When Does Mandatory Price Disclosure Lower Prices? Evidence from the German Fuel Market

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Abstract

The widespread availability of digital technologies has made mandatory price disclosure policies (MPD) a convenient tool for policymakers to increase price transparency and foster competition. The literature has shown that these can increase or decrease prices. We shed light on the circumstances under which MPD lowers prices. We study the introduction of MPD in the German retail fuel market by combining a stylized theoretical model with detailed data on prices, seller characteristics and consumer information. We find that low levels of prior consumer information, a high number of sellers, and complementary information campaigns foster the procompetitive effects of MPD.

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

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1 Introduction

In many markets, sellers have been found to derive market power from consumers' being imperfectly informed.[1] With the widespread availability of digital technologies, policymakers across jurisdictions have started introducing mandatory price disclosure policies (MPD) in many of these markets. The literature finds that these policies sometimes benefit and sometimes harm consumers.[2] This suggests that contextual circumstances such as prior information, market structure, and policy design determine the effects of MPD. Understanding how these factors mediate the competitive effects of MPD is crucial for policymakers, who need to predict the effect of MPD before introducing it.

In this paper, we shed light on the circumstances under which mandatory price disclosure policies foster competition and explore how complementary policies can enhance this effect. In our theoretical and empirical analysis, we hone in on several mediators: consumer information prior to MPD, the number of sellers, and complementary information campaigns. We specify a stylized model in which consumers are imperfectly informed about prices and have heterogeneous costs of accessing an information clearinghouse (e.g., a smartphone app containing all prices). We use this model to simulate how MPD, modeled as a reduction in the clearinghouse access costs for all consumers, affects prices. Subsequently, we test the simulation predictions empirically by studying the introduction of MPD in the German retail fuel market, using high-frequency, station-level price changes for Germany and France before and after the introduction of MPD.

The stylized model features sellers of a homogeneous good who set prices and consumers who inelastically demand a unit of the good but do not know the price of individual sellers. As in Tappata (2009), consumers have the option to purchase access to an information clearinghouse at a fixed cost, after which they know all prices. These costs differ between consumers. A consumer purchases access if her expected saving from being informed is greater than her individual access costs. We model MPD as lowering the clearinghouse access costs for all consumers by a constant amount. Once consumers decide whether to purchase access to the information clearinghouse, the model boils down to a Varian (1980) model, in which sellers set prices using mixed strategies, *informed* consumers purchase at the lowest price seller and *uninformed* consumers visit a single seller, observe its price and decide whether to purchase at that price or not purchase at all.

Several predictions emerge from the simulations: First, marginally reducing clearinghouse access costs (e.g., through MPD) increases the equilibrium share of informed consumers but does so to a lesser extent the higher is the share of informed consumers

[1]Examples include fuel stations in Chile (see Luco, 2019) and Germany (see German Federal Cartel Office, 2011), supermarkets in Israel (see Ater and Rigbi, 2023), and the hospital medical equipment market in the United States (see Grennan and Swanson, 2020).

[2]Even within retail fuel, Luco (2019) finds that MPD increases prices, whereas Rossi and Chintagunta (2016) find that it decreases prices.

pre-MPD, which we call the share of ex ante informed consumers. At the same time, if the share of ex ante informed consumers is above a cutoff share, a marginal increase in the share of informed consumers decreases the expected price to a greater extent the higher is the share of ex ante informed consumers. Second, if the share of ex ante informed consumers is above the cutoff, a marginal decrease in clearinghouse access costs reduces the value of information (VOI), a measure of price dispersion, and does so more markedly the higher is the ex ante share of informed consumers. Third, if the share of ex ante informed consumers is above the cutoff, a marginal decrease in clearinghouse access costs decreases the expected price more than the expected minimum price. Fourth, the presence of more sellers leads to a larger increase in the share of informed consumers resulting from a marginal decrease in clearinghouse access costs. At the same time, the presence of more sellers leads to a smaller decrease in prices resulting from a marginal increase in the share of informed consumers. Finally, a larger reduction in clearinghouse access costs leads to a larger increase in the share of informed consumers and decrease in prices. Whereas we can test only some of these predictions empirically, the untestable predictions help us understand the mechanism through which MPD affects prices.

