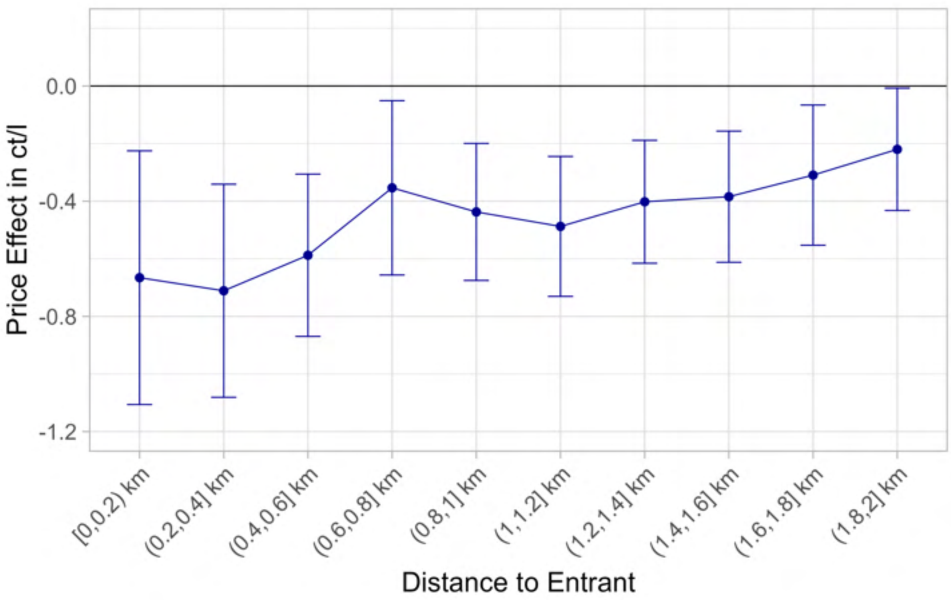


Figure D.5: Effect of Entry on Prices by Distance to Entry

Note: This plot shows the effect of station entry on prices by distance between incumbent and entrant. Only the first entry event for incumbents within 2 km radius is used. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included. Observations after a second entry are not included.

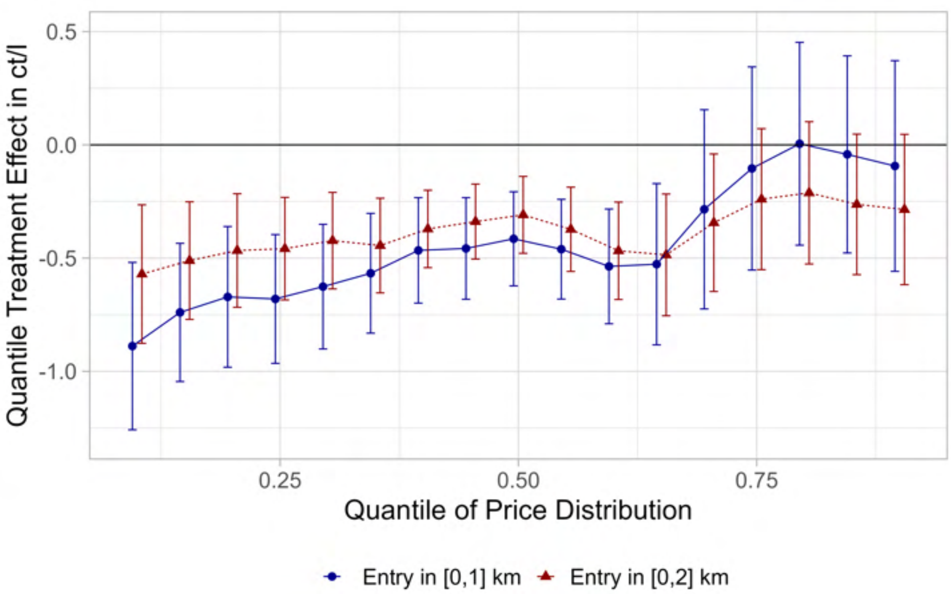
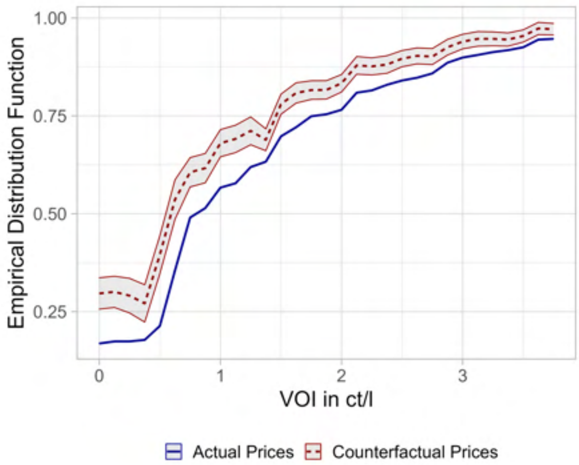
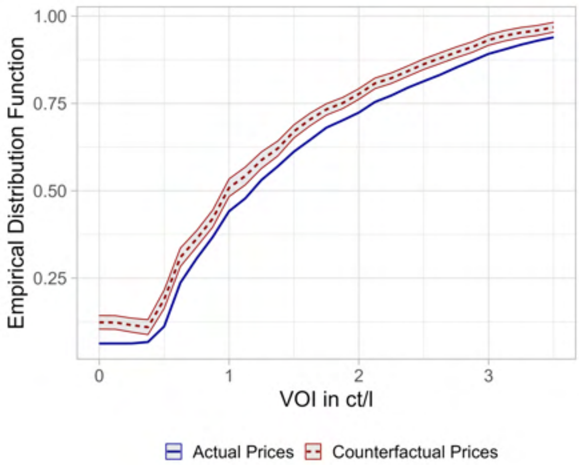


Figure D.6: QTEs of Entry on Prices - Controlling for Wholesale Prices

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius (blue) and 2 km radius (red) estimated using the method of Firpo et al. (2009). Estimates for every 5th percentile between the 10th and 90th percentile are provided. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included. Results obtained from regressions in which we also control for daily, region-specific wholesale price variations.



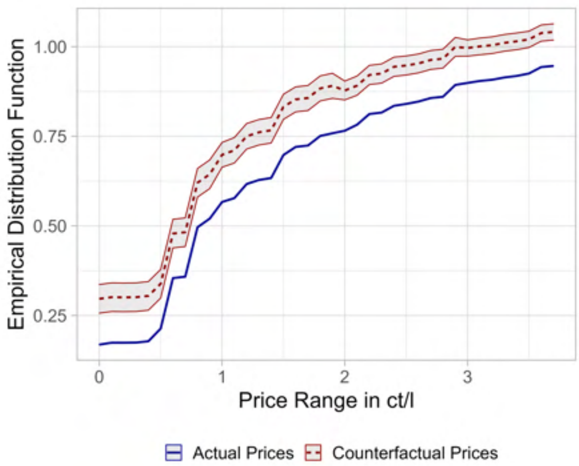
(a) Entry in [0,1] km



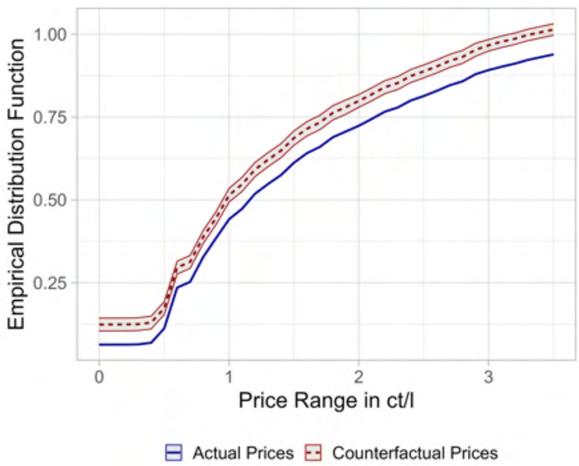
(b) Entry in [0,2] km

Figure D.7: Distributional Effects of Dispersion: VOI

Note: The figures plot the actual price dispersion distribution of markets, which experienced entry (blue) and the estimated counterfactual price dispersion distribution (red) of a scenario without entry in the treated markets. The counterfactual distribution comes from distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for dispersion thresholds in 0.125 ct/l steps. The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. The shaded area indicates the 95% confidence interval.



