Whom to Inform about Prices? Evidence from the German Fuel Market

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Abstract

Combining a theoretical model of imperfect information with empirical evidence, we show how the effect of providing price information to consumers depends on how well informed they are beforehand. Theoretically, an increase in consumer information decreases prices more, the fewer ex ante informed consumers there are. Empirically, we study mandatory price disclosure in the German fuel market for two fuel types that differ in ex ante consumer information. The decline in prices is stronger when there are fewer ex ante informed consumers. The magnitude of the treatment effect declines over time but is intensified by local follow-on information campaigns.

Keywords: Mandatory price disclosure, consumer information, retail fuel market.

JEL classification: D83, L41.

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1 Introduction

Mandatory price disclosure (MPD) is becoming a popular policy tool to make markets more competitive.[1] Studies estimating the local treatment effect of mandatory price disclosure on prices find mixed results.[2] So far, there is limited evidence about why mandatory price disclosure sometimes lowers prices and sometimes does not. However, before introducing MPD, it is crucial to understand what its effect is going to be in the particular setting.

In this paper, we ask what determines the price effect of mandatory price disclosure. More specifically, we focus on two key elements: How well consumers are informed prior to MPD, as well as the persistence of the price effects of MPD. Using a theoretical model with imperfect price information among consumers, we study how the share of uninformed consumers before mandatory price disclosure affects the price effect of MPD. We test the predictions in the context of the introduction of MPD in the German retail fuel market. There are two features of the setting that make it particularly suitable for this analysis: First, we observe high-frequency, station-level price changes for Germany and France before and after the introduction of MPD. Second, MPD was introduced simultaneously for diesel and gasoline. On average, consumers buying gasoline are less informed about prices than consumers buying diesel. Consumers can also not substitute between fuel types. Since the same fuel stations sell both types of fuel, there are no supply-side differences between fuel types. We use a difference-in-differences design to estimate the price effect of MPD for each fuel type. Fuel stations in Germany are part of the treatment group, whereas fuel stations in France are in the control group. Finally, we study whether follow-on local radio reports about fuel prices can intensify the treatment effect.

Several findings emerge: Theoretically, we show that the more uninformed consumers there are prior to the introduction of MPD, the larger is the reduction in prices that it induces. Empirically, we find that MPD decreases prices for all fuels but that this decrease is larger for gasoline, which has a less informed consumer base, than for diesel. In the German retail fuel market, MPD decreases gasoline prices by around 2.7 percent and diesel prices by around 1.8 percent. The difference in treatment effects is particularly strong in the five months after the introduction of MPD. Thereafter, the treatment effect stabilizes at between 1 and 2 percent for diesel and gasoline. Since the level of gasoline prices is higher than the level of diesel prices, the long-term effect of MPD in terms of Eurocents is higher for gasoline than for diesel. Finally, follow-on information treatments

[1] MPD was introduced in numerous sectors, such as supermarkets, retail fuel, cement, or healthcare, and in many countries, such as Israel, Austria, Germany, Chile, Denmark, or the United States.

[2] See, for example, Luco (2019), who finds that mandatory price disclosure increased retail margins in the Chilean fuel market and Ater and Rigbi (Forthcoming), who find that mandatory price disclosure decreased prices at Israeli supermarkets.

through local radio reports about prices can intensify the treatment effect. Overall, this suggests that MPD is most effective in markets where few consumers are well-informed before its introduction and that complementary information campaigns can increase the effect of MPD.

The theoretical analysis builds on Varian (1980). On the supply side, there are sellers that sell a homogeneous good and set prices. On the demand side, there are fully informed *shoppers* that know all prices, as well as uninformed *non-shoppers* that visit a seller at random. All consumers inelastically demand a single unit of the homogeneous good. In equilibrium, sellers set prices by randomizing according to a mixed strategy. Informed *shoppers* know all prices in the market, always buy from the lowest-price seller and pay the minimum price. Uninformed *non-shoppers* visit a single seller, observe its price and decide whether to purchase at that price or not purchase at all.

We model MPD as leading to an increase in the share of *shoppers*. Sellers always know all prices and are thus not directly affected by MPD.[3] We assume that price information coming from MPD always reaches a fixed number of consumers, irrespective of whether these are *shoppers* or *non-shoppers*. The ex ante share of *shoppers* thus affects how MPD changes prices in two ways: First, it affects the *marginal* effect of MPD on prices. Second, it affects how many *non-shoppers* become *shoppers* through MPD.

In the empirical application, we study the introduction of the Market Transparency Unit for Fuels (MTU) in Germany. Since September 2013, all fuel stations in Germany have to report all price changes in real-time to a central database. This aggregates the information and allows information service providers to defuse this information to consumers (e.g., via smartphone applications). This policy was recommended by the German Federal Cartel Office (2011) after diagnosing that a lack of price information on the consumer side was responsible for a lack of competition between fuel stations.

The station-level price reports to the MTU form the basis of our data set. To estimate the price effects of MPD we also need price data for fuel stations in Germany before the introduction of mandatory price disclosure. Here, we leverage that there already existed some smartphone applications prior to MPD that allowed users to self-report fuel prices, which were then collected and diffused to users in a similar fashion to the price information from the MTU.[4] We have access to the pre-MPD price notifications by users for one of these apps. This includes 20.5 million price notifications between the 1 September 2012 and the 31 August 2013. For the control group, we exploit the fact

[3]There is a rich theoretical literature on how improving price transparency on the producer side can stabilize collusion (see, for example, Green and Porter (1984) or Kühn and Vives (1995)). It is likely the reason why MPD led to higher prices in the Danish concrete industry (Albæk, Møllgaard, and Overgaard, 1997) and the Chilean gasoline market (Luco, 2019). Our application is different in that producers already invested heavily in observing their competitors' prices before MPD (German Federal Cartel Office, 2011).

[4]The usage of these apps before MPD was considerably lower than after its introduction. This is why the introduction of MPD led to an important change in the the information set of consumers.

that there exists a similar database containing fuel prices at all fuel stations in France since 2007.

We use a synthetic difference-in-differences (SDID) design to estimate the price effects of mandatory price disclosure (see Arkhangelsky et al., 2021). Similar to regular difference-in-differences, the treatment effect is estimated by isolating the change in prices after the introduction of MPD in the treatment group that is not present in the control group. Similar to synthetic control methods, the unit and time period weights in the control group are optimized as to best match pre-trends in the treatment group. Arkhangelsky et al. (2021) report that SDID performs weakly better than synthetic control and difference-in-differences methods.

By comparing the effect of MPD on gasoline and diesel prices, we can test the prediction about how the pre-MPD level of consumer information affects the price effect of MPD. A key feature of the setting is that the same fuel stations sell both types of fuel at the same pump. Besides the fuel type, the overall product (e.g., the shopping experience or the location) is identical. The key difference between gasoline and diesel is that these are bought by consumers that differ in their incentives to acquire information about prices and so in their ex ante information levels. In Germany, cars with diesel engines are driven by consumers that drive on average twice as many kilometers per year as gasoline buyers.[5] Buying a car with a diesel engine is a fixed cost investment to lower marginal costs.

Already prior to MPD the incentives to become informed about fuel prices and further reduce the price per liter was higher for diesel drivers. Using data on the user-reported price notifications before MPD, we show that the reporting intensity was higher for diesel than for gasoline. Using user-level search data after the MPD introduction, we show that the intensity of usage remained higher for diesel than for gasoline. Both of these pieces of evidence are consistent with our theoretical modeling of MPD.

To further strengthen the robustness of our main results, we rely on alternative identification strategies with which we can study the same theoretical mechanisms. First, we rely on an alternative information shock in which we study the local price effects of regular local radio stations that start reporting the lowest fuel prices in their reception area at some point after MPD. This also sheds light on the question of whether policymakers have any additional levers to ensure that the effect of MPD is persistent. Second, we use alternative identification strategies, where we isolate stations 20 to 100 kilometers from the Franco-German border or study differences in the treatment effect for local monopolists as compared to stations in competitive markets.

To rule out that our results are driven by selection bias in the pre-MPD price reports or the choice of the control country, we estimate the effect of MPD on diesel and gasoline prices using weekly, country-level administrative data and the 26 member countries of the

[5]This is based on the figures from *Verkehr in Zahlen 2018* for the years 2013 and 2014.

European Union except Germany as a control group. Our results confirm the findings in our main analysis.

This paper makes two main contributions. First, we derive empirically verifiable theoretical predictions on the role of ex ante consumer information for the effect of mandatory price disclosure policies. We build on the theoretical model of imperfect consumer information about prices by Varian (1980). We adapt this framework to our empirical application by modeling how MPD affects consumers, accounting for how many consumers are informed *shoppers* ex ante. This yields an unequivocal prediction in which the magnitude of the price effect of MPD monotonically decreases in the ex ante share of *shoppers*. In contrast, there is no monotonic relationship between the ex ante share of *shoppers* and the price effect of a marginal increase in the share of *shoppers*. Thus, tailoring the modeling of the information shock to match how MPD works in practice allows to obtain an unambiguous theoretical prediction.

Second, we extend the existing empirical literature on price transparency policies by studying a novel mechanism of how MPD affects prices. In this context, our analysis highlights the importance of the share of consumers informed about prices before MPD. Importantly, we also show how the effect of MPD evolves over time and how complementary information campaigns can be used to strengthen the effect of MPD.[6] Our findings relate to Albæk, Møllgaard, and Overgaard (1997) and Luco (2019), who find that increasing price transparency in homogeneous goods markets led to an increase in prices. Since price transparency can also affect information on the supply side, this suggests that in those cases it seems to have stabilized collusion. In contrast, the German retail fuel market already had very high supply-side price transparency even before MPD. Ater and Rigbi (Forthcoming) find that MPD for Israeli supermarkets led to more intense competition, because low-price supermarket chains used MPD-enabled price comparisons to lend credibility to their price-based advertising campaigns. Brown (2019b) and Brown (2019a) study the demand- and supply-side responses of increasing price transparency in the U.S. health care market. Rossi and Chintagunta (2016) study how mandating fuel stations on Italian motorways to post the prices of rivals affects prices. There are important differences in the design of this policy as compared to the MTU.[7] However, their simulated price effect of the price disclosure policy leads to results that are of a similar magnitude to our findings. Martin (2020) studies how limiting the publicly distributed prices only to a subset of cheapest fuel stations affects equilibrium prices.

Finally, this paper relates to an extensive empirical literature that analyzes pricing

[6] German Federal Cartel Office (2011) finds that prior to MPD, all vertically integrated oligopolists obliged fuel stations under their own brand to collect price information at local competitors multiple times per day and report to the oligopolist.

[7] The policy only applies to the highly restrictive sample of motorway fuel stations. It also only allows drivers to discover rival prices once they reached a particular station, as opposed to seeing all prices online.

decisions for retail fuel.[8] There is an extensive empirical literature that studies the role of imperfect information in these markets (see, for example, Chandra and Tappata, 2011, Pennerstorfer et al., 2020, Byrne and de Roos, 2017 or Byrne and de Roos, 2022). In contrast, Houde (2012) emphasizes the role of spatial differentiation as opposed to imperfect information. Byrne and de Roos (2019) and Assad, Clark, Ershov, and Xu (2020) study how humans and algorithms learn to tacitly coordinate on softer competition and higher prices. Although understanding pricing decisions and the source of price dispersion in fuel markets is interesting in and of itself, Genakos and Pagliero (2022) and Montag, Sagimuldina, and Schnitzer (2021) show how this affects the pass-through of commodity taxes and thus has broader implications for the effectiveness of other policy tools.

The remainder of this paper is structured as follows: Section 2 outlines the theoretical model. Section 3 describes the institutional setting and the data. Section 4 provides descriptive evidence on the price effects of MPD. Section 5 presents the empirical design and Section 6 includes the empirical results. Section 7 concludes.

2 Theoretical Model

We begin by theoretically shedding light on the effects of mandatory price disclosure policies in a context where consumers are imperfectly informed about prices. In our analysis MPD can be seen as synonymous with any exogenous information shock that makes prices at all sellers perfectly visible for some consumers. However it is different to changes in the visibility of prices at only some sellers or changes in price transparency endogenously chosen by sellers (e.g., through advertising).

Due to the structure of the market in the empirical application and the nature of the information shock, we place the analysis in the context of the Varian (1980) information model. Our focus lies on showing how the share of ex ante informed consumers affects the price effects of MPD.

2.1 Setup

The model features sellers and consumers. Sellers sell a homogeneous good and set prices. Consumers can be divided into two groups: *shoppers*, who know all prices and buy from the lowest-price seller, and *non-shoppers*, who draw a single seller at random, observe its price, and can only decide between buying and not buying at that price. Mandatory price disclosure leads to an exogenous increase in the share of *shoppers* in the population of consumers.

[8]Eckert (2013) provides an overview of the earlier literature on pricing in fuel markets.

On the demand side, there is a unit mass of atomistic consumers that each inelastically demand a single unit of the good. The valuation of the good is the same across consumers and is denoted by v. A fraction ϕ of consumers are *shoppers*. They know all prices and always buy from the lowest price seller. If there is a tie, shoppers are shared equally by the lowest price sellers.[9] A fraction $1-\phi$ of consumers are *non-shoppers*.

On the supply side, there is a fixed and exogenous number of symmetric sellers. Each seller produces the homogeneous good at a marginal cost of production normalized to zero. We denote the number of firms by N, and sellers are indexed by i. Sellers form expectations about rival prices and choose a pricing strategy to maximize expected profits.

Finally, we need to model the impact of mandatory price disclosure. By enabling the creation of smartphone applications with which consumers can access all price information instantaneously at no cost beyond using the application, mandatory price disclosure converts some consumers from uninformed *non-shoppers* to fully informed *shoppers*. Furthermore, mandatory price disclosure is likely to lead to more than just a marginal increase in the share of informed consumers. How many consumers can be converted from being uninformed *non-shoppers* to being fully-informed *shoppers* depends on how many consumers are already fully informed prior to MPD. We therefore assume that MPD increases the share of fully informed *shoppers* by $\Delta_\phi(1-\phi_0)$, where Δ_ϕ is the size of the information shock and ϕ_0 is the ex ante share of *shoppers*.

These two components are essential to model the effect of MPD. Δ_ϕ captures how large the information shock is (e.g., whether the existence of the measure is widely advertised). In contrast, $1-\phi_0$ captures how many uninformed consumers there still are that could be informed by the policy. For example, if most consumers are already *shoppers* prior to the policy, even a heavily advertised MPD policy cannot lead to a large increase in the share of *shoppers*. Intuitively, the functional form of the information technology is such that MPD leads to information about prices being sent to a random subset of the population of consumers. Δ_ϕ determines how many consumers receive this message. $1-\phi_0$ captures how many of these are turned into *shoppers* because they receive the message.

We search for the equilibrium pricing strategy by solving for the Nash Equilibrium of the game. Thereafter, we show how MPD affects equilibrium prices.