In September 2013, Germany's Market Transparency Unit for Fuels (MTU) started operating. Since then, all fuel stations in Germany have had to report all price changes in real time to a central database. The aggregated information can be accessed by information service providers and diffused to consumers (e.g., via smartphone applications). This policy was recommended by the German Federal Cartel Office (2011) after it diagnosed the problem of low competition between fuel stations as resulting from a lack of knowledge about prices among consumers. Because we have access to granular data for the periods before and after the MPD introduction and rich variation along several key dimensions, this setting serves as a unique laboratory for us to study the mechanisms by which MPD affects prices.

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 its introduction. Here, we leverage that, even prior to MPD, there already existed some smartphone applications that allowed users to self-report fuel prices, which were then collected and diffused to users in a fashion similar to how price information is released under MPD.[3] We have access to the pre-MPD price notifications from users for one of these apps. This includes 20.5 million price notifications from between 1 September 2012 and 31 August 2013. For the control group, we exploit the fact that there exists a similar database of the 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). Similarly to regular

[3]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 consumers' information set.

difference-in-differences, SDID estimates the treatment effect by identifying the post-MPD price change in the treatment group that is not present in the control group. As in synthetic control methods, the unit and time period weights for the control group are optimized to match the pretrends in the treatment group.

To test our predictions about the role of the ex ante share of informed consumers, we compare the effect of MPD on gasoline and diesel prices. A key feature of the setting is that the same fuel stations sell both types of fuel. Other than the fuel type, the overall product (e.g., the shopping experience) is identical. The key difference between gasoline and diesel is that consumers of the two fuel types 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 who drive on average twice as many kilometers per year as gasoline buyers.[4] Using data on the pre-MPD user-reported price notifications, we show that the reporting intensity was higher for diesel than for gasoline. On the basis of post-MPD user-level search data, we can show that the app usage intensity remained higher among diesel than among gasoline consumers. Both of these findings are consistent with what we would expect theoretically if we compared two separate markets where consumers have the same valuation for the goods and the same cost of becoming informed but differ in the number of units that they demand.

We find that MPD decreases the VOI for gasoline and diesel, which suggests that the share of ex ante informed consumers was above the cutoff share in both markets. In this case, the stylized model predicts that MPD reduces the expected price more than the expected minimum price. We corroborate this empirically by analyzing their sample equivalents. For both fuel types, MPD reduces the market-level average price more than the market-level minimum price. On average, we find that MPD reduces prices by 2.7% for gasoline compared to 1.8% for diesel. The stylized model suggests that this is the case because the price effects of a larger increase in the share of informed consumers in the market with fewer ex ante informed consumers (the gasoline market) outweighs the larger price reduction caused by a marginal increase in the share of informed consumers in the market with more ex ante informed consumers (the diesel market).

To ensure that the results are not driven by different demand conditions, we repeat the analysis for stations 20–100 km from the France-Germany border. To rule out that our results are driven by selection bias in the pre-MPD price reports or the choice of control country, we estimate the effect of MPD on diesel and gasoline prices using weekly, country-level administrative data and the 26 European Union member countries except Germany as a control group. Both analyses yield estimates that are statistically and economically indistinguishable from the main findings.

Next, we study how the number and identity of sellers affects the price effect of MPD. To compute the number of sellers in a local market, we construct overlapping

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

markets where we count the number of rivals within a 5 km radius around a focal fuel station. Our main finding suggests that the presence of more sellers leads to a larger decrease in average prices under MPD. Although these categories play no role in the stylized model, the German Federal Cartel Office (2011) focused on the role of vertically integrated sellers, which operate at the refinery and the retail level, and, in particular, on a subset of vertically integrated oligopolists, which are allegedly responsible for higher prices. We find no differential effect of MPD on integrated sellers as a whole. When we isolate the integrated sellers defined as integrated oligopolists by the German Federal Cartel Office (2011), we find a stronger MPD-induced price decrease for stations belonging to brands of the integrated oligopolists. This is encouraging if (one of) the aims of the policy was to rein in the market power allegedly held by these oligopolists.