(a) Entry in [0,1] km



(b) Entry in [0,2] km

Figure D.8: Distributional Effects of Dispersion: Range

Note: The figures plot the actual price dispersion distribution of markets, which experienced entry (blue) and the estimated counterfactual price dispersion distribution (red) of a scenario without entry in the treated markets. The counterfactual distribution comes from distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for dispersion thresholds in 0.125 ct/l steps. The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. The shaded area indicates the 95% confidence interval.

E Additional Tables

	$1[\text{Entrant}]_{it}$					
Market Definition:		[0,1] km			[0,2] km	
Station-specific characteristics.						
Price (ct/l)	-0.0175^{***}	-0.0168^{***}	-0.0082	-0.0084^{*}	-0.0073	0.0041
	(0.0049)	(0.0049)	(0.0053)	(0.0046)	(0.0045)	(0.0042)
Gross Margin (ct/l)	0.0043	0.0045	0.0107^{*}	-0.0049	-0.0043	-0.0029
	(0.0059)	(0.0058)	(0.0063)	(0.0052)	(0.0051)	(0.0048)
# Competitors 1 km Radius	-0.2016^{***}	-0.1886^{***}	-0.1707^{***}			
	(0.0110)	(0.0119)	(0.0108)			
1[# Competitors 1 km > 0]×VOI		-0.0305^{***}	-0.0145^{***}			
		(0.0055)	(0.0054)			
# Competitors 2 km Radius				-0.0760^{***}	-0.0699^{***}	-0.0611^{***}
				(0.0055)	(0.0054)	(0.0052)
1[# Competitors 2 km > 0]×VOI					-0.0316^{***}	-0.0233^{***}
					(0.0060)	(0.0044)
County-specific characteristics.						
log(Unemployment Rate)	-0.0429	-0.0453	0.0240	-0.0484	-0.0435	0.0103
	(0.0383)	(0.0374)	(0.0443)	(0.0357)	(0.0344)	(0.0377)
log(Commuters)	0.0015	0.0032	0.0292	-0.1435^{**}	-0.1291^{*}	-0.0670
	(0.0727)	(0.0705)	(0.0781)	(0.0700)	(0.0663)	(0.0640)
log(Population)	0.0155	0.0200	-0.0587	0.1537^{*}	0.1518^{**}	0.1136
	(0.0849)	(0.0830)	(0.0953)	(0.0788)	(0.0766)	(0.0857)
log(Vehicles)	-0.0326	-0.0377	0.0105	-0.0024	-0.0152	-0.0312
	(0.0974)	(0.0966)	(0.1177)	(0.0966)	(0.0941)	(0.1024)
log(GDP p.c.)	0.0253	0.0264	0.0170	0.0718^{**}	0.0721^{**}	0.04427
	(0.0354)	(0.0349)	(0.0381)	(0.0324)	(0.0316)	(0.0354)
log(Available Income p.c.)	-0.1797	-0.1663	-0.0575	-0.2432^{**}	-0.2183^{**}	-0.0750
	(0.1117)	(0.1080)	(0.1263)	(0.1046)	(0.1014)	(0.1064)
Brand FE	×	×	✓	×	×	✓
State-Date FE	✓	✓	✓	✓	✓	✓
Observations		1,177,198			1,932,535	

Table E.1: Differences in Levels Between Entrants and Incumbents

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the municipality level. Linear probability model with dichotomous outcome. Only observations of entrants and incumbents after entry included. Post-treatment observations of incumbents dropped.

	$1[\text{Incumbent}]_{it}$					
Market Defintion:		[0,1] km			[0,2] km	
Station-specific characteristics.						
Price (ct/l)	0.0008	0.0008	0.0005	0.0009	0.0008	0.0004
	(0.0006)	(0.0006)	(0.0006)	(0.0013)	(0.0013)	(0.0013)
Gross Margin (ct/l)	−0.0002	−0.0002	−0.0001	0.0001	0.0001	0.0005
	(0.0007)	(0.0007)	(0.0007)	(0.0015)	(0.0015)	(0.0015)
# Competitors 1 km Radius	0.0020^{*}	0.0020^{*}	0.0020^{*}			
	(0.0011)	(0.0012)	(0.0012)			
1[# Competitors 1 km > 0]×VOI		−0.0000	−0.0002			
		(0.0008)	(0.0007)			
# Competitors 2 km Radius				0.0052^{***}	0.0049^{***}	0.0047^{***}
				(0.0015)	(0.0017)	(0.0017)
1[# Competitors 2 km > 0]×VOI					0.0017	0.0011
					(0.0013)	(0.0013)
County-specific characteristics.						
log(Unemployment Rate)	−0.0053	−0.0053	−0.0069	−0.0138	−0.0140	−0.0175
	(0.0065)	(0.0065)	(0.0063)	(0.0145)	(0.0145)	(0.0143)
log(Commuters)	0.0006	0.0006	−0.0005	0.0044	0.0044	0.0024
	(0.0110)	(0.0110)	(0.0111)	(0.0264)	(0.0264)	(0.0261)
log(Population)	−0.0028	−0.0028	−0.0020	−0.0123	−0.0128	−0.0109
	(0.0120)	(0.0120)	(0.0121)	(0.0297)	(0.0297)	(0.0293)
log(Vehicles)	0.0011	0.0011	0.0011	−0.0008	−0.0005	−0.0011
	(0.0130)	(0.0129)	(0.0131)	(0.0341)	(0.0341)	(0.0336)
log(GDP p.c.)	0.0014	0.0014	0.0013	0.0004	0.0004	0.0010
	(0.0052)	(0.0052)	(0.0053)	(0.0128)	(0.0128)	(0.0127)
log(Available Income p.c.)	-0.0258^{*}	-0.0258^{*}	-0.0264^{*}	−0.0619	−0.0625	-0.0643^{*}
	(0.0154)	(0.0154)	(0.0150)	(0.0396)	(0.0396)	(0.0388)
Brand FE	×	×	✓	×	×	✓
State-Date FE	✓	✓	✓	✓	✓	✓
Observations		24,852,588			24,097,251	

Table E.2: Differences in Levels Between Incumbents and Outsiders

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the municipality level. Linear probability model with dichotomous outcome. Observations of entrants dropped. Post-treatment observations of incumbents dropped.

	rr_{AB}	
	(1)	(2)
1[0 km ≤ Distance ≤ 0.25 km]	-0.050^{***}	
	(0.005)	
1[0.25 km < Distance ≤ 0.5 km]		0.008
		(0.006)
1[0.5 km < Distance ≤ 1 km]		0.009^{*}
		(0.005)
1[1 km < Distance ≤ 2.5 km]		0.028^{***}
		(0.005)
1[2.5 km < Distance ≤ 5 km]		0.064^{***}
		(0.006)
Observations	81,586	81,586

Table E.3: Rank Reversal for Different Station Distances

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are twoway-clustered for each station included in the couple. All station pairs of maximum distance 5km are included.