2.2 Equilibrium price distribution

There exists no equilibrium in pure strategies. Instead, there is a unique symmetric mixed strategy Nash equilibrium, which is characterized by the density function $F(p_i)$ and the closed and bounded support $[\underline{p}, p_r]$. p_r is the reservation price of non-shoppers

[9] In practice, there are no ties when there are no mass points in pricing strategies.

and $\underline{p}$ is the minimum of the support from which a seller draws prices in the symmetric Nash equilibrium. In equilibrium, *shoppers* always buy from the lowest price seller and *non-shoppers* buy from the seller that they visit at random. Details on the derivation of these objects can be found in Appendix A.

Non-shoppers draw a single seller and observe its price. They purchase the good so long as the price is weakly below their valuation v. Their reservation price p_r is thus equal to v. Since no one purchases at a price above v, no seller charges a price above v in equilibrium and all *non-shoppers* buy the good at the randomly drawn seller.

The remaining equilibrium objects are derived using two equiprofit conditions that are based on the fact that in the symmetric mixed strategy Nash equilibrium, any price that a seller sets with positive probability should yield the same expected profit. A seller that sets the reservation price sells to its share of *non-shoppers*. A seller that sets the lowest price among all sellers sells to all *shoppers* and to its share of *non-shoppers*.[10] We solve for the minimum element of the support from which sellers draw prices in equilibrium, $\underline{p}$, by setting the expected profit under that price equal to the expected profit under the reservation price. We then derive the equilibrium density function by setting the expected profit under a price p_i equal to that under the reservation price.

The minimum element of the support from which sellers draw prices in equilibrium is

$$\underline{p} = \frac{v}{\frac{\phi N}{1-\phi} + 1}\,.$$

The cumulative density function from which sellers draw prices in equilibrium is

$$F(p_i) = 1 - (\frac{v - p_i}{p_i}\frac{1-\phi}{N\phi})^{\frac{1}{N-1}}\,.$$

In equilibrium, the expected profit of seller i is

$$E[\pi_i] = v\frac{1-\phi}{N}\,.$$

We can define two further objects, the expected price and the expected minimum price. Since *non-shoppers* always buy from the seller that they visit at random, the expected price reflects the average price paid by *non-shoppers*. In turn, since fully informed *shoppers* always buy from the lowest price seller, the expected minimum price corresponds to the average price paid by *shoppers*.

The expected price is

$$E[p] = \underline{p} + (\frac{1-\phi}{N\phi})^{\frac{1}{N-1}} \int_{\underline{p}}^{v} (\frac{v-p}{p})^{\frac{1}{N-1}} dp\,.$$

[10] There are no mass points in the equilibrium pricing strategies.

The expected minimum price is

$$E[p_{min}] = \frac{1-\phi}{\phi}\left(v - E[p]\right) .$$

2.3 Effect of mandatory price disclosure

Let us now turn to how mandatory price disclosure affects the equilibrium price distribution. We begin by highlighting how the share of fully informed *shoppers* affects the equilibrium price distribution. Since the reservation price of non-shoppers corresponds to their valuation of the good v, this remains unaffected. We thus focus on how the minimum element of the support from which sellers draw prices, $\underline{p}$, and the equilibrium density function, $F(p_i)$, are affected when the share of shoppers ϕ increases.

Lemma 1. *With $0 < \phi < 1$, for any $\hat{\phi} > \phi$ the minimum element of the support of the equilibrium pricing strategy $\hat{\underline{p}} < \underline{p}$ and the Nash equilibrium pricing strategy with $\hat{\phi}$ first-order stochastically dominates (FOSD) the pricing strategy with ϕ, i.e. $\hat{F}(p) \geq F(p)\ \forall\ p$.*

This means that when $0 < \phi < 1$ and the share of *shoppers* ϕ increases, the minimum element of the support from which sellers draw prices decreases. Thus, the support of prices from which firms draw in equilibrium shifts to lower prices. At the same time, for each price on this support, the likelihood that a drawn price is lower than said price increases if ϕ increases.

When ϕ converges to zero, the Nash equilibrium converges to a degenerate distribution at the monopoly price. In this case, the monopoly price corresponds to the reservation price of non-shoppers, which is equal to the valuation of the good v. When ϕ converges to one, so nearly all consumers in the market are fully informed about prices of all sellers, the Nash equilibrium converges to a degenerate distribution at the marginal cost (i.e., zero), which is the full-information Bertrand equilibrium.

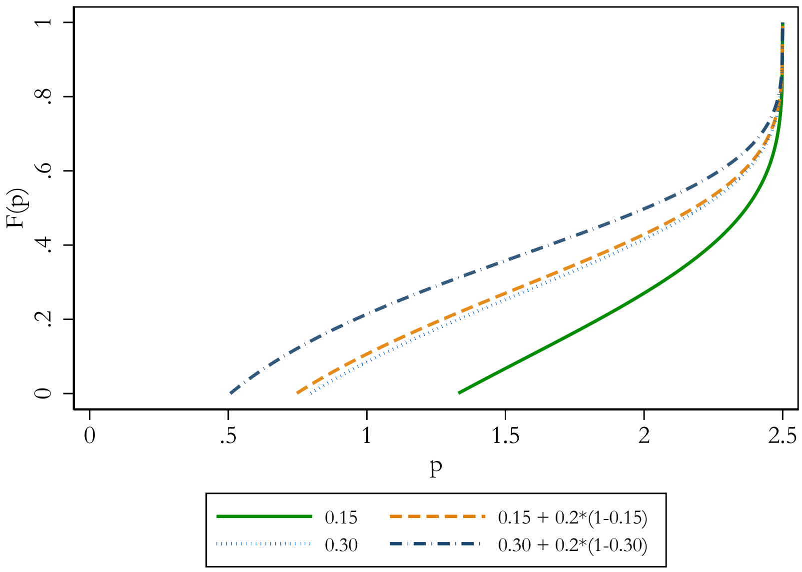
Since an increase in the share of fully informed consumers in the market leads to a shift of the equilibrium density function towards lower prices, and to the downward shift of the minimum price a seller may choose in equilibrium, $E[p]$ and $E[p_{min}]$ also decrease. This means that when consumers become on average more informed, the average price paid by shoppers and the average price paid by non-shoppers decline and the expected price paid decreases for all consumers.

After establishing that more fully informed *shoppers* always lead to lower prices, we want to understand how the size of the effect of MPD varies with market conditions (i.e., the ex ante share of *shoppers*). That is, we want to understand how the effect of Δ_ϕ on equilibrium prices varies with ϕ_0.

Proposition 1. *With $0 < \Delta_\phi < 1$ and $\phi = \phi_0 + \Delta_\phi(1-\phi_0)$, for any $\hat{\phi}_0 > \phi_0$ the change in the minimum element of the support of the equilibrium pricing strategy due to Δ_ϕ is $\Delta\hat{\underline{p}} > \Delta\underline{p}$, and the Nash equilibrium pricing strategy is such that $\frac{\partial^2 F(p)}{\partial \Delta_\phi \partial \phi_0} < 0$.*

The proof can be found in Appendix A. This means that the shift in the equilibrium price distribution towards lower prices due to the information shock Δ_ϕ is smaller in magnitude for markets with a higher ex ante share of *shoppers*. The effect of the information shock on the minimum element of the support of the equilibrium pricing strategy is also smaller when there are more *shoppers* before MPD. Figure 1 illustrates how the effect of MPD varies with the ex ante share of *shoppers* graphically.

Figure 1: Effect of the information shock on the equilibrium pricing strategy



Note: The Figure shows simulation results of how the distribution from which sellers draw prices in the symmetric Nash equilibrium changes if the information shock Δ_ϕ hits the market. Parameter values: $\upsilon = 2.5$, $N = 5$, $\phi_{01} = 0.15$, $\phi_{02} = 0.30$ and $\Delta_\phi = 0.20$. The solid line and the short-dashed line capture the equilibrium price distribution when the ex ante share of *shoppers* is at 15% and 30%, respectively. The long-dashed line and the dot-dashed line show the corresponding density functions after the information shock of 0.2 hits the market. The information shock shifts the equilibrium price distribution towards lower prices, and the downward shift is larger in magnitude when the ex ante share of informed consumers is lower.

MPD shifts the entire distribution of prices more strongly towards lower prices if there are few *shoppers* ex ante. Therefore, the same holds true for the expected price, paid by *non-shoppers* in expectation, and the expected minimum price, paid by *shoppers* in expectation.

3 Institutional Setting

In the empirical application we study how mandatory price disclosure affects equilibrium prices in the German retail fuel market.

3.1 The German retail fuel market

Retail fuels are products with a very high degree of homogeneity within their product category. Although filling stations also sell other products, we focus our attention on the sale of fuel.

The two main fuel categories are diesel and gasoline. Consumers cannot substitute between the two in the short-term, as vehicles can only either run on one or the other type. In our analysis, we focus on gasoline with an octane rating of 95 and an ethanol share of 5 percent (also referred to as *E5*), as well as on diesel, which were correspondingly used in 56 and 29 percent of passenger vehicles with combustion engines in Germany in 2013.[11]

On the demand side, diesel and gasoline motorists differ in how much they drive. Diesel motorists tend to drive longer distances. According to the figures from *Verkehr in Zahlen 2018*, in 2013 to 2014 drivers of diesel passenger vehicles drove on average $20,500$ kilometers, whereas drivers of gasoline passenger vehicles on average drove only $11,000$ kilometers per year.

A potential explanation for why diesel motorists are more frequent drivers could be that buying a diesel vehicle is considered as a fixed cost investment to incur lower marginal costs afterwards. Diesel vehicles tend to be more expensive than gasoline vehicles, however, the per liter price for diesel fuel is consistently lower than that for gasoline. Motorists who expect to drive longer distances can therefore self-select into paying more upfront for a diesel vehicle in order to save on fuel costs later on. Diesel motorists are thus likely to have a higher incentive to search for lower fuel price and be on average more informed about prices than gasoline motorists.

One could still argue that since diesel vehicles are oftentimes used for business purpose, diesel motorists may actually be less prone to search for lower prices. However, this is not a valid concern in our case. As of January 2013, out of 12.6 million diesel passenger vehicles in circulation in Germany, 4.6 million vehicles, including those with gasoline and diesel engine, were in use for commercial purpose. This means that at least 63 percent of diesel vehicles are owned and operated by private individuals (Kraftfahrt-Bundesamt, 2013). Among the remaining 37 percent of diesel vehicles used for business purpose, some drivers receive a lump-sum or a per mile fuel allowance or are self-employed, which creates additional incentives to save on fuel costs. Thus, many diesel vehicles being used for commercial purpose does not invalidate our observation that diesel motorists are on average more price sensitive than gasoline drivers.[12]

On the supply side, the retail fuel market in Germany is vertically organized. In the

[11]This is based on 2013 statistics from *Verkehr in Zahlen 2018* and *Bundesverband der deutschen Bioethanolwirtschaft 2013*.

[12]In Section 4, we provide further descriptive evidence which suggests that diesel drivers are on average more informed about fuel price than gasoline drivers both before and after MPD.

upstream market, crude oil is refined into retail products. These are sold and distributed to the downstream market, where filling stations sell the retail products to motorists. According to the German Federal Cartel Office (2011), concentration is high in both the upstream and downstream markets. Furthermore, some firms are vertically integrated, whereas others are not.

3.2 Mandatory price disclosure

Before the introduction of MPD, consumers were much less informed about prices than firms and hence found it difficult to assess the competitiveness of a particular fuel price. In the absence of an information clearinghouse, consumers faced significant search costs. To find the prices of all potential sellers, a motorist would need to drive to all stations.[13]

A market investigation ending in 2011 led the German Federal Cartel Office (GFCO) to find that prices in regional fuel markets had been higher than under functioning competition. After the market investigation, the GFCO and the German Monopolies Commission concluded that a lack of price transparency on the consumer side caused the lack of competition and therefore called for an increase in price transparency in the downstream market. In 2012, parliament passed a law which set out the creation of the market transparency unit for petrol under the management of the GFCO and on 12 September 2013 the operation of the MTU began. The MTU is an information clearinghouse that collects prices in real-time and allows app creators to diffuse the information to users. It hence provides consumers access to live price data and increases price transparency.

3.3 Data

Our core data set contains station-level prices and retail margins for the universe of fuel stations in Germany and France for the years 2013 and 2014. We supplement this with consumer search data from a major fuel price app provider in Germany after mandatory price disclosure.

3.3.1 Prices, retail margins and fuel station characteristics

Our primary data set contains station-level prices and retail margins for *E5* gasoline and diesel on weekdays at 5 pm between 12 April 2013 and 31 August 2014 in Germany.[14] Throughout most of our analyses we use the station-level gross retail price, which includes taxes and duties, as an outcome variable. In order to estimate heterogeneities in the

[13] There were already some apps that allowed users to self-report fuel prices, which were then collected and diffused to users in a similar fashion to the price information from MPD, but the usage of these apps before MPD was considerably lower than after its introduction.

[14] We choose prices at 5 pm since this is the time around which most fuel is bought in Germany. More details on daily price cycles and purchase patterns are included in Appendix B.

treatment effect, we add station characteristics such as information on the brand, address and geographic coordinates to our data set.

To illustrate how the MTU affects fuel stations, we carry out some analyses using retail margins as an outcome variable. We compute retail margins by subtracting the share of the price of crude oil that goes into the production of diesel or gasoline from the net retail price using the daily crude oil price at the port of Rotterdam.[15] Although these retail margins still contain different cost types, such as the cost of refining or transportation costs, the main source of input cost variation, the price of crude oil, is eliminated.

A novel and unique feature of our data is that we have rich station-level price information *before* the introduction of MPD. At that time, some smartphone apps existed that allowed their users to self-report station-level fuel prices. Although the usage of these apps was only a fraction of the usage of price comparison apps after MPD and the publicity that came with it, the pre-MTU apps contain rich price information. We use price data for the pre-MPD period supplied by one of the leading apps collecting self-reported prices. This data set comprises 17 million price reports for more than 13,500 stations between 1 January and 12 September 2013. Although the MTU went into operation on 12 September 2013, we only have access to its data from the 1 October 2013 onwards. Since our self-reported pre-MPD data only goes until the 12 September 2013, the period in between is not subject of our analysis.

For most days in the pre-MPD period, we have prices for more than 80% of fuel stations.[16] In case the reporting of prices is not random, selection could harm the validity of our estimation results. The most natural selection mechanism is that fuel stations themselves report prices onto the apps when they are low to attract *shoppers*. At the same time, they could refrain from posting prices when they are high in order not to discourage consumers from driving to their fuel station and discover the price. In this case, prices in our sample before MPD should be downward-biased. However, since we find that prices decreased after the introduction of MPD, this selection mechanism would work against us, and our estimates can be seen as a lower bound.

Another concern could be that the composition of fuel stations changed in our sample before and after the introduction of MPD. Table 1 presents summary statistics of our data. As can be seen in Panel A, the composition of fuel stations does not change significantly between the pre- and post-MPD periods concerning the share of integrated stations, the share of oligopoly stations or the number of competitors in local fuel markets.