Next, we explore the dynamic effects of MPD and levers related to the design of MPD policies. We show that, whereas the price decrease for diesel was relatively stable over time, the price decrease for gasoline was largest approximately five months after the introduction of MPD and declined to the same level as that for diesel a couple of months later, after which the price effect remained stable. The large initial price decrease for gasoline coincided with a fading of the strong initial public interest in MPD after six months, which we measure by means of Google searches for MPD-related search terms. At the same time, monthly usage data for three of the price comparison apps shows that these apps continued to be used intensely all through 2014, in line with the persistent price reduction that we find. These results suggest that complementary information campaigns that remind consumers of the existence of price information can further reduce prices. We test this by studying regular broadcasts by local radio stations of the lowest fuel prices in their reception area after the introduction of MPD. Our results suggest that this practice can lead to a further price decrease.

This paper makes two main contributions. First, we specify a simple stylized model that allows us to simulate how different market conditions, such as the share of ex ante informed consumers or the number of sellers, mediate the price effect of MPD. The model is a simplified version of that of Tappata (2009), who studies price cycles in retail fuel markets, and boils down to the Varian (1980) model once consumers choose whether to become informed. With an exogenous share of informed consumers, Pennerstorfer et al. (2020) show that there is a global inverse U-shaped relationship between the share of informed consumers and measures of price dispersion, such as the VOI. Whereas there is a rich theoretical literature describing how increasing seller information can stabilize collusion (e.g., Green and Porter, 1984; Kühn and Vives, 1995), we assume that seller information is unaffected by MPD because, according to the German Federal Cartel Office (2011), sellers invested heavily in observing their competitors' prices before MPD.[5]

[5]Schultz (2005), Petrikaite (2016) and Schultz (2017) show that increasing consumer information only can also stabilize collusion. We abstract from these considerations, as they do not seem empirically

Second, the detailed data and variation make the German retail fuel market an ideal laboratory for us to explore the different mechanisms that can shape the price effects of MPD in a single application. Our findings relate to a rich empirical literature studying the price effects of various MPD policies and finding mixed results. Albæk, Møllgaard, and Overgaard (1997) and Luco (2019) find that MPD in the Danish ready-mix concrete and Chilean retail fuel markets increased prices because it improved seller information. Ater and Rigbi (2023) find that MPD for Israeli supermarkets intensified competition as low-price supermarket chains used MPD-enabled price comparisons to lend credibility to their price-based advertising campaigns. Rossi and Chintagunta (2016) find that mandating that fuel stations on Italian motorways post rivals' prices lowered prices.[6]

Since a key feature of our setting is that we can shed light on different aspects of the effect of MPD policies, after our analysis, we discuss the policy implications of our results and findings from prior literature. We conclude that the most promising intervention is to target MPD at markets with a low ex ante share of informed consumers but a high degree of seller information. Similarly, markets that have a high number of sellers but are far from the perfectly competitive price are likely to benefit most from MPD. A comparison of our findings with those of Luco (2019) and Byrne et al. (2023) suggests that MPD is most likely to be successful at lowering prices if consumer uptake is high. This can be facilitated by low entry barriers for consumer apps and complementary information campaigns. Another policy lever is explored by Martin (Forthcoming), who goes beyond studying the simple binary decision of whether to introduce MPD and instead explores whether diffusing only a subset of prices to consumers can lower prices even further. He finds an inverse U-shaped relationship between the share of prices disclosed and consumer welfare, with the effect maximized by the display of only the cheapest 20% of prices.

Finally, our paper contributes to an extensive empirical literature that analyzes pricing decisions in retail fuel markets.[7] Lewis (2008) studies the relationship between price dispersion and the local competitive environment. A key consideration in this literature is the role of imperfect information (e.g., Chandra and Tappata, 2011, Byrne and Roos, 2017 and Byrne and de Roos, 2022). In contrast, Houde (2012) emphasizes the role of spatial differentiation. Byrne and de Roos (2019) and Assad et al. (2024) 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 et al. (2023) show how these mechanisms channel the pass-through of commodity taxes and thus have broader implications for the effectiveness of other policy tools.

The remainder of this paper is structured as follows: Section 2 outlines the theoret-

relevant in our application.

[6]Brown (2019b) and Brown (2019a) find that increasing price transparency decreased out-of-pocket prices for medical imaging procedures in New Hampshire and shifted sales toward lower-price sellers.

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

ical 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 the empirical results. Section 7 discusses policy implications, and Section 8 concludes.

2 Stylized Model

To guide our empirical analysis, we specify a stylized information clearinghouse model in the spirit of Varian (1980), in which consumers can endogenously choose to become informed as in Tappata (2009).