	$Price_{it}$	
	Entry in [0,1] km	Entry in [0,2] km
$1[Post - Entry]_{it}$	-0.498^{***}	-0.417^{***}
	(0.082)	(0.062)
Station FE	✓	✓
State-Date FE	✓	✓
Observations	25,352,812	25,324,103

Table E.4: (Average) Effect of Entry on Prices

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the municipality level. County-level controls included. Observation numbers differ across treatment allocation as observations of stations, which experience entry more than once, are dropped from the sample after the date of the second entry.

	Simulated $Price_{it}$			
Entry in ...	[0,1] km		[0,2] km	
$1[Post-Entry]_{it}$		-0.696^{***}		-0.623^{***}
		(0.097)		(0.070)
$1[Post-Entry]_{it} \times 1[k=1]$	-0.696^{***}		-0.623^{***}	
	(0.097)		(0.070)	
$1[Post-Entry]_{it} \times 1[k=2]$	-0.721^{***}	-0.025	-0.650^{***}	-0.027
	(0.105)	(0.025)	(0.073)	(0.016)
$1[Post-Entry]_{it} \times 1[k=3]$	-0.917^{***}	-0.221^{***}	-0.738^{***}	-0.115^{***}
	(0.112)	(0.040)	(0.075)	(0.024)
$1[Post-Entry]_{it} \times 1[k=4]$	-0.978^{***}	-0.282^{***}	-0.781^{***}	-0.157^{***}
	(0.112)	(0.042)	(0.076)	(0.027)
$1[Post-Entry]_{it} \times 1[k=5]$	-0.999^{***}	-0.303^{***}	-0.800^{***}	-0.176^{***}
	(0.113)	(0.043)	(0.076)	(0.029)
$1[Post-Entry]_{it} \times 1[k=n]$	-1.001^{***}	-0.310^{***}	-0.828^{***}	-0.205^{***}
	(0.112)	(0.044)	(0.075)	(0.031)
Type k × Station FE	✓	✓	✓	✓
Type k × State-Date FE	✓	✓	✓	✓
Observations	80,475,582		114,827,280	

Table E.5: Effect on Simulated Transaction Prices

Note: *p<0.1; **p<0.05; ***p<0.01. Standard errors are clustered at the municipality level. County-level controls included. Observation numbers differ across treatment allocation as observations of stations, which experience entry more than once, are dropped from the sample after the date of the second entry. Only markets with more than one firm included. Included interactions term $1[Incumbent]_i \times 1[k=z]\ \forall\ z$ with $z \in \{1,2,3,4,5,n\}$ are suppressed for convenience.

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Online Supplementary Material for The Heterogeneous Effects of Entry on Prices

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S.1 Additional Figures

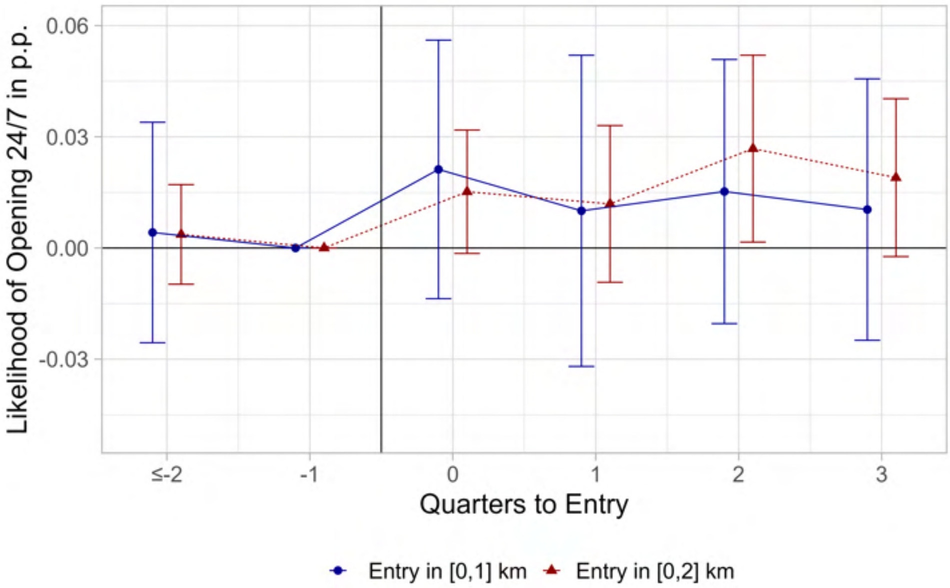
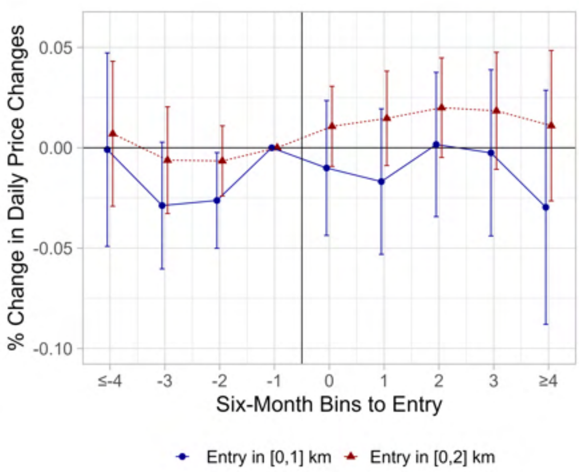
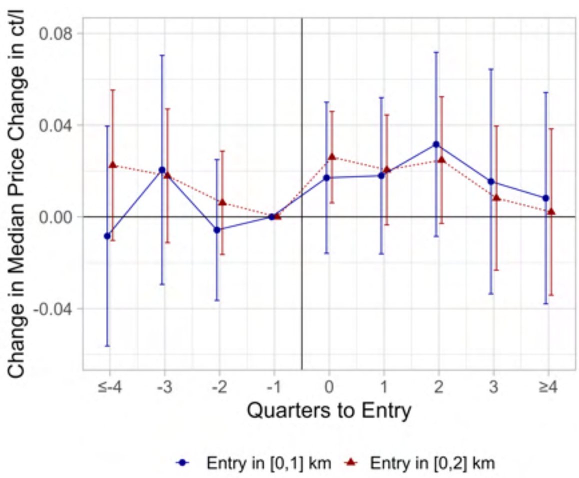


Figure S.1: Robustness Check: Effect of Entry on Opening Hours

Note: This figure provides the leads and lags, β_τ, of the event study regression (3) with a shorter effect window and thinner (quarterly) bins as opening hours are observed for the period January 2019 to March 2020. The outcome is a dummy equal to one if a station is open 24/7, and zero otherwise. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.