[15]For a detailed description of the calculation of prices and margins, see Appendix B.

[16]The daily number of fuel stations with price reports and the number of daily price changes are reported in Figures 11 and 12 in Appendix B. We exclude days after the MTU introduction from our analysis, where the number of price changes compared to the previous day drop by more than 40%. Since we observe the universe of price changes after the introduction of the MTU, and the average number of daily price changes is usually stable, we conclude that these days are affected by technical difficulties. In total, this affects ten days during the 15 months of data used from the MTU.

Table 1: Summary statistics

A. Station characteristics			
	D pre-MTU	D post-MTU	France
Number of Stations	13,782	14,606	9,224
Share of integrated stations	59%	57%	
Share of oligopoly stations	47%	46%	
Median # comp. (5 km catchments)	4	3	2
Share of local monopolists	15%	15%	19%
B. Prices and Margins			
	D pre-MTU at 5 p.m.	D post-MTU at 5 p.m.	France at 5 p.m.
Mean price, gasoline	1.60	1.50	1.54
Mean retail margin, gasoline	0.08	0.05	0.10
Mean daily spread, gasoline	0.09	0.07	0.14
Mean price, diesel	1.41	1.33	1.34
Mean retail margin, diesel	0.11	0.09	0.10
Mean daily spread, diesel	0.09	0.08	0.13

Notes: "D pre-MTU" and "D post-MTU" refer to fuel stations in Germany before and after the introduction of the MTU, respectively. The pre-MTU phase goes from 1 January 2013 until 12 September 2013. The post-MTU phase goes from 1 October 2013 until 31 December 2014. For France, all figures are for the full period 1 January 2013 until 31 December 2014. The average daily spread is measured as the average of the difference between the retail margin at the 95^{th} percentile and the 5^{th} on each day.

A detailed split of fuel stations by brand before and after the MPD introduction can be found in Table 4 of Appendix B.1. Overall, the composition of brands is very similar.

The largest share of the retail price for fuel in Germany consists of taxes and input costs. To analyze the share of the fuel price that can be influenced by fuel stations, we further analyze the effect on retail margins. First, we subtract taxes and levies to compute net fuel prices. Thereafter, we subtract the daily crude oil price at the port of Rotterdam to obtain retail margins.

Since January 2007, all fuel stations in France selling more than $500m^3$ of fuel per year have to report all price changes to a government agency similar to the MTU in Germany. Regular checks are carried out and fines imposed on fuel stations that do not comply with this rule. The French government makes all price information since 2007 publicly available on a government website.[17] We thus observe the universe of price changes of these fuel stations in France for our observation period. The data is regarded to be of very high quality and has previously been used by other researchers.[18]

The data set contains a list of notifications with the price, the type of fuel, the

[17] https://www.prix-carburants.gouv.fr/rubrique/opendata/, last accessed March 2021.

[18] Gautier and Saout (2015), for example, use this data to study the speed at which market prices of refined oil are transmitted to retail petrol prices.

address and geographic coordinates of the fuel stations and the opening times. In contrast to the data of the MTU in Germany, it does not contain any information on the brand of the station or any other company-related information.

To compute retail margins, we also need a measure for input prices in France. Similarly to Germany, we use daily market prices for crude oil at the port of Rotterdam as a proxy for ex-refinery prices in France.

3.3.2 Local radio reports

After the introduction of mandatory price disclosure, some local radio stations started broadcasting local fuel prices over the air. Since some of the radio stations only started broadcasting prices at a time after the introduction of MPD, we exploit these introductions to study the effect of a follow-on information shock on prices. To facilitate the data collection, we restrict this analysis to the German state of Bavaria.

There are 381 radio stations in Germany broadcasting via short-wave out of which 83 are active in Bavaria. Among these, we identified 60 radio stations that could potentially broadcast fuel prices, which we contacted. Among these stations, we identified four local radio stations that broadcasted local fuel prices (e.g., the three lowest price fuel stations in their reception area) more than once a day at some point after the introduction of MPD in 2013 and 2014 and know the exact period of time of these broadcasts. We merge this information with data on the geographic availability of radio stations which we received from *fmlist.org*.

3.3.3 Search data, Google trends, and app usage

We complement our data set with information that paints a fuller picture of who is informed about prices, salience of the information, and its usage over time.

First, we use a data set that includes search queries in 2015 from a major smartphone app displaying fuel prices to users in Germany. For each search query there is a unique searcher device ID, as well as a time stamp and the fuel type that was searched for. We can therefore analyze how the extensive and intensive margins of search differ between the fuel types.

Second, we analyze information from Google trends on keywords surrounding the MTU. This tells us when public attention for the measure is particularly high and so when salience of the price information is high.

Third, we have data on the monthly usage of three major price comparison applications in Germany starting in May 2014.

4 Descriptive Evidence

Before moving to the econometric analysis, let us present some descriptive evidence to analyze the interplay between the level of ex ante price information, the usage of the price information, and the price effect of mandatory price disclosure.

4.1 Consumer information

According to the industry description in Section 3 and the theoretical assumptions on the effect of MPD, we would expect drivers fueling their cars with diesel to be more informed before and after the introduction of MPD.

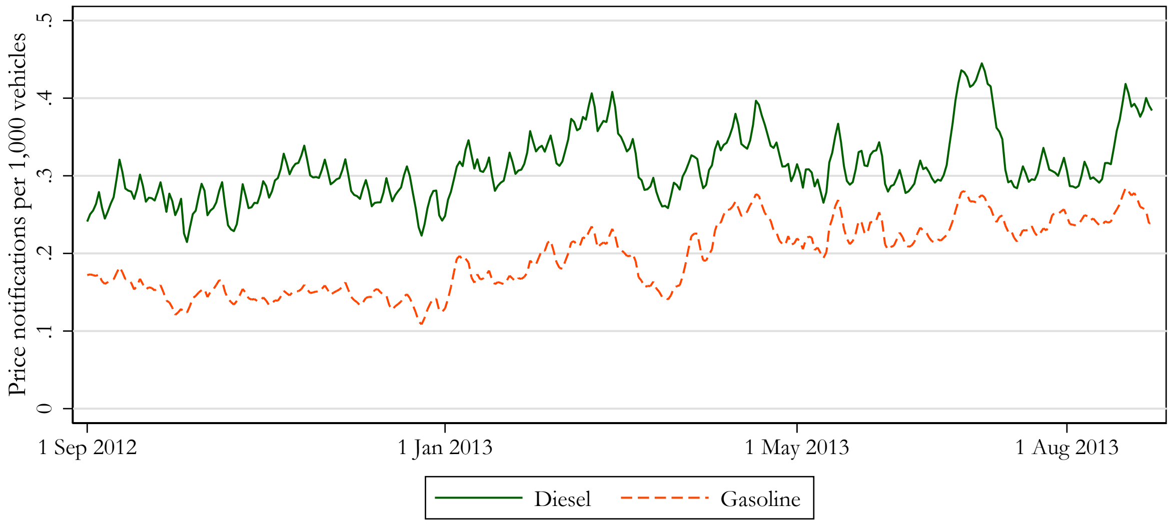
Differences in price notifications by fuel type in the period before MPD provides suggestive evidence for differences in the information levels between fuel types. Intuitively, since fuel prices for price comparison apps before MPD were self-reported by users, motorists that report more prices are also likely to use this price information more. To proxy for how informed diesel and gasoline motorists were before MPD, we adjust the daily number of diesel and gasoline price reports to the number of diesel and gasoline vehicles in circulation in Germany.[19] Figure 2 shows the daily number of price notifications per 1,000 vehicles in circulation for each day in Germany between September 2012 and August 2013. The number of diesel price notifications per diesel car in circulation is about 64 percent higher than that of gasoline notifications. This strongly suggests that before MPD, diesel motorists were on average more informed about prices than gasoline drivers.

After the introduction of MPD, self-reporting of prices became obsolete. Information on differences in app usage between users searching for prices for different fuel types can nevertheless provide evidence on relative differences in the information levels. To this end, we use data on search queries from a major fuel price app provider in Germany in 2015. Figure 3 shows the number of daily unique users searching for gasoline and diesel prices per 1,000 vehicles of the particular fuel type in circulation. The data is available for January to May 2015 and October to December 2015. The number of unique searchers (as opposed to the number of searches) captures the extensive margin of information usage and is thus similar to capturing differences in information through the share of *shoppers* in the theoretical model. Similarly to the pre-MPD pattern, the number of searchers is consistently higher for diesel than for gasoline prices.

Next, we investigate the intensive margin of price search, namely whether there are differences in the number of price searches per diesel or gasoline user. Figure 4 shows the

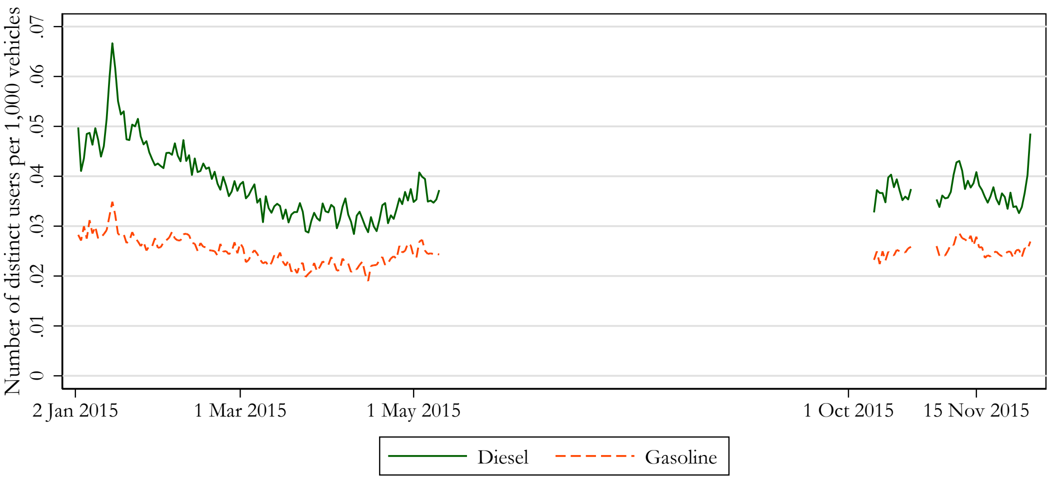
[19] From the count of price notifications, we drop all instances when *E5* gasoline, *E10* gasoline and diesel prices are reported during the same minute and for the same station, since this likely reflects self-reporting of prices by stations and not by motorists. 16 percent of all price notifications are individual reports for either gasoline or diesel price.

Figure 2: Price notification patterns, pre-MPD (Germany)



Notes: The Figure shows the daily number of self-reported price notifications by fuel type to a major German smartphone app per 1,000 diesel or gasoline vehicles in circulation. The data is available from September 2012 to August 2013. The solid line corresponds to the notification intensity for diesel. The dashed line corresponds to the notification intensity for gasoline.

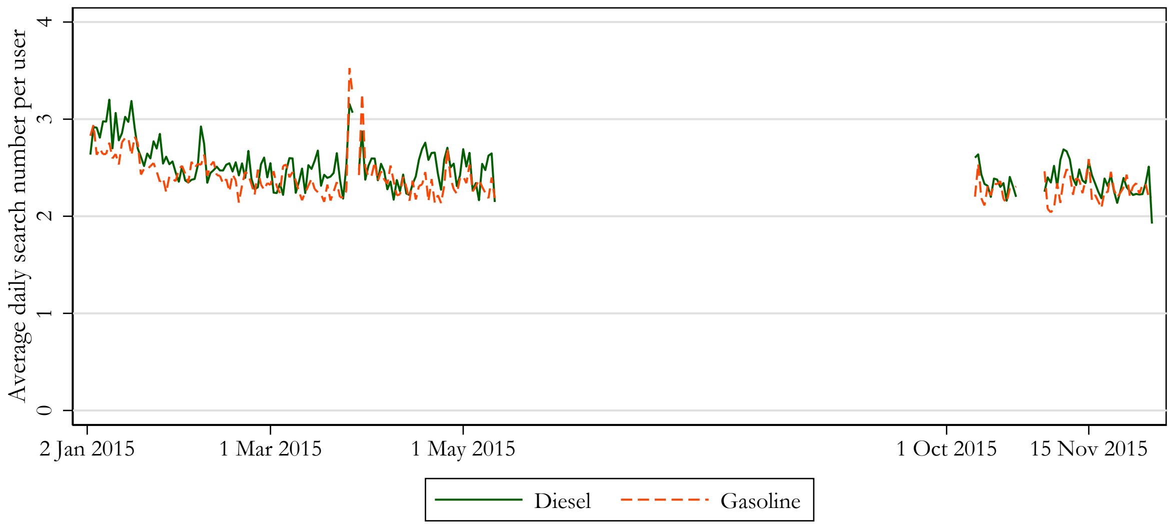
Figure 3: Unique daily price searchers by fuel type, post-MPD (Germany)



Notes: The Figure shows the daily number of distinct users who search for diesel or gasoline price in Germany in 2015, per 1,000 diesel or gasoline vehicles in circulation.

average number of daily searches per unique user for diesel and gasoline. As becomes clear from the figure, there are no systematic differences in the number of searches between fuel types.

Figure 4: Average daily search number per user by fuel type, post-MPD (Germany)



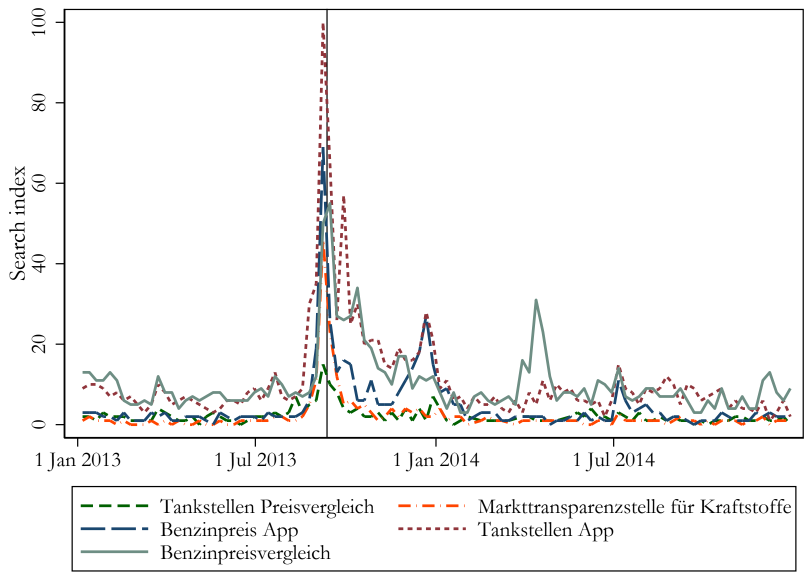
Notes: The Figure shows the daily number of price searches by fuel type at a major German smartphone app per 1,000 diesel or gasoline vehicles in circulation. The data is available for January to May and October to December 2015. The solid line corresponds to the search intensity for diesel. The dashed line corresponds to the search intensity for gasoline.