2.1 Setup

The model features sellers and consumers. Sellers sell a homogeneous good and set prices. There is a unit mass of atomistic consumers who each inelastically demand a single unit of the good. The valuation of the good is the same across consumers and is denoted by υ. Consumers can buy access to an information clearinghouse (e.g., a price comparison app). Once they have access to this clearinghouse, they know all prices and buy from the lowest-price seller. If they do not, they draw a single seller at random, observe its price, and can decide only between buying and not buying at that price.

Consumers differ in the costs they incur to obtain access to the information clearinghouse. A fraction λ of consumers are *shoppers*. They have negative clearinghouse access costs and therefore always know all prices. The remaining $(1-\lambda)$ consumers are *nonshoppers*. They have clearinghouse access costs drawn from a continuous and differentiable probability density function $g(z_i)$, with $z_i \in Z = [0, z_{max}]$. z_{max} is sufficiently high that some consumers never choose to become informed.

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 j.

Sellers and consumers play a simultaneous-move Bayesian game. They form expectations about consumers' decision to become informed and about rivals' prices and choose a pricing strategy to maximize expected profits. Sellers choose a price $p_j \in P = [0, \upsilon]$. Consumers form expectations over prices when deciding whether to become informed. They choose an action $a_i \in A = \{0, 1\}$, where $a_i = 1$ means that they buy access to the information clearinghouse. We call consumers who buy access to the information clearinghouse *informed* and all other consumers *uninformed*. The share of informed consumers is denoted by $\mu = \int_0^1 a_i di$. Since no seller chooses a price above the valuation of consumers, they always purchase a single unit of the good.

We model mandatory price disclosure as decreasing the clearinghouse access costs for all consumers by the same amount. This means a parallel shift of the clearinghouse access cost curve z_i to the right. Two components are important in clarifying the price effects of MPD: how a shift in z_i affects the equilibrium share of informed consumers μ and how this change in μ affects prices.

To analyze these two components, we first illustrate the simultaneous-move Bayesian equilibrium and then simulate how the effect of MPD on prices is mediated by market conditions and the design of the policy.

2.2 Equilibrium prices and information acquisition

There is a unique symmetric Bayesian Nash equilibrium (SBNE) in which firms set prices by playing a mixed strategy given the share of informed consumers and consumers choose to become informed given their correct belief about the firms' pricing strategies.[8] The equilibrium 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 uninformed consumers, and $\underline{p}$ is the minimum of the support from which a seller draws prices in equilibrium.

Uninformed consumers purchase the good as long as the price is weakly below their valuation υ. Their reservation price p_r is thus equal to υ. Since no one purchases at a price above υ, no seller charges a price above υ in equilibrium, and all uninformed consumers buy the good at the randomly drawn seller. The derivation of the pricing strategies can be found in Varian (1980).

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

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

The cumulative density function from which sellers draw prices is

$$F(p) = 1 - \left(\frac{\upsilon - p}{p} \frac{1-\mu}{N\mu} \right)^{\frac{1}{N-1}} .$$

The value of information to consumers, i.e., the value from their knowing all prices, is the savings they expect from buying from the lowest-price seller instead of the first seller they encounter. The VOI is therefore the difference between $E[p]$ and $E[p_{min}]$. Since consumers are atomistic, their individual decision to become informed or not has no effect on μ. All shoppers, as well as all nonshoppers with clearinghouse access costs $z_i \leq VOI = E[p - p_{min}|\mu]$, become informed.

[8]This is a simplified version of the presentation in Tappata (2009), which features a detailed discussion of the equilibrium.

The equilibrium share of informed consumers is therefore

$$\mu = \lambda + G\left(E\left[p - p_{min}|\mu\right]\right) \, .$$

Finally, the expected price can be written as

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

and the expected minimum price as

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

As shown by Tappata (2009), starting from $\mu = 0$, the VOI is an increasing function in μ, and there exists a $\hat{\mu}$ that maximizes the VOI. Thereafter, further increasing μ leads $E[p]$ to decline faster than $E[p_{min}]$ and results in a decline in the VOI.