(a) Price Changes



(b) Median Price Change

Figure S.2: Robustness Check: Price Change Characteristics

Note: This figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

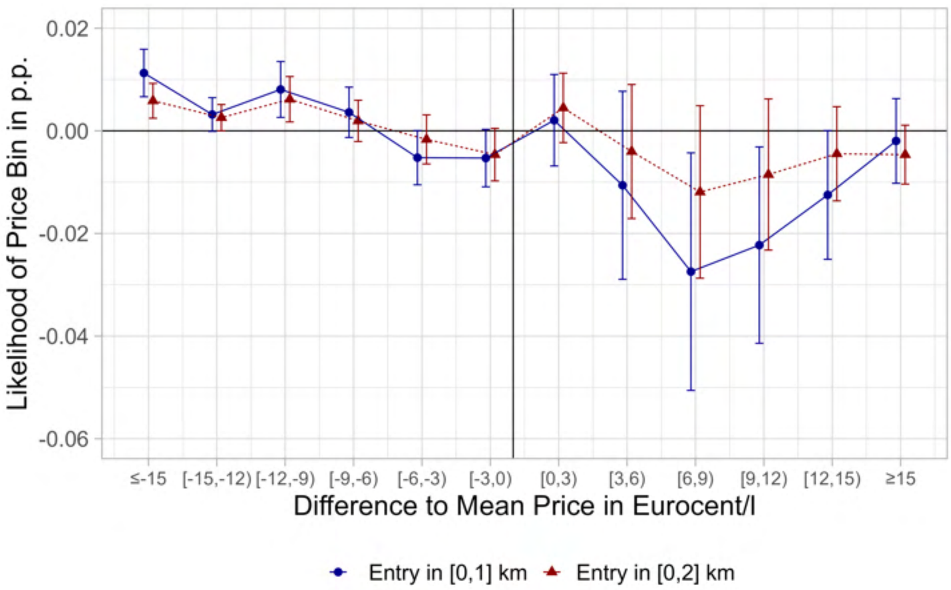
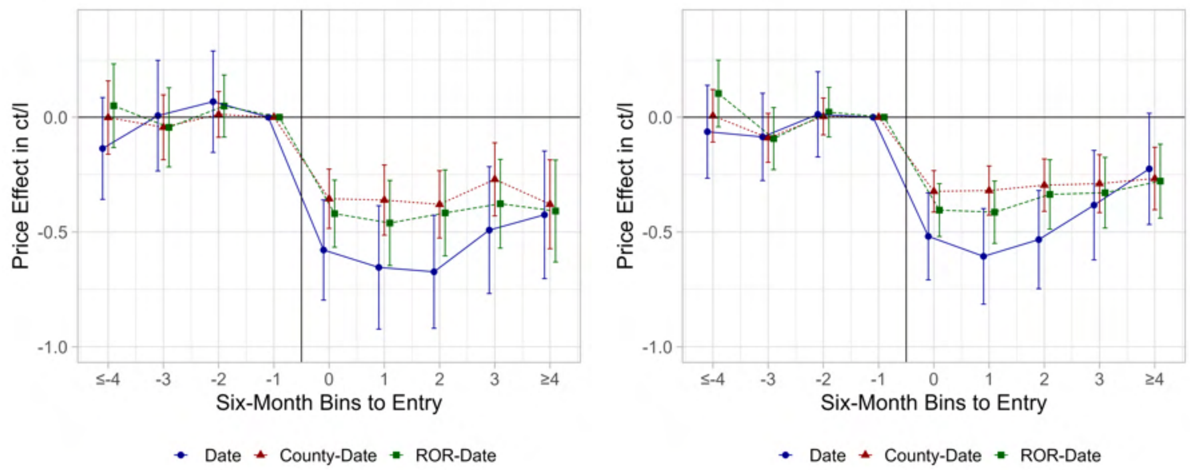


Figure S.3: Robustness Check: Distributional Analysis as in Cengiz et al. (2019)

Note: This figure plots the results of the distributional analysis in the spirit of Cengiz et al. (2019). Results come from difference-in-differences regressions in the style of equation (2). Outcome variables for each regression are dummies whether prices are in a specific price bin. We chose price bins of three ct/l width. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.

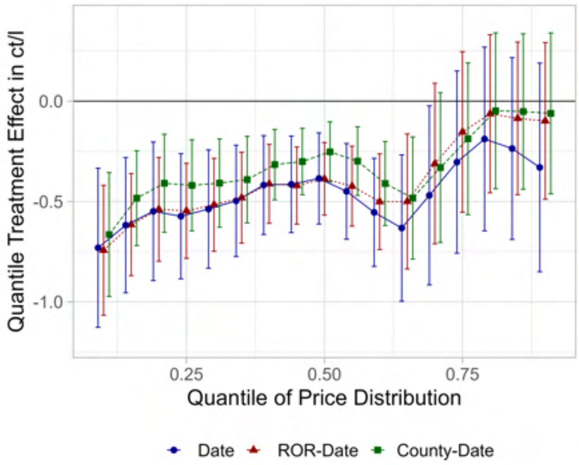


(a) Entry in [0,1] km

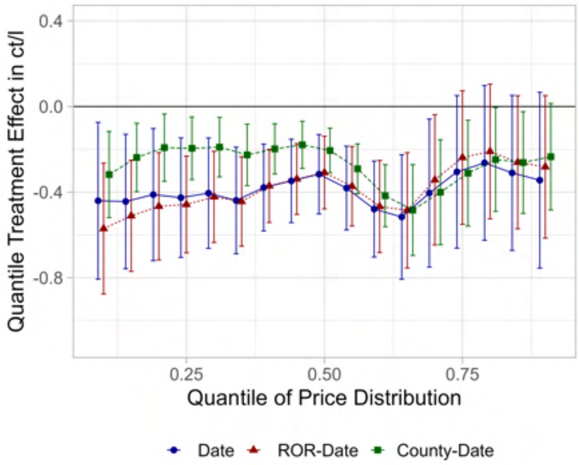
(b) Entry in [0,2] km

Figure S.4: Robustness Check: Identification Cells

Note: This figure gives the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Fixed effects are varied. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.



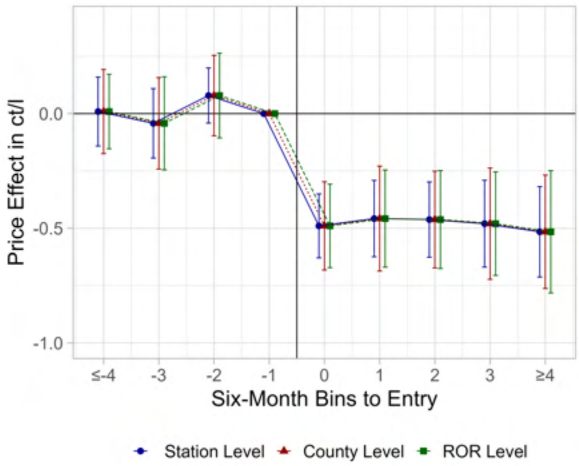
(a) Entry in [0,1] km



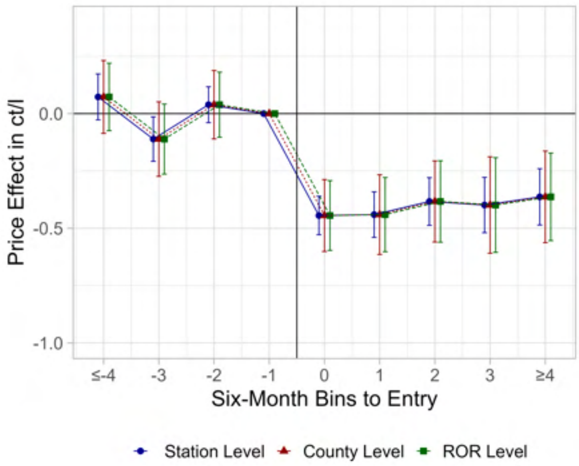
(b) Entry in [0,2] km

Figure S.5: Robustness Check: Identification Cells - QTEs

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius (left) and 2 km radius (right) estimated using the method of Firpo et al. (2009). Estimates are given for every 5th percentile between the 10th and 90th percentile. Fixed effects are varied. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.