Before and after the introduction of MPD there is strong evidence suggesting that diesel drivers are systematically more informed about prices than gasoline drivers. This is driven by the extensive margin (i.e., a higher share of informed diesel drivers) as opposed to the intensive margin (i.e., informed diesel drivers knowing more than informed gasoline drivers). Thus, more diesel than gasoline drivers decide to become informed but conditional on becoming informed, the search behavior appears to be similar.

To understand the usage of the price data made available to consumers by MPD over time, we analyze two pieces of evidence. The first is shown in Figure 5, which plots the search indicator for different keywords surrounding the MTU, fuel prices and price comparison apps on Google in Germany between January 2013 and December 2014. These are indexed such that 100 corresponds to the week-keyword combination that has the most search queries. Searches for all keywords peak in mid-September, when operations of the MTU began. Whereas searches for the MTU itself declined again quickly, searches for "Tankstellen App" (fuel station app), "Benzinpreis App" (fuel price app), or "Benzinpreisvergleich" (fuel price comparison) remain high until mid-January 2014.

The second piece of evidence is included in Figure 6, which shows the evolution of monthly page impressions for three mobile price comparison applications for which

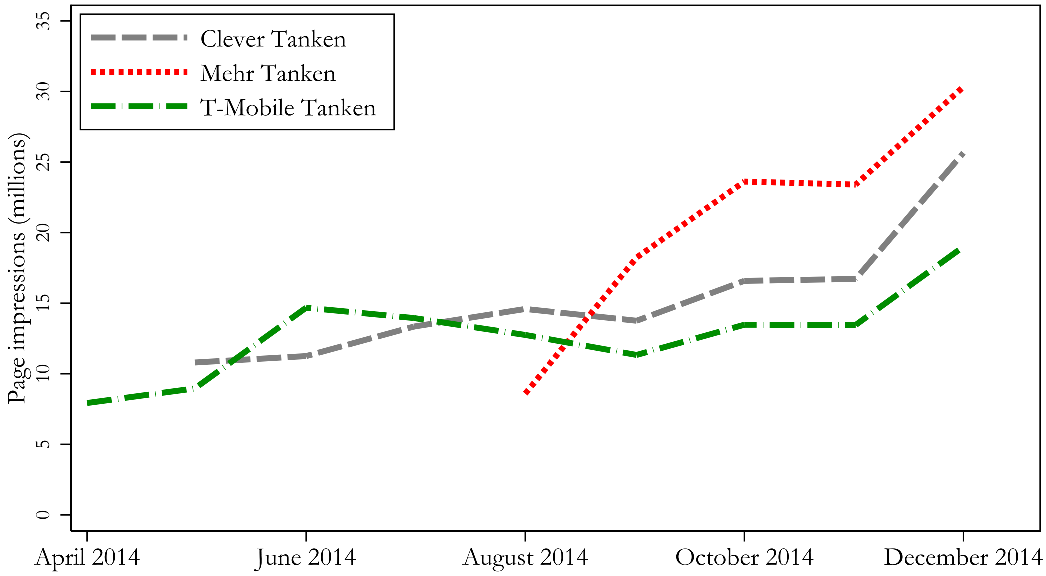
Figure 5: Evolution of Google searches for MPD-related search terms in Germany



Notes: The figure shows the evolution of Google searches in Germany between 1 January 2013 and 31 December 2014 for MPD-related keywords. Searches are indexed such that 100 corresponds to the moment in time and keyword with the highest number of searches during the observation period. The search terms are "Tankstellen Preisvergleich" (fuel station price comparison), "Marttransparenzstelle für Kraftstoff" (market transparency unit for fuel), 'Benzinpreis App" (fuel price app), 'Tankstellen App" (fuel station app), and "Benzinpreisvergleich" (fuel price comparison). The vertical solid line marks the beginning of the MTU.

data is available starting in April 2014, which is after the period of high interest based on searches between September 2013 and January 2014. Although these three mobile applications are only a fraction of the German mobile fuel price comparison market, they together have more than 70 million page impressions in December 2014. This shows that mobile price comparison applications were widely used. Usage per app also is steadily increasing between April 2014 and October 2014 for *Clever Tanken* and *T-Mobile Tanken*.

Figure 6: Monthly page impressions



Notes: The Figure shows the evolution of monthly page impressions for three popular mobile price comparison applications. Each line begins when data for the particular app becomes available and ends at the end of our sample period, in December 2014.

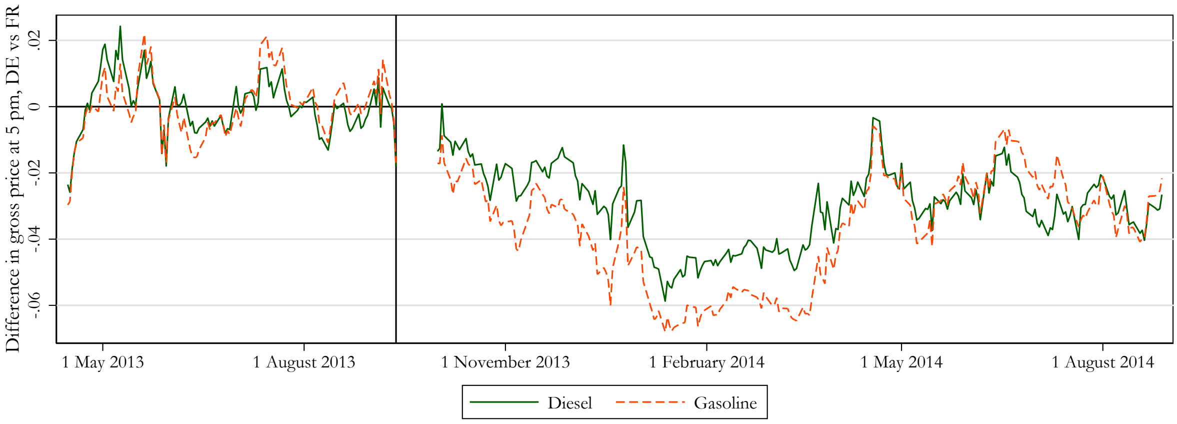
4.2 Price effect of mandatory price disclosure

To study the effect of mandatory price disclosure on diesel and gasoline prices we begin by comparing how the difference between prices in Germany and France evolve over time for diesel and gasoline, respectively. Figure 7 shows the evolution of gross prices in Germany relative to France between April 2013 and September 2014 for diesel and gasoline. The solid line plots the difference in daily diesel prices between Germany and France, demeaned by the average difference prior to MPD. The dashed line plots the same for gasoline.

Before MPD, the difference in gross prices between Germany and France oscillates around zero for both types of fuel. After MPD, it appears as though prices fall more strongly for gasoline than for diesel. The effect of MPD appears to be strongest in January 2014, stagnate thereafter and then become weaker but still existant after May 2014.

Relating this to the descriptive evidence on consumer information, it appears as though the price effect of MPD is stronger for gasoline, where we expect a lower share of ex ante informed consumers. This is in line with the theoretical prediction in Proposition 1. The strength of the treatment effect of mandatory price disclosure also appears to coincide with the public attention devoted to fuel price comparison apps shown in Figure 5. This suggests that public attention to this information and active usage are key to fully exploit the potential of MPD.

Figure 7: Evolution of the difference in gross prices between Germany and France



Notes: The solid line shows the evolution of the difference in daily diesel prices between Germany and France, demeaned by the corresponding average difference prior to MPD. The dashed line shows the evolution of the analogous difference in gasoline prices. The vertical solid line marks the beginning of the MTU.

5 Empirical Strategy

After providing descriptive evidence on the effect of MPD, we test whether the descriptive results withstand more rigorous econometric analysis. In our main specification we use station-level fuel prices in Germany and France and a synthetic difference-in-difference strategy to estimate the price effects of MPD for diesel and gasoline. We test the robustness of the results and how these relate to the theoretical model by estimating the price effect of follow-on radio reports that enhance the diffusion of price information.

5.1 The effect of mandatory price disclosure

To estimate the average effect of mandatory price disclosure on fuel prices, we use a synthetic difference-in-differences (SDID) framework in which we compare log fuel prices at stations in Germany to those in France, before and after MPD.

The synthetic difference-in-differences is a method recently proposed by Arkhangelsky et al. (2021). It combines the advantages of difference-in-differences with those of synthetic control methods. Similarly to difference-in-differences, SDID estimates the treatment effect by comparing the difference in outcomes of a treatment and a control group before and after the treatment, and relies on the parallel trends assumption. Similarly to the synthetic control method, SDID re-weighs units in the control group to make pre-trends in outcomes as similar as possible to those of the treatment group. Arkhangelsky et al. (2021) report that SDID performs weakly better than synthetic control and difference-in-differences methods.

The estimation proceeds in two steps. In the first step, we compute weights for the control units and for the pre-treatment time periods. SDID unit weights are designed to minimize the difference in pre-trends of outcomes between exposed and unexposed units prior to the treatment. SDID time weights are set to balance time periods before and after the treatment for the control units and emphasize pre-treatment time periods most predictive of the post-treatment ones. In the second step, we estimate the treatment effect with the use of the unit and time weights from the first step.[20] Standard errors are computed via the jackknife method.[21]

Specifically, we solve the following minimization problem:

$$(\hat{\beta}^{sdid}, \hat{\mu}, \hat{\alpha}, \hat{\gamma}) = \underset{\beta,\mu,\alpha,\gamma}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \gamma_t - MPD_{it}\beta\right)^2 \hat{w}_i^{sdid} \hat{\tau}_t^{sdid} \right\} \tag{1}$$

where $\hat{\beta}$ corresponds to the estimated effect of the MTU introduction, and $\hat{w}_i$ and $\hat{\tau}_t$ are SDID unit and time weights. Y_{it} is the logarithm of the fuel price at station i and week t. α_i and γ_t are fuel station and week fixed effects. The variable MPD_{it} is a dummy that equals one for treated units after the treatment. These are fuel stations in Germany after the introduction of the MTU.[22]

Estimation of the treatment effect with SDID requires a balanced panel. We compute weekly average fuel prices and restrict our sample to fuel stations in Germany and France that have no missing weekly price observations.[23] This is the case for 47% of stations in Germany and 94% of stations in France. Since we estimate the effect of MPD using this restricted sample, in Appendix C we report the results estimated using regular difference-in-differences when we use the full, unbalanced panel and daily price observations. The results hold.

To study the effect of MPD over time, we estimate the parameters of the following regression model:

$$ln(p_{it}) = \sum_{j=-5}^{11} \beta_j MPD_{it} + \alpha_i + \gamma_t + \epsilon_{it}, \tag{2}$$

where $ln(p_{it})$ is the logarithm of the weekly average fuel price at station i. β captures the effect of the mandatory price disclosure starting five months before its introduction and up to eleven months after. The regression is weighted by the SDID unit and time weights, and we control for fuel station and week fixed effects.

[20]In Appendix B, we show the geographic distribution of control stations that receive a disproportionately higher unit weight in estimation via SDID. These stations are scattered throughout France and do not appear to cluster in a particular region. Therefore potential clustering of control stations due to re-weighting by SDID does not affect our results.

[21]The jackknife method produces a conservative estimate of the variance in large panels with a high number of treated units. We use the jackknife method instead of bootstrapping as the latter is too computationally intensive in this case.

[22]We solve the minimization problem using the *synthdid* package in R developed by Arkhangelsky et al. (2021).

[23]We employ weekly average fuel prices since a high share of stations in Germany have at least one day without a reported fuel price during the time period used in the estimation of the treatment effect.

5.2 France as a control group

We identify the effect of MPD using the evolution of fuel prices at fuel stations in France as a comparison. Two assumptions need to be met to identify the effect of MPD in our framework: The first is that there cannot be any other transitory shocks affecting fuel stations in France and Germany differently before and after the introduction of MPD other than MPD itself. The second is that there are no spillovers from the treatment onto the control group. Subsequently, we provide evidence that suggests that both assumptions hold.

The station fixed effects capture time-invariant differences between fuel stations in France and Germany. The week fixed effects capture transitory shocks that affect French and German fuel stations equally. Due to its similarities in size, wealth and geographic location, as well as our narrow observation period, there should not be any additional transitory demand and supply shocks that affect France and Germany differently. We nevertheless discuss the most obvious candidates.

Important transitory demand shocks in the retail fuel market are school and public holidays, as well as local economic shocks. School and public holidays in France and Germany are highly correlated. In addition, since holidaymakers in Europe often cross several countries on the way to their holiday destination and France and Germany are popular holiday destinations and important transit countries, they are usually hit similarly and at the same time by these demand shocks.

Transitory supply shocks affect fuel stations much in the same way. Due to their geographic proximity, fuel stations in France and Germany procure most of their fuel from similar sources. Furthermore, the European Single Market and the Schengen Agreement mean customs, border controls or other regulatory hurdles do not restrict arbitrage possibilities between the two countries. To nevertheless ensure the elimination of any transitory shocks to input prices and to restrict our analysis to the share of the fuel price that can be affected by fuel stations, we additionally use retail margins as outcome variables. These retail margins are net of taxes, levies and the wholesale price of Brent oil in Rotterdam on a given day.

Also, fuel stations in France constitute a good control group because there were no important regulatory changes in the French fuel market over our observation period. The impact of the introduction of mandatory price disclosure in 2007 should have stabilized by 2013 and thus not affect different French fuel stations differently over our observation period. In contrast to other countries, France, like Germany, did not restrict its fuel stations in their price-setting behavior other than by imposing mandatory price disclosure.[24]

One might be worried that there may still be idiosyncratic developments, which add random noise to the data and thus lead to an underestimation of the absolute value of the

[24]In 2011, Austria, for example, introduced a rule banning fuel stations from raising prices more than once a day.

effects. We therefore, re-run our analysis for a sub-sample of the data around the Franco-German border, for which the economic conditions should be similar due to geographic proximity. First, we restrict our analysis to fuel stations that are 100 kilometers left and right to the border. Fuel stations in the treatment and control groups are thus in the same economic area and only exposed to common transitory shocks. Second, to eliminate any potential spillover effects, we drop all fuel stations that are less than 20 kilometers left and right of the border. We are left with a Donut-SDID, where stations on both sides of the border are geographically close, but stations that are potentially subject to spillover effects are dropped.

Finally, a potential concern could be that the drop in the price of crude oil in the second half of 2014 could bias our results. For the analysis of fuel prices and retail margins where we control for station and week fixed effects, this would require the pass-through of input prices to change differently for the treatment and the control group over time. This is unlikely to be a concern because most of our analysis only uses data until 31 August 2014, whereas the largest share of the decrease in the price of crude oil occurred between October and December 2014. We also directly account for potentially differential pass-through of oil cost shocks by including an interaction of the country indicator with the crude oil price in our estimation.

Furthermore, our data set allows us to robustly estimate the treatment effect using different treatment groups and different identification strategies. Two analyses are of particular interest, as the approaches are very different to the strategies used to obtain the main results: In the first, we treat local monopolists in Germany as the control group and all other German stations as the treatment group.[25] In the second, we use country-level weekly fuel prices for all countries in the European Union and treat Germany as the treatment group and all other countries as the control. The results are reported in Appendix C and are in line with our main findings.