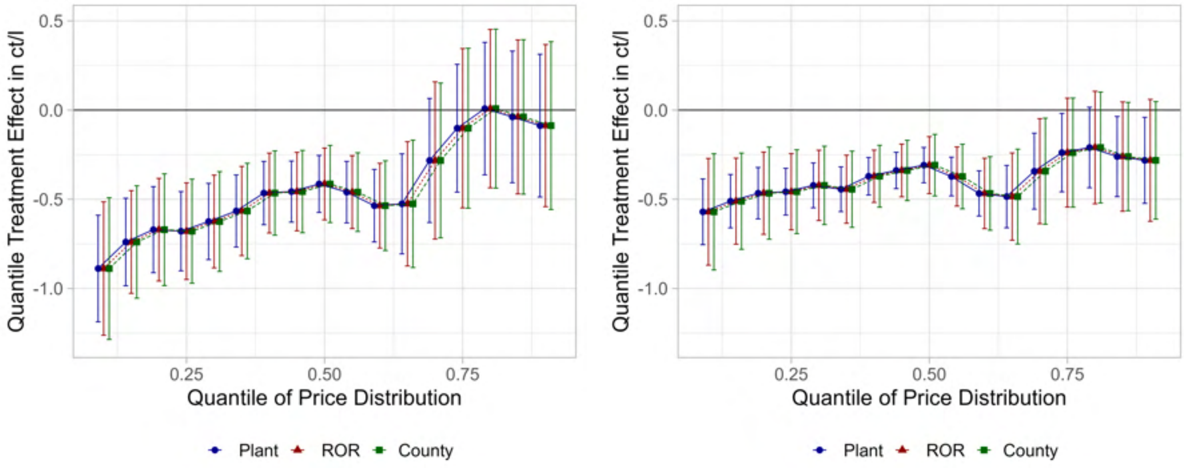
(a) Entry in [0,1] km



(b) Entry in [0,2] km

Figure S.6: Robustness Check: Inference

Note: This figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Inference approaches are varied. Standard errors are clustered at different aggregation levels. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.

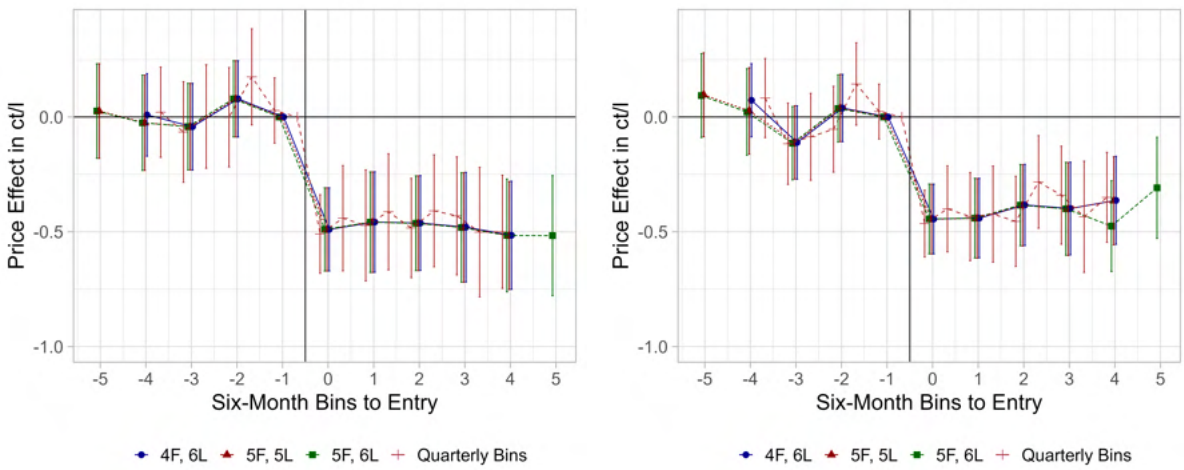


(a) Entry in [0,1] km

(b) Entry in [0,2] km

Figure S.7: Robustness Check: Inference - QTEs

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius (left) and 2 km radius (right) estimated using the method of Firpo et al. (2009). We present estimates for every 5th percentile between the 10th and 90th percentile. Standard errors are clustered at different aggregation levels. Vertical bars indicate 95% confidence intervals. County-level controls included.

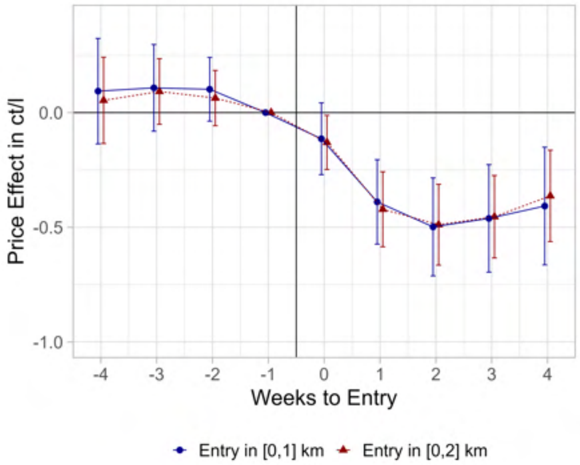


(a) Entry in [0,1] km

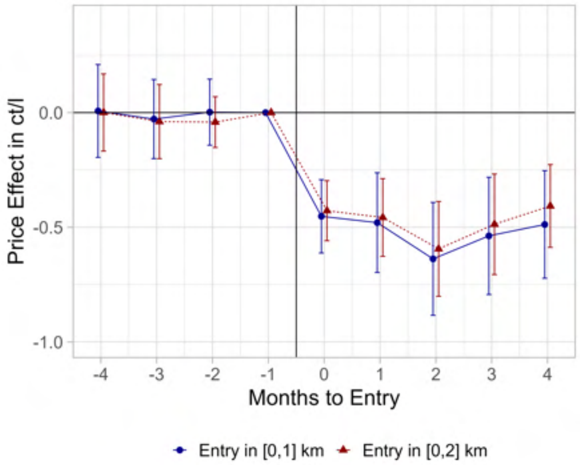
(b) Entry in [0,2] km

Figure S.8: Robustness Check: Choice of Leads and Lags

Note: This figure provides the leads and lags of the event study regression (3) with a varying effect window. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.



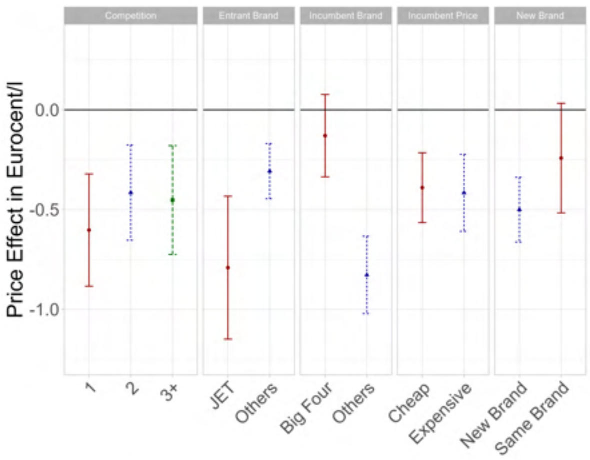
(a) Weekly Bins



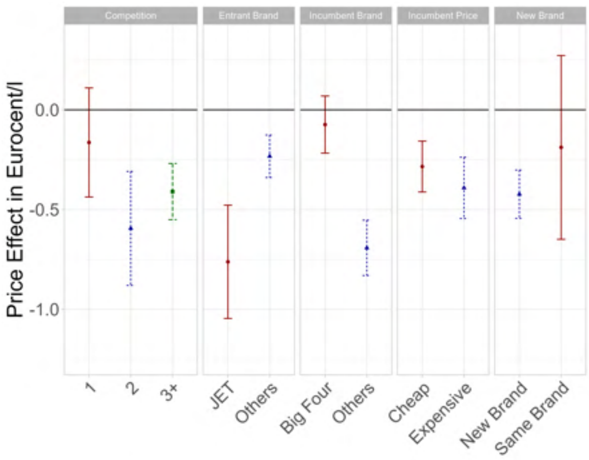
(b) Quarterly Bins

Figure S.9: Robustness Check: Short-Run Effects

Note: This figure provides the leads and lags of the event study regression (3) with a varying effect window. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.