5.3 Radio reports

As discussed in Section 3, some local radio stations started broadcasting local fuel prices over the air after the introduction of MPD. This allows us to test the robustness of our main result. If MPD increases the share of fully informed *shoppers*, thereby decreasing prices, then local radio reports should further increase the share of *shoppers*, thereby leading to a further local decrease in prices.

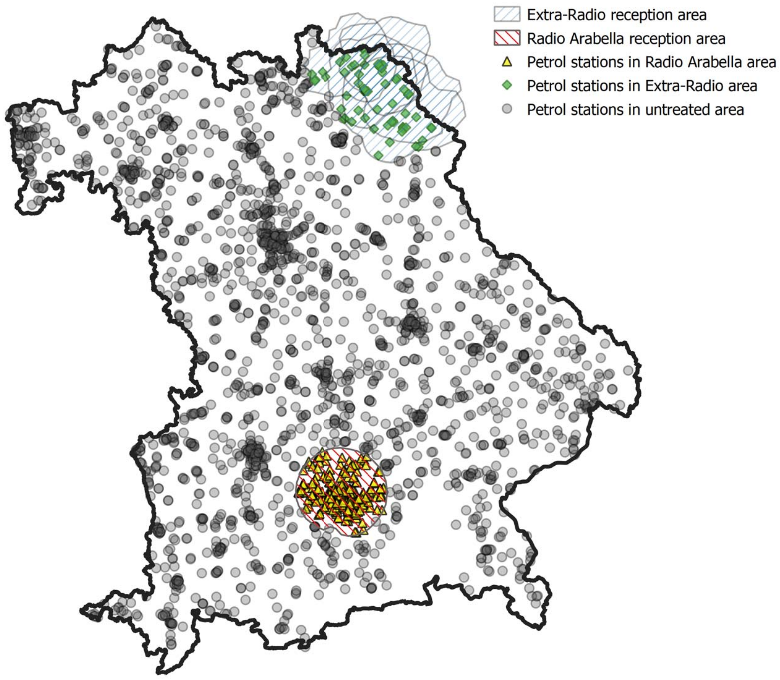
To limit the burden on data collection, we restrict the analysis of radio reports to the

[25] The empirical literature analysing price dispersion in retail fuel markets considers different geographic market definitions. For example, Chandra and Tappata (2011) consider a 1 mile as well as a 2 miles radius, while Barron, B. A. Taylor, and Umbeck (2004), Hosken, McMillan, and C. T. Taylor (2008) and Lewis (2008) consider a radius of 1.5 miles. We use different catchment sizes in further results in Appendix C.5.

German state of Bavaria.[26] As described in Section 3, we identify four stations that have segments that recur at least daily and in which they broadcast the prices at the cheapest fuel stations in the reception area. We discard two of the radio stations because they already broadcasted the lowest fuel prices amongst those called in by their listeners before MPD started. We exclude all fuel stations in their reception areas from the analysis, as they are treated throughout the observation period. The two remaining radio stations are *Radio Arabella*, which started its broadcast on 25 April 2014 and *Extra-Radio*, which started its broadcasts on 2 February 2014.

Figure 8 shows the reception areas of *Radio Arabella* and *Extra-Radio*. For each fuel station we know whether, on a particular day, it is within the reception area of a radio station broadcasting prices or not.

Figure 8: Radio reception areas and fuel stations in Bavaria



Using a difference-in-differences design, we estimate the following fixed effects regression model:

$$ln(p_{it}) = \beta_0 + \beta_1 Radio_{it} + \alpha_i + \gamma_t + \epsilon_{it} \tag{3}$$

where $ln(p_{it})$ corresponds to the logarithm of the gross price for diesel or gasoline at station i at time t and $Radio_{it}$ is a dummy equal to one if fuel station i lies in the reception area of a radio station broadcasting local fuel prices at date t. α_i are fuel station fixed effects, and γ_t are date fixed effects.

[26]Fuel stations in the treatment and control groups are therefore also all in Bavaria.

We can thus exclude that fuel stations in the control group are affected by reports of radio stations we have not surveyed. We restrict our analysis to the period October 2013 until September 2014, which is the twelve months after the beginning of the MTU.

To estimate the effect of radio reports on fuel prices we need to ensure that there are no spillovers of radio reports onto fuel stations in the control group and that the decision of radio stations to report was not because they anticipated evolutions in their local market that would also affect fuel prices.

There are two possibilities which could lead to spillover effects between the treatment and control groups: First, motorists outside of the reception area of the radio station could listen to the radio station via the internet. Second, commuters driving through the reception area of the radio station could update their information set by listening to the broadcasts and change their behavior accordingly after leaving the reception area. Both of these threats to identification are unlikely to be strong. Radio stations were still predominantly listened to via short-wave in 2013 and 2014. In particular, in more rural areas, mobile internet reception was still weak, making it difficult to listen to radio via the internet when on the road. Furthermore, although commuters learn something about the distribution of prices by listening to the radio, which may still be valuable outside the reception area, the value of this information is likely decreasing with distance to the reception area. In any event, both concerns lead to the control group being partially treated and would thus lead us to underestimate the treatment effect.

Another potential threat to identification could be that radio stations anticipated a trend that would create local demand for reports about fuel prices and that also affected fuel prices. This seems unlikely. After multiple interviews with program directors we learned that the decision of broadcasting fuel prices is not based on a market analysis but rather based on the fit of such a segment to the existing program.

We now turn to the radio stations that define our treatment group. We consider radio reports about fuel prices by *Extra-Radio*, which broadcasts in and around Hof, a city in North-Eastern Bavaria, close to the Czech border, and *Radio Arabella*, which is a radio station broadcasting in and around Munich. Whereas *Extra-Radio* broadcasted the lowest fuel prices in its reception area daily between 2 February 2014 and 5 March 2017, *Radio Arabella* started reporting the lowest prices several times a day on 25 April 2014 and reports are still ongoing at the time of writing.

The presence of a country border is important. In particular, the reception area of *Extra-Radio* is very close to the border with the Czech Republic, the focal city Hof being less than 10 kilometers away from the border. Since Germany and the Czech Republic are both members of the Schengen Area, there are no border controls and shopping in the neighboring country is frequent. Due to lower taxes and levies, fuel prices are consistently 20 Eurocent lower in the Czech Republic. It therefore seems plausible that independent of price reports by radio stations or smartphone apps, price-sensitive consumers always buy fuel in the Czech Republic, whereas only inelastic consumers buy from fuel stations treated by *Extra-Radio*. We would therefore expect that reports by *Extra-Radio* have little to no effect on fuel prices. To test this hypothesis, we estimate the regression model for both radio stations separately. In each of these regressions we exclude fuel stations within the reception area of the other radio station from the control group.

6 Results

6.1 Effect of mandatory price disclosure by fuel type

Table 2 includes the main estimation results. Columns (1) and (2) include the effect of MPD on the logarithm of fuel prices for gasoline and diesel, respectively, using the full sample of French and German fuel stations. Columns (3) and (4) include results where the sample is restricted to fuel stations 20 to 100 kilometers away from the Franco-German border.[27]

The main takeaway from these results is that MPD is successful at decreasing prices and that its effectiveness is higher for gasoline than for diesel. In line with the theoretical predictions and the descriptive evidence the effect of MPD is larger when the share of ex ante informed consumers is lower. Since the same fuel stations offer diesel and gasoline, supply side characteristics cannot explain these differences in the effect of the MTU across the two fuel types.

Figure 9 shows the time-varying effects of mandatory price disclosure on the logarithm of weekly average gross prices for gasoline and diesel. After the start of MPD prices decline for both fuel types, however more strongly for gasoline than for diesel. The largest effect of MPD is in January 2014. This also coincides with the end of widespread public attention for the MTU and price comparison apps, as seen in Figure 5. Following this period of high attention, the effect of MPD becomes smaller in magnitude again but remains stable. This is in line with evidence that there is a stable and continuous use of price comparison apps after April 2014. The MPD induced price effect stabilizes at approximately the same percentage point for diesel and gasoline. As the price level of gasoline is higher than for diesel, the long-term price effect in Eurocents is stronger for gasoline than for diesel.

We report the effect of MPD on retail margins in Eurocents in Table 8 of Appendix 8. We find that MPD decreases gasoline margins at 5 pm by around 3 Eurocent and diesel margins by around 2 Eurocent. For reference, according to the industry data provider *Energie Informationsdienst (EID)*, gross margins were on average 10.7 Eurocent for gasoline and 11.0 Eurocent for diesel in the twelve month period ending in August

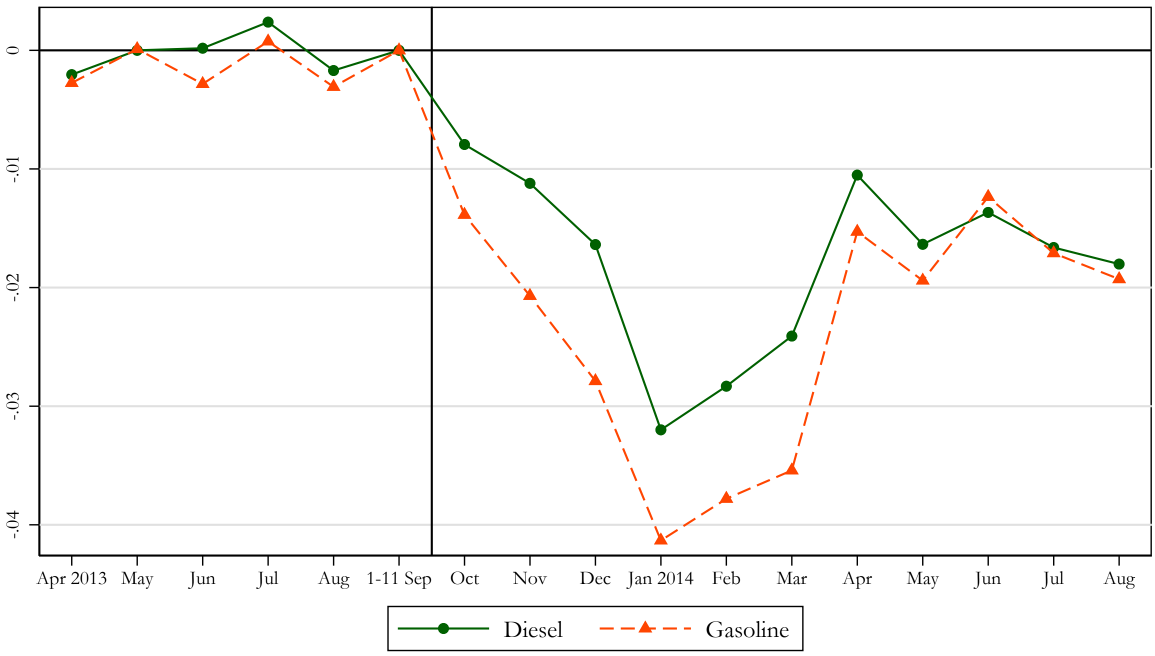
[27]The results are robust to changes to the distance thresholds. We provide estimates for alternative thresholds in Appendix C.2.

Table 2: Effect of MPD on the logarithm of gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.027***	-0.018***	-0.029***	-0.021***
	(0.0005)	(0.0004)	(0.001)	(0.001)
95% Confidence interval	[-0.028, -0.026]	[-0.019, -0.018]	[-0.032, -0.027]	[-0.023, -0.019]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	632,884	751,219	49,539	55,517

Notes: Columns (1) and (2) include estimates of the effect of MPD on log weekly prices for gasoline and diesel, respectively, using all fuel stations in Germany and France. Columns (3) to (4) include the same estimates for a restricted sample of fuel stations 20 to 100 kilometers away from the Franco-German border. The observation periods goes from 15 April 2013 to 31 March 2014. Standard errors are computed using the jackknife method and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 9: Time-varying effect of MPD on the logarithm of gross prices



Notes: The Figure shows time-varying monthly treatment effects of MPD on log weekly prices for gasoline and diesel between April 2013 and August 2014. The vertical solid line marks the beginning of the MTU.

2013. As we do not observe quantities and use prices at 5 pm, where most motorists fuel their car according to survey evidence shown in Figure 14, the volume-weighted price effect of MPD is likely to be lower than this. A simple comparison of gross margins for Germany from the *EID* and using the same time period as in our main estimation (but without France as a control) leads us to find price effects of 1 to 2 Eurocents from MPD. Intertemporal price differentiation could thus be becoming more important over time, where prices at cheap times of day, where well-informed shoppers buy fuel, become even cheaper and prices at more expensive times of the day, where only uninformed consumers purchase fuel or those that absolutely need to fill up their tank, become more expensive. Montag, Sagimuldina, and Schnitzer (2021) document an increase in intra-day price cycles in Germany between 2014 and 2019, as well as an increase in the price difference between the least and most expensive times of the day.

In Appendix C, we demonstrate the robustness of our results. First, we use the full, unbalanced sample of gasoline stations and a regular difference-in-differences estimator. Second, we estimate the Donut-SDID using alternative distance thresholds. Third, we control for an interaction of the crude oil price and a country dummy, to allow for differential pass-through of crude oil shocks in each country. Fourth, we estimate the effect of MPD on retail margins. Fifth, we focus only on stations in Germany and use local monopolists, whose competitive environment did not change as a result of MPD, as a control group. Sixth, we use country-level weekly average prices for all 27 countries in the European Union from the Weekly Oil Bulletin, using Germany as the treatment group and all other countries as a control group to estimate the effect of MPD for diesel and gasoline. Our results hold in all of these alternative specifications.

6.2 Radio reports

In Table 3 we report the results from regressing the logarithm of prices on the existence of local radio reports about fuel prices. Columns (1) and (2) include the results of the effect of reports by *Extra-Radio* and *Radio Arabella* on gasoline prices. Columns (3) and (4) include the results for diesel.

We find that whereas reports by *Radio Arabella* lead to lower fuel prices, this is not the case for reports by *Extra-Radio*. This is consistent with our expectation, since the reception area of *Extra-Radio* lies on the border to the Czech Republic, where fuel is significantly cheaper, and so radio reports do not add any relevant information for price sensitive consumers. Overall, we find that where follow-on radio reports add further information for consumers, they lead to a further decrease in prices.

Table 3: Effect of radio reports on the logarithm of gross prices

	Gasoline		Diesel	
	(1)	(2)	(3)	(4)
Treatment group:	Extra-Radio	Arabella	Extra-Radio	Arabella
Radio reports	0.003	-0.002***	0.002	-0.005***
	(0.003)	(0.0004)	(0.002)	(0.0004)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	350,655	452,481	355,928	457,559
Adjusted R^2	0.694	0.705	0.625	0.643

Notes: There are 70 fuel stations in the reception area of *Extra-Radio* and 585 fuel stations in the reception area of *Radio Arabella*. Columns (1) and (3) compare log prices for gasoline and diesel, respectively, at fuel stations in the reception areas of *Extra-Radio* to other fuel stations in Bavaria before and after the beginning of radio reports. Columns (2) and (4) do the same for radio reports by *Radio Arabella*. Standard errors, clustered at the fuel station level, are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7 Conclusion

In this paper, we study the determinants of the price effect of mandatory price disclosure. Theoretically, we derive novel predictions about how MPD affects prices in the context of the Varian (1980) model. We show that the magnitude of the price effect of MPD monotonically decreases in the share of consumers that are well informed about prices ex ante.