(a) Entry in [0,1] km



(b) Entry in [0,2] km

Figure S.10: Robustness Check: Heterogeneity in (Average) Effect of Entry on Prices

Note: The plots give simple difference-in-differences results as in equation (2), where the treatment variable is interacted with the respective heterogeneity dummy. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.

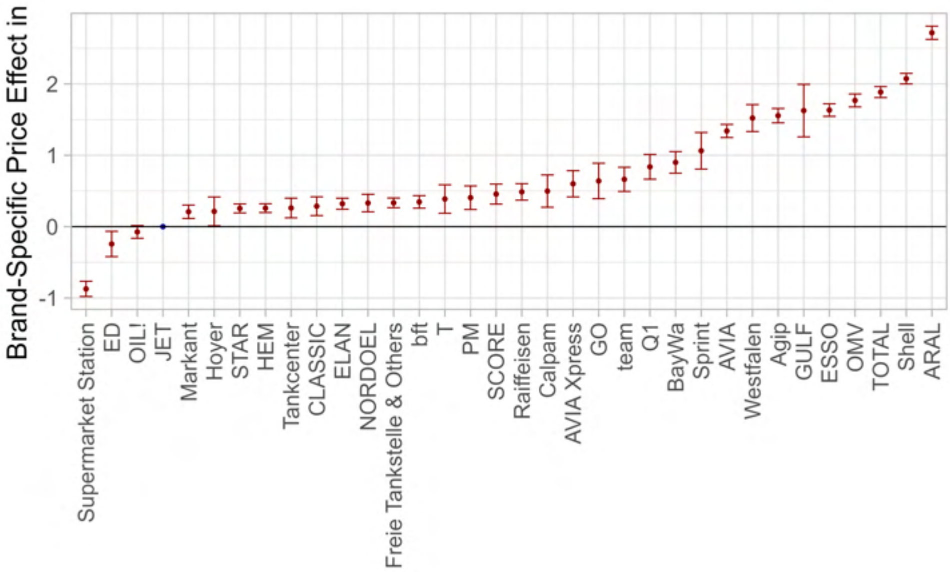


Figure S.11: Brand-Specific Price Premia

Note: Coefficients obtained from a regression of prices on brand fixed effects, municipality fixed effects, date fixed effects. Standard errors are clustered at municipality level. Vertical bars indicate 95% confidence intervals.

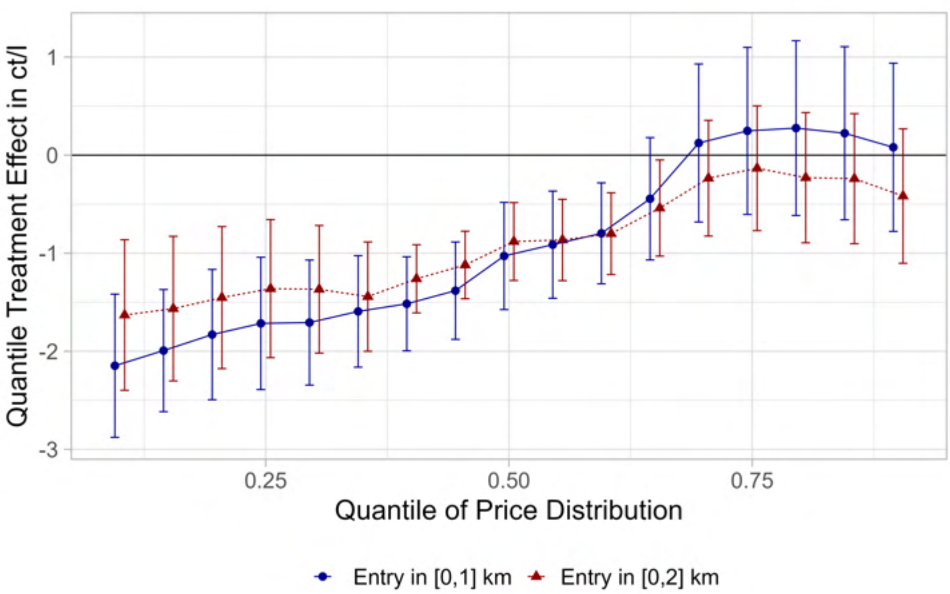
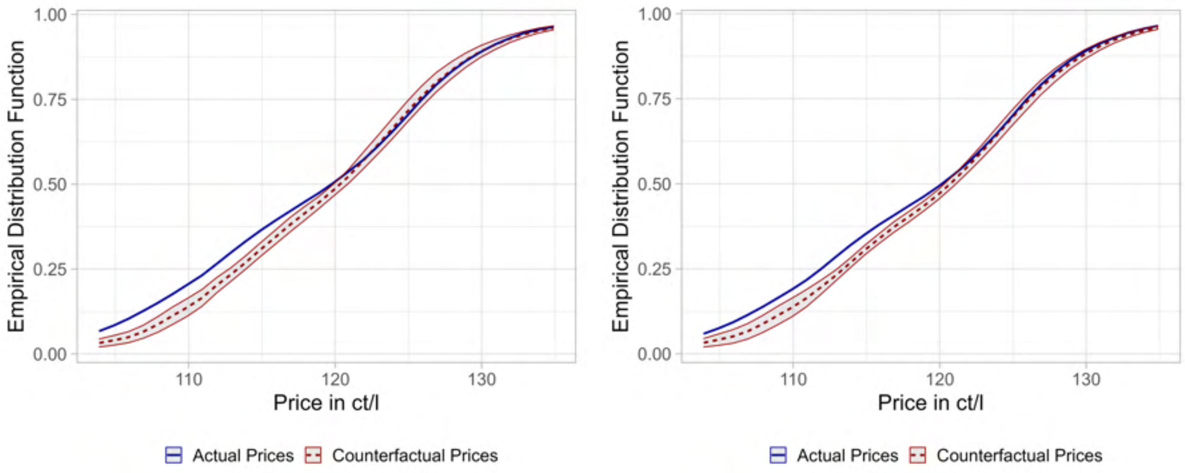


Figure S.12: Robustness Check: JET Entry - QTEs

Note: This figure plots quantile treatment effects of entry by JET on prices for entry in 1 km radius (blue) and 2 km radius (red) estimated using the method of Firpo et al. (2009). Estimates are given for every 5th percentile between the 10th and 90th percentile. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.

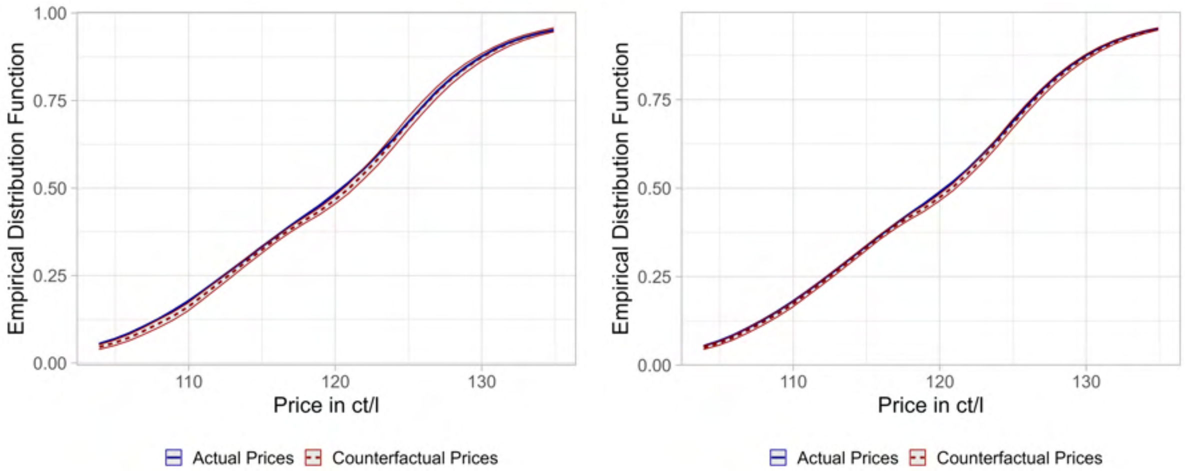


(a) Entry in [0,1] km

(b) Entry in [0,2] km

Figure S.13: Robustness Check: JET Entry - Counterfactual Distribution

Note: The figures plot the actual price distribution of incumbents' prices, which experienced entry by JET (blue) and the estimated counterfactual price distribution (red) of a scenario without entry in the treated markets. The counterfactual distribution comes from distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for price thresholds at each integer ct/l. The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. The shaded area indicates 95% confidence interval.