Empirically, we study the price effect of mandatory price disclosure in the German retail fuel market. Overall, we find that MPD led to lower prices. There are two important mechanisms that we uncover in our empirical analysis: First, we confirm the theoretical prediction that the effect of MPD is stronger for markets where there are fewer ex ante well informed consumers (i.e., gasoline). Second, we find that the magnitude of the price effect of MPD declines over time, before staying constant at between 1 and 2 percent for diesel and gasoline. Since the gasoline price level is higher than of diesel, this means that there is a higher long-run effect of MPD on gasoline prices in terms of Eurocents. At the same time, follow-on information campaigns, such as local radio reports about fuel prices, appear to be able to strengthen the effect of MPD.

There are two implications for policy that we draw from this analysis: First, assessing the level of consumer information prior to mandatory price disclosure is essential. If few consumers are well informed, mandatory price disclosure can lead to important price reductions. Should most consumers already be well informed, the pro-competitive potential of MPD is limited. Second, making price information available may not be sufficient to reap the pro-competitive benefits. We find that when public attention to the policy declines, so do the price effects of MPD. However since local radio reports are able to deliver a pro-competitive follow-on information shock, policymakers could achieve the same by regularly pushing for large-scale information adoption through public information campaigns.

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Appendix

A Appendix to Section 2: Theoretical Model

A.1 Equilibrium price distribution

Lemma 2. *Given some exogenous number of entrants N, there is no pure strategy Nash equilibrium.*

Proof. Suppose all sellers set some price p above marginal cost which is normalized to zero. Then each firm sells to its share of *non-shoppers* and *shoppers*. This cannot be an equilibrium since a seller could profitably deviate by marginally decreasing the price to $p - \epsilon$ and capture all the *shoppers*.

Suppose now that in equilibrium all sellers set a price at the marginal cost normalized to zero, i.e. $p_i = 0$ for any $i \in \{1, ..., N\}$. This cannot be an equilibrium since a seller could profitably deviate by increasing its price above the marginal cost, which will still allow to sell to its share of *non-shoppers* and make a positive profit.

Suppose that one seller sets a lower price with all other sellers choosing the same higher price. This cannot be an equilibrium since the lowest price seller could profitably deviate by marginally increasing its price and still capture all the *shoppers*.

More generally, there cannot be an equilibrium where firms play different pure strategies.

□

Lemma 3. *There are no mass points in the equilibrium pricing strategies.*

Proof. Suppose that in equilibrium some price p is charged with positive probability by the sellers. This means that there is a positive probability of a tie at this price. In this case, a seller has an incentive to deviate from p to $p - \epsilon$, which is set with the same probability, since undercutting other sellers allows the deviating seller to capture all *shoppers* and increase its profits. Thus, charging any price with positive probability cannot be an equilibrium.[28]

□

Lemma 4. *There is a symmetric mixed strategy Nash equilibrium, in which firms draw prices from $[\underline{p}, p_r]$ according to the density function $F(p_i)$, where the reservation price p_r is*

$$p_r = \upsilon \, .$$

[28]See Varian (1980) for a detailed proof.

The minimum price which firms may set in equilibrium is

$$\underline{p} = \frac{\upsilon}{\frac{\phi N}{1-\phi} + 1} \,.$$

The cumulative density function from which firms draw prices in equilibrium is

$$F(p_i) = 1 - (\frac{\upsilon - p_i}{p_i} \frac{1-\phi}{N\phi})^{\frac{1}{N-1}} \,.$$

The expected profit of a firm i in equilibrium is

$$E[\pi_i] = \upsilon \frac{1-\phi}{N} \,.$$

The expected price is

$$E[p] = \underline{p} + (\frac{1-\phi}{N\phi})^{\frac{1}{N-1}} \int_{\underline{p}}^{\upsilon} (\frac{\upsilon - p}{p})^{\frac{1}{N-1}} dp \,.$$

The expected minimum price is

$$E[p_{min}] = \frac{1-\phi}{\phi}[p_r - E[p]] \,.$$

Proof. We begin with the reservation price. Since *non-shoppers* visit a seller at random and purchase a unit of the good if its price is below their reservation price, the reservation price corresponds to the valuation of the good υ by *non-shoppers*. No firm sets a price above the reservation price of *non-shoppers*.

Next, we derive the minimum price which firms may set in equilibrium, $\underline{p}$. For that, we utilize the equiprofit condition in the mixed strategy Nash equilibrium. The expected profit that a firm receives from setting the minimum price $\underline{p}$ should be the same as the expected profit from setting the reservation price p_r:

$$E[\pi(\underline{p})] = E[\pi(p_r)] \,. \tag{4}$$

Since there are no mass points in equilibrium pricing strategies, a firm that sets the minimum price $\underline{p}$ sells to all *shoppers* and its share of *non-shoppers*. A firm that sets the reservation price p_r only sells to its share of *non-shoppers*. The equiprofit condition can then be rewritten as

$$\underline{p}(\phi + \frac{1-\phi}{N}) = p_r \frac{1-\phi}{N} \,. \tag{5}$$

Simplifying this expression and replacing the reservation price with υ, we can solve for the minimum element of the support of prices $\underline{p}$:

$$\underline{p} = \frac{\upsilon}{\frac{\phi N}{1-\phi} + 1} \,. \tag{6}$$

To derive the equilibrium density function, we again use the equiprofit condition, namely that in the symmetric mixed strategy Nash equilibrium any price that a seller sets with positive probability should yield the same expected profit, i.e.

$$E[\pi(p_i)] = E[\pi(p_r)] \qquad \forall \quad p_i \in [\underline{p}, p_r] \,. \tag{7}$$

A firm that sets the price p_i has the lowest price among all sellers with the probability $(1 - F(p_i))^{n-1}$. In this case, a firm i sells to all *shoppers* and to its share of *non-shoppers*. With the probability $1-(1-F(p_i))^{n-1}$, a firm that sets the price p_i is not the lowest price seller in the market. In this case, it sells the product only to its share of *non-shoppers*. Finally, if a firm i chooses the reservation price $p_r = \upsilon$, it sells the product to its share of *non-shoppers*.

We can now rewrite the equiprofit condition as

$$\begin{aligned} p_i(\phi + \frac{1-\phi}{N})(1-F(p_i))^{N-1} + p_i(\frac{1-\phi}{N})(1-(1-F(p_i))^{N-1}) = \\ p_r\frac{1-\phi}{N} \,. \end{aligned} \tag{8}$$

Simplifying this expression and solving for $F(p_i)$, we derive that the equilibrium density function from which sellers draw prices from the interval $[\underline{p}, p_r]$ is

$$F(p_i) = 1 - (\frac{\upsilon - p_i}{p_i}\frac{1-\phi}{N\phi})^{\frac{1}{N-1}} \,. \tag{9}$$

The reservation price p_r, the minimum price $\underline{p}$ and the equilibrium density function $F(p_i)$ uniquely define the symmetric mixed strategy Nash equilibrium of the game, assuming that there is a fixed and exogenous number of firms N in the market.

We can now compute the expected profit that each seller obtains in equilibrium, which by the equiprofit condition is identical to the expected profit from setting the reservation price $p_r = \upsilon$:

$$E[\pi_i] = E[\pi(p_r)] = \upsilon\frac{1-\phi}{N} \,. \tag{10}$$

Finally, we can derive the expected price, which is the average price paid by *non-shoppers*, and the expected minimum price, which is the average price paid by *shoppers*.

The expected price is

$$E[p] = \int_{\underline{p}}^{p_r} pf(p)dp = p_r - \int_{\underline{p}}^{p_r} F(p)dp \,. \tag{11}$$

Inserting the equilibrium density function $F(p)$ and the reservation price $p_r = \upsilon$, and simplifying yields

$$E[p] = \underline{p} + (\frac{1-\phi}{N\phi})^{\frac{1}{N-1}} \int_{\underline{p}}^{\upsilon} (\frac{\upsilon - p}{p})^{\frac{1}{N-1}} dp \,.$$

The expected minimum price is

$$E[p_{min}] = \int_{\underline{p}}^{p_r} p f_{min}(p) dp \,,$$

where the probability density function of the minimum price is

$$f_{min}(p) = N(1 - F(p))^{N-1} f(p) \,. \tag{12}$$

After inserting the equilibrium density function $F(p)$ into the above expression, we can simplify the probability density function of the minimum price to

$$f_{min}(p) = \frac{p_r - p}{p} \frac{1-\phi}{\phi} f(p) \,. \tag{13}$$

We can now substitute $f_{min}(p)$ into the expression for the expected minimum price:

$$E[p_{min}] = \int_{\underline{p}}^{p_r} p f_{min}(p) dp = \int_{\underline{p}}^{p_r} p \frac{p_r - p}{p} \frac{1-\phi}{\phi} f(p) dp \,,$$

which after simplification is equivalent to

$$E[p_{min}] = \frac{1-\phi}{\phi} \left[\int_{\underline{p}}^{p_r} p_r f(p) dp - E[p] \right] \,.$$

Finally, after further simplification, the expected minimum price becomes

$$E[p_{min}] = \frac{1-\phi}{\phi} \left[\upsilon - E[p] \right] \,.$$

□

A.2 Proofs for Section 2

Proof of Lemma 1. Let us begin by analyzing how a change in the share of *shoppers* affects the minimum price which firms may set in equilibrium. Recall that in equilibrium

$$\underline{p} = \frac{\upsilon}{\frac{\phi N}{1-\phi} + 1} \,.$$

Then, for $0 < \phi < 1$, the derivative of the minimum price with respect to the share of *shoppers* ϕ is strictly negative:

$$\frac{\partial \underline{p}}{\partial \phi} = -\frac{\upsilon N}{(\phi N + 1 - \phi)^2} < 0\,.$$

Next, we study how the share of *shoppers* affects the equilibrium price distribution. We therefore derive the derivative of the cumulative density function with respect to ϕ:

$$\frac{\partial F(p)}{\partial \phi} = \frac{1}{N(N-1)\phi^2}\frac{\upsilon - p}{p}\left[\frac{\upsilon - p}{p}\frac{1-\phi}{N\phi}\right]^{\frac{1}{N-1}-1} \geq 0\,.$$

Thus, with $0 < \phi < 1$, for any $\hat{\phi} > \phi$, $\hat{F}(p) \geq F(p) \quad \forall p \in [\underline{p}, p_r]$.

□

Proof of Proposition 1. We first study how an information shock affects the minimum price that sellers may set in equilibrium. We assume that after the information shock, the share of fully informed consumers is $\phi = \phi_0 + \Delta_\phi(1-\phi_0)$, where ϕ_0 is the ex ante share of fully informed shoppers and $\Delta_\phi(1-\phi_0)$ captures an increase in the share of informed consumers due to the shock Δ_ϕ.

Then, taking the first order derivative of the minimum element of the support of the equilibrium pricing strategy with respect to the information shock Δ_ϕ, we obtain

$$\frac{\partial \underline{p}}{\partial \Delta_\phi} = -\frac{\upsilon N}{(\frac{\phi N}{1-\phi}+1)^2}\frac{(1-\phi_0)(1-\phi)+\phi(1-\phi_0)}{(1-\phi)^2} < 0\,.$$

We can simplify this to obtain

$$\frac{\partial \underline{p}}{\partial \Delta_\phi} = -\frac{\upsilon N(1-\phi_0)}{(\phi(N-1)+1)^2} < 0\,.$$

The minimum price that sellers may set in equilibrium strictly declines in the information shock Δ_ϕ.

We now take the first order derivative of the above expression with respect to the ex ante share of fully informed consumers in the market ϕ_0:

$$\frac{\partial^2 \underline{p}}{\partial \Delta_\phi \partial \phi_0} = \upsilon N \frac{(\phi(N-1)+1)^2 + 2(1-\phi_0)(1-\Delta_\phi)(N-1)(\phi(N-1)+1)}{(\phi(N-1)+1)^4} > 0\,.$$

We can simplify this to obtain

$$\frac{\partial^2 \underline{p}}{\partial \Delta_\phi \partial \phi_0} = \upsilon N \frac{1+(2-\phi)(N-1)}{(\phi(N-1)+1)^3} > 0\,.$$

This means that the information shock Δ_ϕ leads to a stronger downward shift in the minimum price that sellers choose in equilibrium when ex ante consumers are on average less informed.

Next, we study how the magnitude of the effect of the information shock varies with the ex ante share of fully informed consumers for the equilibrium density function. We start by taking the first order derivative of the equilibrium density function with respect to Δ_ϕ:

$$\frac{\partial F(p)}{\partial \Delta_\phi} = \frac{\upsilon - p}{pN(N-1)} \left(\frac{\upsilon - p}{p} \frac{1-\phi}{N\phi} \right)^{\frac{1}{N-1}-1} \frac{1-\phi_0}{\phi^2} \geq 0\,.$$

This means that an information shock that increases the share of informed consumers in the market shifts the equilibrium density function from which firms draw prices towards lower prices.

To analyze how ex ante share of shoppers affects the magnitude of this downward shift in prices, we take the first order derivative of the above expression with respect to the initial level of the share of shoppers ϕ_0 and simplify to obtain

$$\frac{\partial^2 F(p)}{\partial \Delta_\phi \partial \phi_0} = -\frac{1}{N-1} \left(\frac{\upsilon - p}{pN} \right)^{\frac{1}{N-1}} \left(\frac{1-\phi}{\phi} \right)^{\frac{1}{N-1}-1} \left(\frac{1}{N-1} + (1+\phi_0)\,(1-\Delta_\phi) \right) \leq 0\,. \tag{14}$$

Thus for any $\hat{\phi}_0 > \phi_0$, $\Delta\underline{\hat{p}} > \Delta\underline{p}$ and $\frac{\partial F(p)}{\partial^2 \Delta_\phi \partial \phi_0} < 0 \quad \forall p.$

□

B Appendix to Section 3: Institutional Setting

B.1 Retail margins and fuel station characteristics in Germany

Figure 10 shows the distribution of fuel stations in Germany over our sample period. Fuel stations are spread across the country and clustered around urban areas.

Table 4 shows the share of the vertically integrated firms, as well as the share of non-integrated firms before and after the MTU introduction. Overall, the brand composition is very similar before and after the introduction of the MTU.

Although there are no restrictions on the number of times fuel stations can change prices in France or Germany, there are strong differences in the number of times they do. Whereas fuel stations in Germany change their prices on average four times a day over our observation period, French fuel stations change prices less than once a day.[29] Since we do not observe volume data, we cannot compute volume-weighted average fuel prices or retail margins over the day. We could thus either pick a particular time of day at which to measure prices and margins or calculate a simple average of prices and margins at different times of the day. Since fuel prices in France stay fairly constant during the day,

[29]This is consistent with findings by Haucap et al. (2017) for Germany and Gautier and Saout (2015) for France.

Figure 10: Distribution of fuel stations across Germany

Note: The Figure shows the geographic distribution of fuel stations in Germany.

Table 4: Share of stations in percent by brand

	Pre-MTU	Post-MTU
Aral	21.1	18
Shell	13.9	14.2
Esso	5.1	5.3
Total	7.3	4.6
Jet	5.2	4.6
Orlen	4.9	4.2
Agip	1.8	3.1
Hem	3.2	2.8
OMV	2.7	2.2
Non-integrated	34.9	41

Notes: The "Pre-MTU" column shows the share of fuel stations by brand in the sample for Germany before the introduction of the MTU. The "Post-MTU" column shows the share of fuel stations by brand in the sample for Germany after the introduction of the MTU. We consider all fuel stations that have at least one price entry in the sample before or after the MTU introduction, respectively.

either approach should lead to a similar result for France. The frequent price changes in Germany however, make it important to select the right time for which to calculate fuel prices and retail margins.

We choose to use prices at 5 pm in our analysis, and we construct retail margins based on these prices. A representative survey among motorists commissioned by the German Ministry for Economic Affairs and Energy (2018) in 2016 found that around 60 percent of respondents buy fuel between 4 pm and 7 pm, of which two-thirds buy fuel between 5 pm and 6 pm. At the same time, less than 5 percent of respondents buy fuel before 10 am.[30] The German Ministry for Economic Affairs and Energy (2018) furthermore documents daily price cycles with high prices in the morning, which fall over the day and rise again in the evening at around 8 pm.[31] This suggests that consumers are aware of these price cycles and fuel during the low price period in the late afternoon.[32] To gauge the effect of introducing mandatory price disclosure on consumers, it is therefore sensible to focus on fuel prices and retail margins at times where consumers buy fuel in large volumes.

In the estimation with SDID, we use weekly fuel prices. We compute the weekly fuel prices by averaging Monday to Friday prices at 5 pm. We exclude weekend prices from the analysis.

Figure 11 shows the daily number of fuel stations for which the price panel contains a price entry at 5 pm. There is no structural break in the daily number of fuel stations for which there is an entry in the price panel before and after the MTU introduction. For most days in the pre-MTU period, we have prices for approximately $12,000$ fuel stations in our panel. This number stays approximately the same after the introduction of the MTU and only increases to around $13,500$ at the end of February 2014, when reporting issues of Total and Esso stop.[33] At any point in time over the observation period, our panel therefore includes prices for most of the approximately $14,700$ fuel stations in Germany.

Figure 12 shows that there are fewer price changes per day in our data prior to the MTU introduction than after the MTU was introduced. This is because whereas after the introduction of the MTU we observe the universe of price changes in Germany, before the introduction of the MTU we only observe the subset of prices that was reported by users to the app.

Figure 13 shows the number of notifications of price changes over the day, before

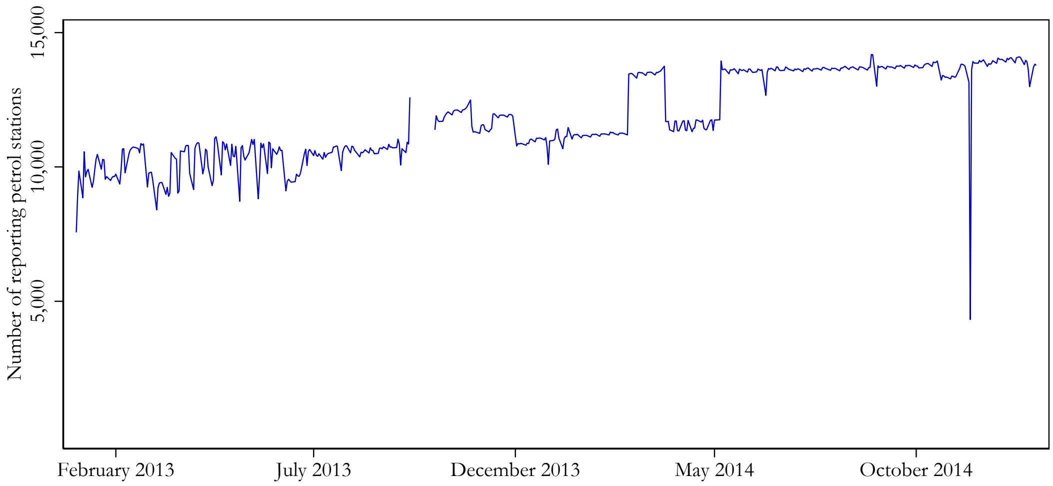
[30]The daily fuelling patterns are described in detail in Figure 14 in Appendix B.1.

[31]This is consistent with pricing patterns in the data described in Figure 15 in Appendix B.1.

[32]There are numerous newspaper articles on intertemporal price dispersion during our observation period, which suggest that consumers are aware of these patterns.

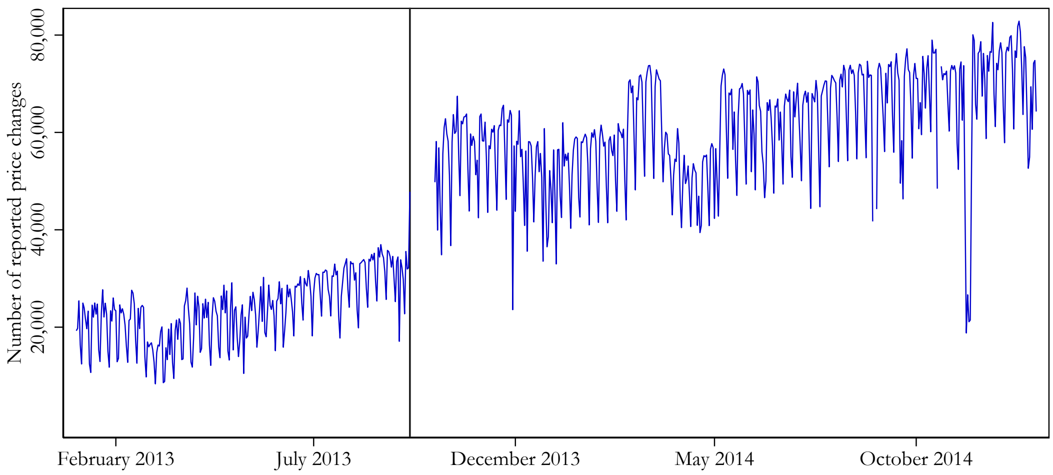
[33]Total and Esso report normally in October 2013. Esso reports only a very limited amount of prices between November 2013 and mid-February 2014. Total only reports a very limited amount of prices between December 2013 and mid-February 2014. Both experienced reporting issues in April 2014, after which they returned to full reporting.

Figure 11: Number of fuel stations with positive price reports at 5pm



Notes: The Figure shows the average daily number of fuel stations with a positive price report at 5 pm in Germany in our sample.

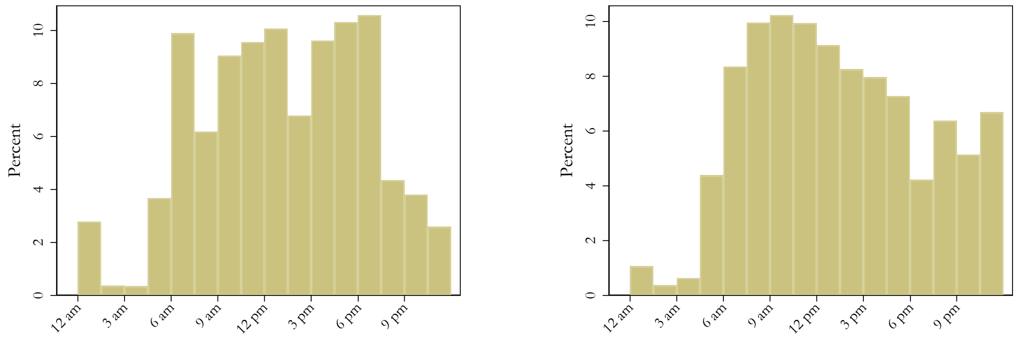
Figure 12: Number of daily price changes



Notes: The Figure shows the average daily number of price changes in Germany in our data. In the pre-MTU period consecutive reports of the same price are not considered a price change.

and after the introduction of the MTU. Whereas before the introduction of the MTU there is a notification every time a user of the app reports a price, after the MTU there is a notification every time that there is a price change.

Figure 13: Notification patterns over the day



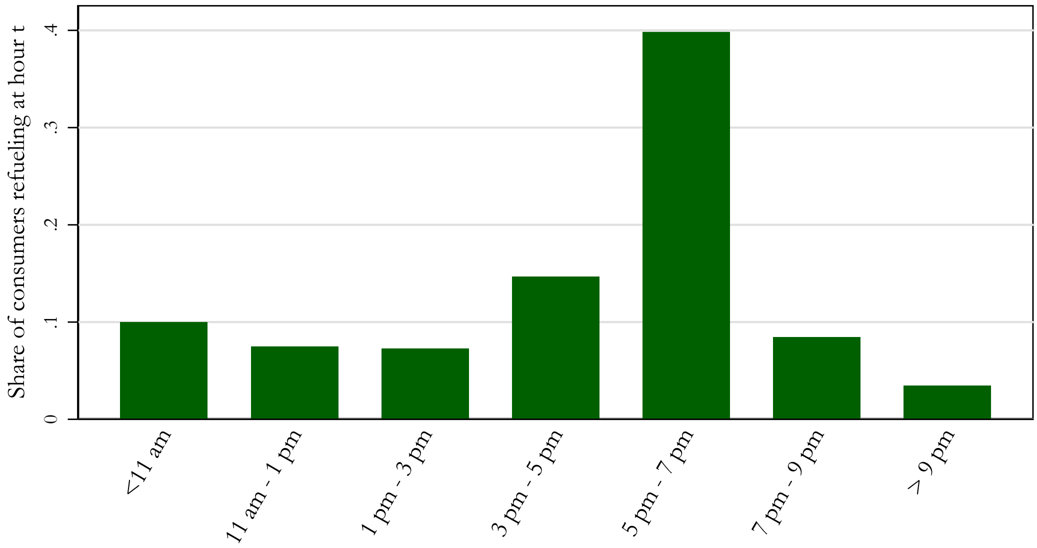
(a) Pre-MTU **(b)** Post-MTU

Notes: Panel (a) shows the share of price notifications in our data set for every hour of the day for the pre-MTU period. Panel (b) shows the share of price notifications in our data set for every hour of the day for the post-MTU period. Pre-MTU, each price report by users notifying a price change to the information service provider is a price notification. Post-MTU, each price change notified by fuel stations to the MTU is a price notification.

Figure 14 shows the hourly fuelling patterns as reported in a representative survey among drivers commissioned by the German Federal Ministry of Economic Affairs. As discussed in Section 3, the majority of drivers buy fuel between 5 pm and 7 pm, whereas only very few drivers buy fuel in the morning.

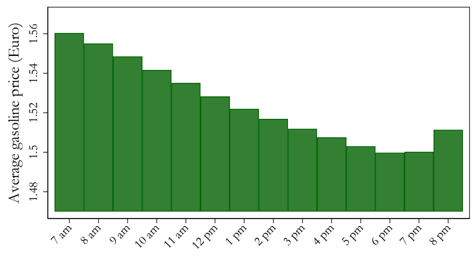
The fuelling patterns are also consistent with price patterns reported in Figure 15. Whereas gasoline and diesel prices are highest in the morning, they fall during the day until the early evening and start rising again at around 8 pm.

Figure 14: Daily fuelling patterns

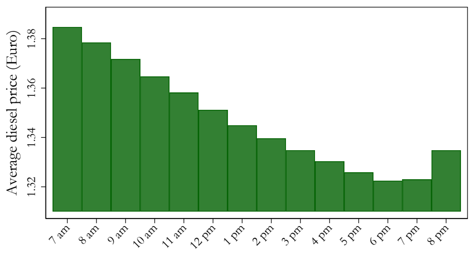


Notes: The Figure shows the average fuelling patterns by German motorists over the day. Data is based on a representative survey among drivers commissioned by the German Federal Ministry of Economic Affairs.

Figure 15: Daily price patterns



(a) Gasoline



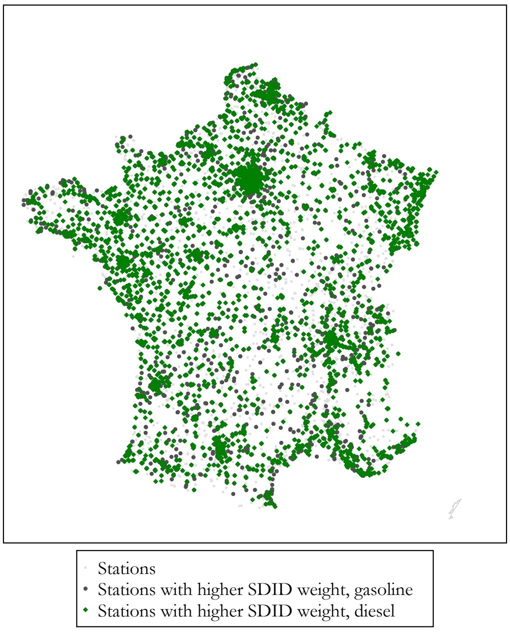
(b) Diesel

Notes: Panel (a) shows the average gasoline price for every hour between 7 am and 8 pm in Germany between 2013 and 2014. Panel (b) shows the average diesel price for every hour between 7 am and 8 pm in Germany between 2013 and 2014.

B.2 Distribution of fuel stations by SDID unit weights in France

Figure 16 shows the geographic distribution of stations in France. Stations that receive a disproportionately high unit weight in the SDID estimation following Equation 1 either for gasoline or diesel are highlighted in the figure. The disproportionately weighted stations in the control group scatter throughout France. This means that potential geographic clustering via re-weighting by SDID unit weights does not affect our results.

Figure 16: Geographic distribution of fuel stations by SDID unit weights, France



Notes: The Figure shows the geographic distribution of fuel stations in France. Stations that receive a disproportionally high unit weight in the SDID estimation are highlighted.

C Appendix to Section 6: Results

In this Section we provide further empirical evidence on the average effect of the MTU on gasoline and diesel prices in Germany. It shows that our results in Section 6 are robust to using alternative specifications.