(a) Entry in [0,1] km

(b) Entry in [0,2] km

Figure S.14: Robustness Check: Non-JET Entry - Counterfactual Distribution

Note: The figures plot the actual price distribution of incumbents' prices, which experienced entry by non-JET brands (blue) and the estimated counterfactual price distribution (red) of a scenario without entry in the treated markets. The counterfactual distribution comes from distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for price thresholds at each integer ct/l. The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. The shaded area indicates the 95% confidence interval.

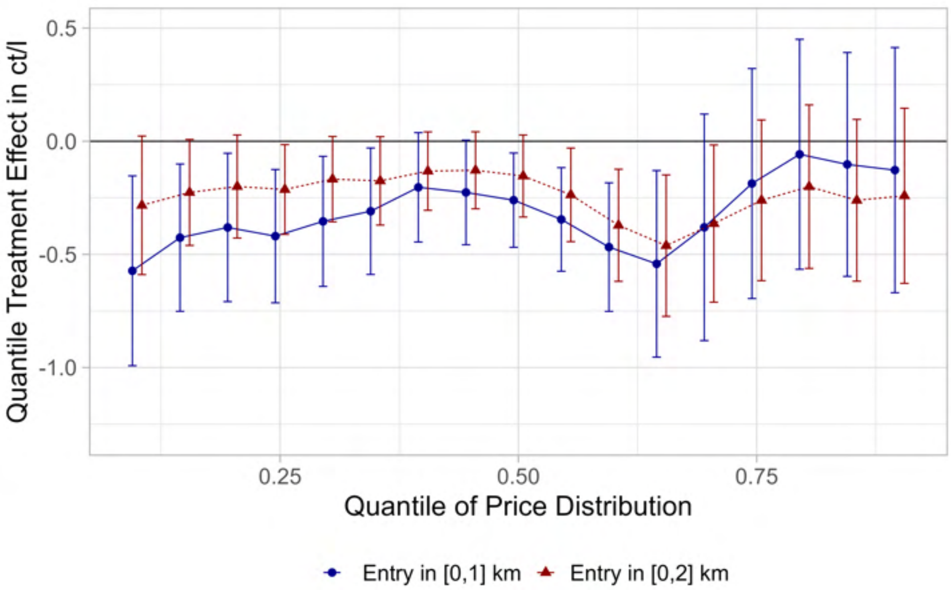
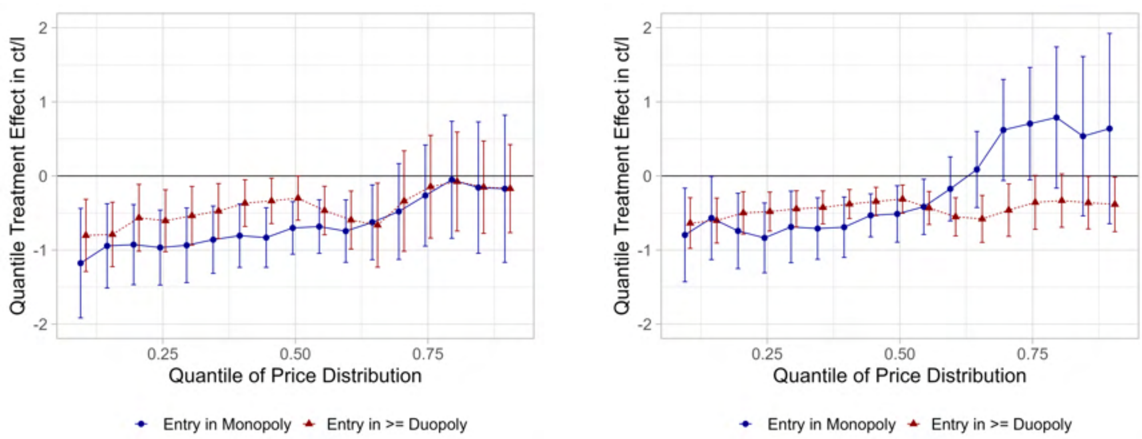


Figure S.15: Robustness Check: Non-JET Entry - QTEs

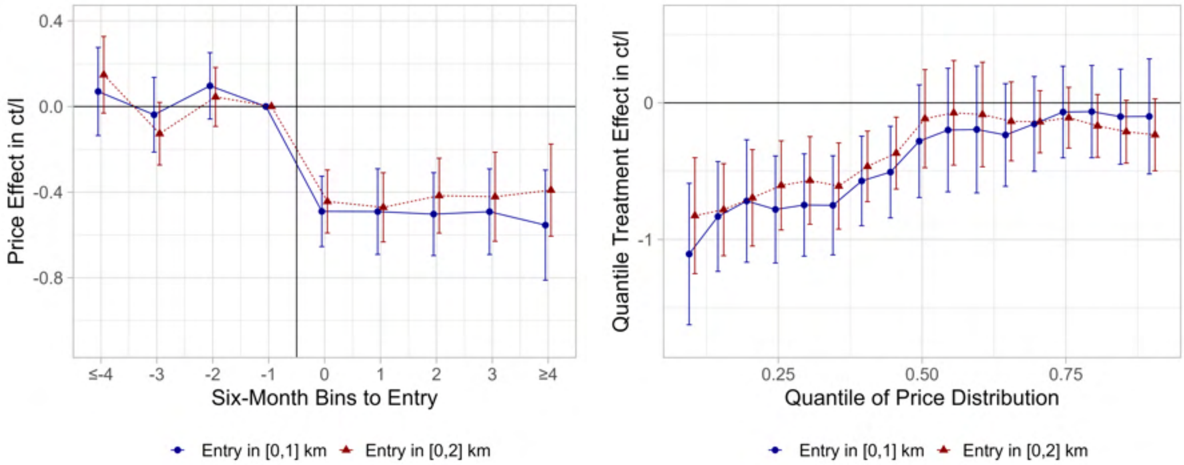
Note: This figure plots quantile treatment effects of entry by non-JET on prices for entry in 1 km radius (blue) and 2 km radius (red) estimated using the method of Firpo et al. (2009). Estimates are given for every 5th percentile between the 10th and 90th percentile. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.



(a) Entry in [0,1] km (b) Entry in [0,2] km

Figure S.16: Robustness Check: Distributional Effects and Market Concentration

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius and 2 km radius estimated using the method of Firpo et al. (2009). The plots differentiate between markets with few (blue) or many (red) non-entrant stations. As the number of firms in the market increases for a wider market definition, we differently split the sample for comparison reasons. Estimates for every 5th percentile between the 10th and 90th percentile are provided. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included. Results obtained from regressions in which we also control for daily, region-specific wholesale price variations.

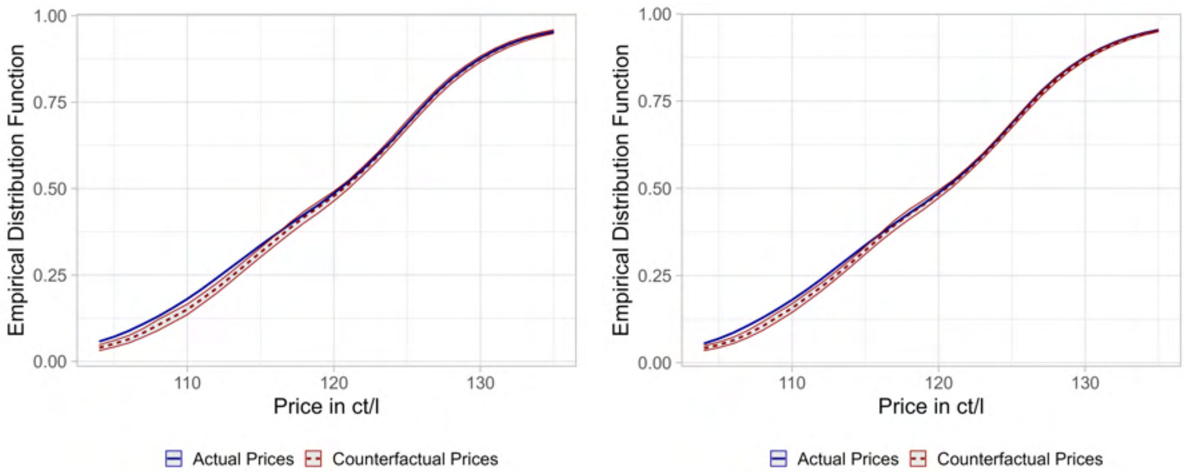


(a) Sun and Abraham (2021) - Event Study

(b) Sun and Abraham (2021) - QTEs

Figure S.17: Robustness Check: Heterogeneous Treatment Effects

Note: The left figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. The right figure plots quantile treatment effects of entry on prices for entry in 1 km radius (blue) and 2 km radius (red) estimated using the method of Firpo et al. (2009). We present estimates for every 5th percentile between the 10th and 90th percentile. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls are included.

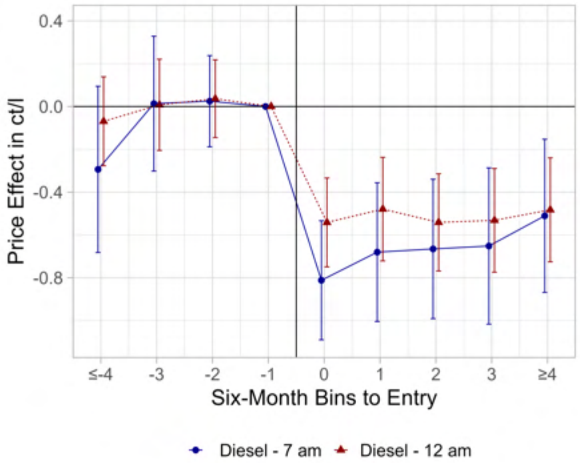


(a) Entry in [0,1] km

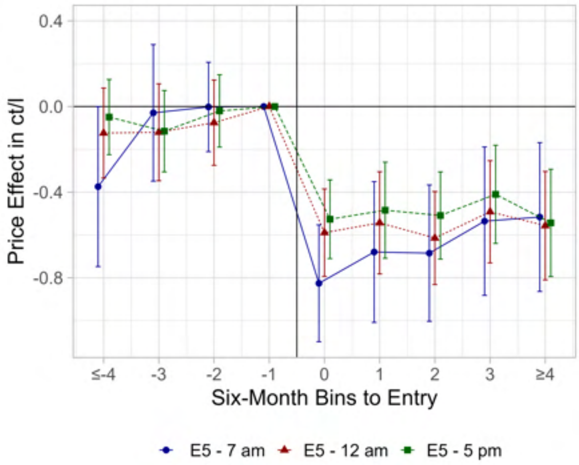
(b) Entry in [0,2] km

Figure S.18: Robustness Check: Observed Prices and Counterfactual Distribution - Sun and Abraham (2021)

Note: The figures plot the actual price distribution of incumbents' prices, which experienced entry (blue) and the estimated counterfactual price distribution (red) of a scenario without entry in the treated markets. The counterfactual distribution comes from distribution regressions as proposed by Chernozhukov et al. (2013), i.e. the regressions as in equation (2) for price thresholds at each integer ct/l. We employ the estimator proposed by Sun and Abraham (2021). The estimated treatment effect per distribution regression is then added to the quantile of the empirical distribution function of actual prices at the respective threshold price. The figure is truncated at the 5th and 95th percentile of the actual price distribution. Standard errors are clustered at the municipality level. The shaded area indicates the 95% confidence interval.



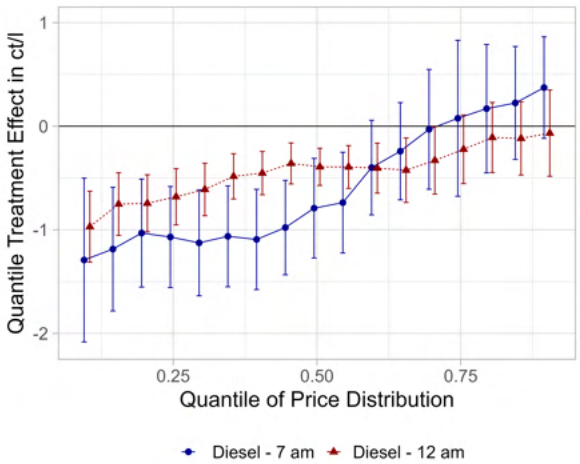
(a) Entry in [0,1] km - Diesel



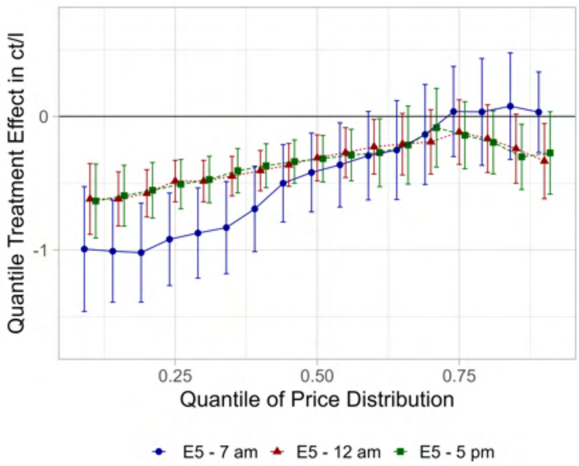
(b) Entry in [0,1] km - E5

Figure S.19: Robustness Check: Type of Fuel and Time of the Day

Note: This figure provides the leads and lags of the event study regression (3) with an effect window of four bins before and five bins after the entry event. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. Endpoints are binned. County-level controls included.



(a) Entry in [0,1] km - Diesel



(b) Entry in [0,1] km - E5

Figure S.20: Robustness Check: Fuel and Time of the Day - QTEs

Note: This figure plots quantile treatment effects of entry on prices for entry in 1 km radius estimated using the method of Firpo et al. (2009). Estimates are given for every 5th percentile between the 10th and 90th percentile. Standard errors are clustered at the municipality level. Vertical bars indicate 95% confidence intervals. County-level controls included.

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Firpo, Sergio, Nicole M Fortin, and Thomas Lemieux, "Unconditional quantile regressions," *Econometrica*, 2009, *77* (3), 953–973.

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