C.1 Difference-in-differences analysis

Since estimation by SDID requires a balanced panel, we additionally report the average treatment effect of the MTU introduction on log gross fuel prices using difference-in-difference analysis based on the full, unbalanced panel. Specifically, we estimate the following model:

Table 5: Effect of MPD on the logarithm of gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.030***	-0.024***	-0.031***	-0.028***
	(0.0002)	(0.0002)	(0.001)	(0.001)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,110,958	4,706,894	357,816	387,949
Adjusted R^2	0.830	0.806	0.815	0.743

Notes: Columns (1) and (2) include estimates of the effect of MPD on log daily prices for gasoline and diesel, respectively, using all fuel stations in Germany and France. Columns (3) to (4) include the same estimates for a restricted sample of fuel stations 20 to 100 kilometers away from the Franco-German border. The observation periods goes from 15 April 2013 to 31 March 2014. Standard errors are clustered at the fuel station level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$Y_{it} = \beta_0 + \beta_1 MPD_{it} + \mu_i + \gamma_t + \epsilon_{it}, \tag{15}$$

where Y_{it} corresponds to the log gross fuel price at station i at date t and MPD_{it} is a dummy equal to one, if a fuel station i has to report its prices to the MTU at date t. This affects all fuel stations in Germany after the 1 October 2013. μ_i are fuel station fixed effects, and γ_t are date fixed effects.

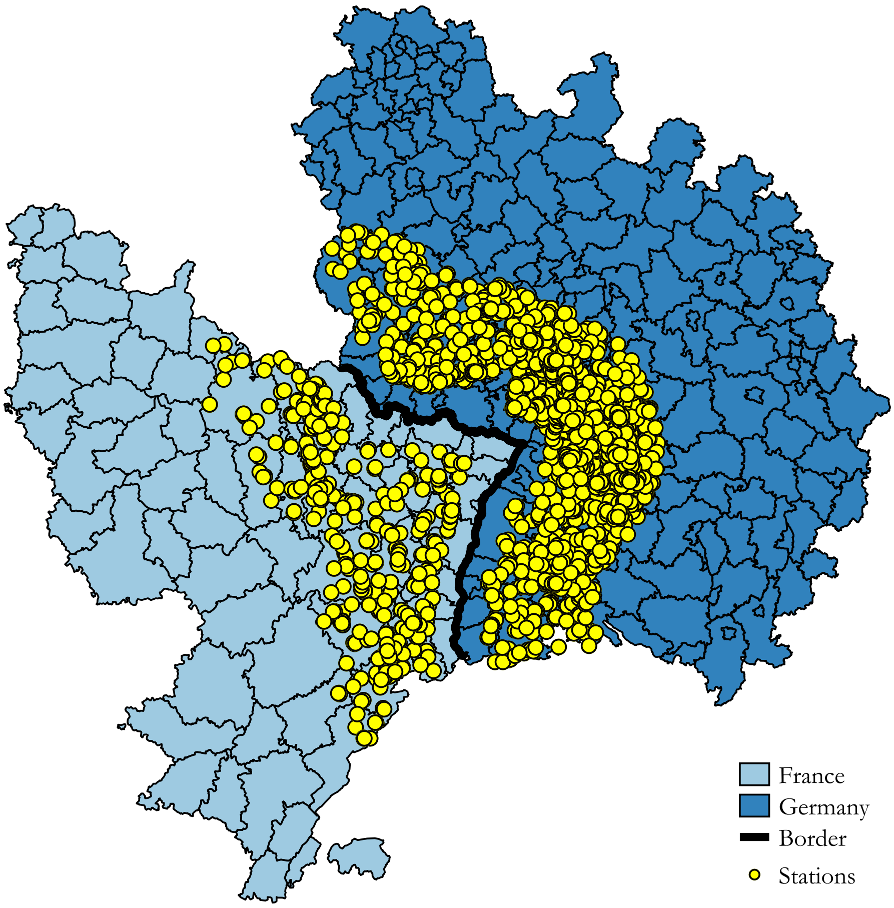
Table 5 reports the effects of the MTU introduction using Equation 15. The outcome variable in all columns is logarithm of gross prices, and the estimation is based on data from 15 April 2013 to 31 March 2014. The results in Columns (1) and (2) of Table 5 are based on the full, unbalanced panel. Columns (3) and (4) report estimates when we only use data on stations located within 20 to 100 km from the Franco-German border.

Table 5 shows that the introduction of MPD led to a decline in prices of 3.0% to 3.1% for gasoline and 2.4% to 2.8% for diesel. The effects are economically and statistically significant, and, similarly to the results estimated via SDID, remain larger for gasoline.

C.2 Donut-SDID analysis

Figure 17 illustrates the identification strategy for the Donut-SDID analysis graphically. To compare stations in economic regions that are as comparable as possible across countries, we restrict the panel to stations within 100 kilometers of the Franco-German border. Fuel stations that are less than 20 kilometers away from the Franco-German border are not considered, because these could be in direct competition to each other and so spillovers of the treatment effect could occur. This would threaten the stable unit treatment value assumption. Each point in Figure 17 thus represents a fuel station, either in France or in Germany, which is 20 to 100 kilometers away from the border.

Figure 17: Fuel stations 20 to 100 kilometers from the Franco-German border



Notes: The thick, solid line represents the Franco-German border. Each point on the right of the border represents a fuel station in Germany, which is 20 to 100 kilometers away from the border. Each point on the left side of the border represents a fuel station in France, which is 20 to 100 kilometers away from the border. These are the fuel stations considered in our Donut-SDID analysis, when they have no missing weekly price observations.

In Table 6, we re-estimate the Donut-SDID regression for the analysis period 15 April 2013 until 31 March 2014 using different distances to the Franco-German border. We find that the results are robust to changing distance thresholds and the average effect of the MTU introduction is always larger for gasoline.

Table 6: Effect of MPD on the logarithm of gross prices using alternative donuts

	Gasoline	Diesel	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)	(5)	(6)
MPD	-0.031***	-0.021***	-0.029***	-0.020***	-0.028***	-0.020***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)
95% CI	[-0.034, -0.028]	[-0.025, -0.018]	[-0.032, -0.026]	[-0.023, -0.017]	[-0.031, -0.026]	[-0.022, -0.018]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	9,408	11,711	20,874	24,843	37,338	42,875

Columns (1) and (2) include estimates of the effect of MPD on log weekly prices for gasoline and diesel, respectively, using a restricted sample of fuel stations 20 to 40 kilometers away from the Franco-German border. Columns (3) and (4) include the same estimates for fuel stations 20 to 60 kilometers away from the border. Columns (5) and (6) include the same estimates for fuel stations 20 to 80 kilometers away from the border. The observation periods goes from 15 April 2013 to 31 March 2014. Standard errors are computed using the jackknife method and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.3 Estimation with control for crude oil price

As discussed in Section 5, crude oil price experienced a sizable decline in the second half of 2014. The fluctuations in the price of crude oil could bias our estimates of the MTU effects if input costs were passed through differentially between stations in Germany and France. Even though we restrict our analysis to August 2014 in our main empirical specification, we additionally estimate the effect of the MTU introduction by directly allowing the differential pass-through of oil cost shocks between stations in Germany and France.

Table 7 shows the effect of the MTU introduction on log gross weekly average gasoline and diesel price when we control for the indicator of stations in Germany interacted with the crude oil price at the port of Rotterdam. Columns (1) and (2) use the full balanced panel, and Columns (3) and (4) restrict the sample to stations located within 20 to 100 km from the Franco-German border. The effects are estimated via SDID, and all columns use data between 15 April 2013 and 31 March 2014. In addition to allowing for the differential pass-through of the input cost shocks between stations in Germany and France, we control for fuel station and time fixed effects.

Columns (1) and (2) in Table 7 show that the introduction of the mandatory price disclosure led to the decrease in weekly average prices of 4.2% for gasoline and 1.8% for diesel. When the sample is restricted to the Donut-SDID, the corresponding estimates indicate a decline of 4.2% for gasoline and 2.4% for diesel. Overall, the magnitude of the MTU effect and its ranking with respect to the two fuel types remain robust to allowing for differential pass-through of the crude oil price between stations in Germany and France.

Table 7: Effect of MPD on the logarithm of gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.042***	-0.018***	-0.042***	-0.024***
	(0.011)	(0.003)	(0.008)	(0.001)
95% Confidence interval	[-0.064, -0.020]	[-0.023, -0.012]	[-0.057, -0.026]	[-0.027, -0.021]
Germany × crude oil price	*Yes*	*Yes*	*Yes*	*Yes*
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	632,884	751,219	49,539	55,517

Notes: Columns (1) and (2) include estimates of the effect of MPD on log weekly prices for gasoline and diesel, respectively, using all fuel stations in Germany and France. Columns (3) and (4) include the same estimates for a restricted sample of fuel stations 20 to 100 kilometers away from the Franco-German border. The observation periods goes from 15 April 2013 to 31 March 2014 and include a control for the interaction of an indicator for Germany with the crude oil price at the port of Rotterdam. Standard errors are computed using the jackknife method and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Effect of the MTU introduction on retail margins

Table 8 shows the effects of the MTU introduction on retail margins, estimated using the SDID model in Equation 1. The outcome variable in all columns is weekly average retail margins, and the estimation is based on data from 15 April 2013 to 31 March 2014. All columns include fuel station and week fixed effects.

Results in Columns (1) and (2) show that the mandatory price disclosure led to the decrease in weekly average retail margins by 3.4 and 1.9 Eurocent for gasoline and diesel, respectively. In Columns (3) and (4), we restrict the analysis to stations within 20 to 100 km from the Franco-German border. Using this Donut-SDID, Columns (3) and (4) show that after the MTU introduction weekly average retail margins decline by 3.7 Eurocent for gasoline and 2.3 Eurocent for diesel. The effect of the MTU introduction is statistically and economically significant, and is larger for gasoline.

Table 8: Effect of MPD on retail margins in Eurocent

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-3.357***	-1.930***	-3.663***	-2.286***
	(0.071)	(0.043)	(0.121)	(0.111)
95% Confidence interval	[-3.495, -3.218]	[-2.014, -1.846]	[-3.900, -3.426]	[-2.502, -2.069]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	632,884	751,219	49,539	55,517
Mean retail margin	8.36	10.77	8.51	11.20

Notes: Columns (1) and (2) include estimates of the effect of MPD on weekly average retail margins for gasoline and diesel, respectively, using all fuel stations in Germany and France. Columns (3) and (4) include the same estimates for a restricted sample of fuel stations 20 to 100 kilometers away from the Franco-German border. The observation periods goes from 15 April 2013 to 31 March 2014. Standard errors are computed using the jackknife method and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.5 Local monopolists as a control group

Driving to another fuel station is costly and hence retail fuel markets are usually segmented geographically. We define local markets as driving distance catchment areas around a focal station. We assume that stations that do not face competition from another station in their catchment area act as local monopolists. Like in the analysis of Albæk, Møllgaard, and Overgaard (1997) for the cement industry, these local monopolists are unaffected by increasing transparency and can therefore serve as a control group.

In Table 9, we report the results of an estimation strategy in which we analyse the effect of the MTU on logarithm of gross prices of fuel stations in Germany for gasoline and diesel. We compare fuel stations in Germany, which have at least one competing fuel station in their catchment area to fuel stations that are local monopolists, and we estimate the effects via difference-in-differences approach. Only fuel stations that are of a different brand are considered as competitors. Whereas we consider local monopolists as untreated by the introduction of the MTU, because consumers have no alternative in the vicinity and can thus not act upon the new information, stations that have a competitor in their market are considered treated. In Columns (1) and (4), we define a local monopolist as not having any other station within a 1 kilometer radius. We find a treatment effect of 0.04 to 0.1 percent, however, according to this definition 64% of fuel stations in Germany are local monopolists. We thus consider broader markets in Columns (2) and (3) for gasoline and in Columns (5) and (6) for diesel. In Columns (2) and (5), we define local monopolists as not having a competing station within a 3 kilometers radius. We drop all fuel stations with a competitor within a 3 kilometers radius, but without a competitor within a 1 kilometer radius from the control group, as

Table 9: Effect of MPD on the logarithm of gross prices (local monopolies)

	Gasoline			Diesel		
	(1)	(2)	(3)	(4)	(5)	(6)
MPD	-0.001***	-0.002***	-0.002***	-0.0004	-0.001***	-0.002***
	(0.0002)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	2,619,823	1,589,155	1,301,738	2,645,827	1,605,201	1,315,465
Share local monopolists	64.3%	42.3%	29.4%	64.3%	42.3%	29.4%
Adjusted R^2	0.813	0.815	0.815	0.662	0.669	0.669

Columns (1) and (4) include estimates of the effect of MPD on log prices for gasoline and diesel, respectively, using fuel stations that are local monopolists within 1 kilometer as the control group and all other stations as the treatment group. Columns (2) and (5) repeat the same analyses for a 3 kilometer radius. Columns (5) and (6) repeat the same analyses for a 5 kilometer radius. The observation periods goes from 15 April 2013 to 31 March 2014. Standard errors are clustered at the fuel station level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

these are local monopolists according to the market definition in Column (1) and (4). We find a treatment effect of 0.1 to 0.2 percent using 3 kilometers catchment areas. In Columns (3) and (6), we repeat this analysis for 5 kilometers catchment area and find a similar treatment effect to Columns (2) and (5). Overall, our results are consistent with Lemus and Luco (2021), who find that mandatory price disclosure reduced the time to reach a new equilibrium for oligopoly markets, but not for local monopolies.

Overall, the average effect of the MTU that we find using this specification is consistent with our estimates for the average effect of the MTU using France as a control group. The treatment effect of the MTU remains larger for the ex ante less informed consumer group. We are likely to underestimate the treatment effect using the local monopolist identification strategy, since consumers in monopoly markets are likely also partially treated by the MTU. It therefore makes sense that the magnitude of the effect that we find using local monopolists is smaller than when comparing gross fuel prices in Germany and France.

C.6 Difference-in-differences analysis: European countries as a control

To test the validity of France as a counterfactual, we also estimate the effect of the MTU introduction on fuel prices in Germany using 26 other European countries as a control group.[34] To do so, we use information on country-level weekly average net gasoline and diesel prices that are reported by the European Commission in the Weekly Oil Bulletin.

[34] Austria, Belgium, Bulgaria, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden form the control group.

Table 10: Effect of MPD on the logarithm of net prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.033***	-0.018***	-0.030***	-0.015***
	(0.003)	(0.003)	(0.006)	(0.005)
Country × crude oil price	*No*	*No*	*Yes*	*Yes*
Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Country FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	1,258	1,258	1,258	1,258
Adjusted R^2	0.868	0.836	0.879	0.860

Notes: Columns (1) and (2) include estimates of the effect of MPD on log net prices for gasoline and diesel, respectively, using Germany as a treatment group and all other EU countries as a control. Columns (3) to (4) include additional interactions between the crude oil price and an indicator variable for each country. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10 shows the effects of the MTU introduction on the logarithm of net gasoline and diesel prices, using a difference-in-differences strategy. As in our main analysis, the estimation is based on data between 15 April 2013 and 31 March 2014 and we control for week and country fixed effects in all columns. In Columns (3) and (4), we additionally control for the crude oil price at the port of Rotterdam interacted with country indicators, which allows for differential pass-through of oil cost shocks across countries.

Table 10 shows that when we use other European countries as a control, the MTU introduction led to a decline of 3.0% to 3.3% for gasoline and 1.5% to 1.8% for diesel. The ranking of the effects with respect to the fuel types and their magnitude remain robust to using this alternative control group.