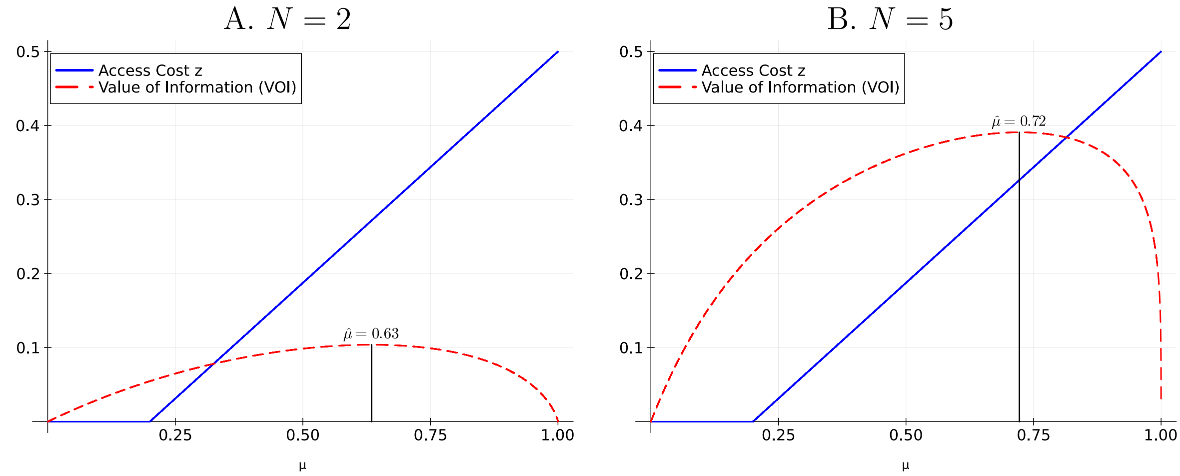
Depending on the shape of $g(\cdot)$, there can be more than one level of informed consumers μ where the VOI equals the clearinghouse access costs for the marginal consumer. A sufficient (but not necessary) condition for a unique equilibrium is that $g(\cdot)$ be a uniform distribution. Tappata (2009) derives more general conditions under which there is a unique equilibrium to the consumers' information acquisition problem.

2.3 Effect of mandatory price disclosure

To understand the effect of mandatory price disclosure on the share of informed consumers and equilibrium prices, we simulate the key components of the model. The equilibrium share of informed consumers is determined by the VOI and the clearinghouse access costs. In this model, the VOI depends only on the share of informed consumers, the willingness to pay for the good, υ, and the number of sellers, N. We model MPD as a shift to the right of the clearinghouse access cost curve (i.e., a decrease in clearinghouse access costs by the same amount for every consumer).

Figure 1 plots the VOI and clearinghouse access costs as a function of the share of informed consumers. The VOI depends only on υ and the number of sellers. As we show in Appendix Figure A1, the share of informed consumers that maximizes the VOI, $\hat{\mu}$, is independent of υ and increases in N. For simplicity, we illustrate the distribution of clearinghouse access costs among nonshoppers using a uniform distribution, but our discussion holds more generally for any continuous and differentiable probability density function that satisfies the necessary conditions for a unique equilibrium in the clearinghouse access decision problem.

Figure 1: VOI and clearinghouse access costs by share of informed consumers



Notes: The figure shows simulations of the VOI and the clearinghouse access costs by the share of informed consumers. The clearinghouse access costs are for the marginal consumer if all consumers with lower costs purchase clearinghouse access. We use the following parameter values in the simulations: $v = 1$, $\lambda = 0.2$, and a uniform distribution of access costs between 0 and 1 for all nonshoppers. Panel A uses $N = 2$, and Panel B uses $N = 5$. Appendix Figure A1 shows that the share of informed consumers maximizing VOI, $\hat{\mu}$, is independent of v and increases in N.

Prediction 1. *A downward shift of the clearinghouse access cost curve increases the equilibrium share of informed consumers, μ^*.*

The equilibrium share of informed consumers, μ^*, is where the clearinghouse access cost of the marginal consumer equals the VOI. It is easy to see that the lower the clearinghouse access costs, the higher is the equilibrium share of informed consumers.

Next, we denote the ex ante (i.e., pre-MPD) share of informed consumers by μ_0. The smaller the slope of the VOI, the smaller is the increase in μ^* for a given downward shift of the clearinghouse access cost curve.[9]

Prediction 2. *A marginal downward shift of the clearinghouse access cost curve increases the equilibrium share of informed consumers to a smaller extent the higher μ_0 is.*

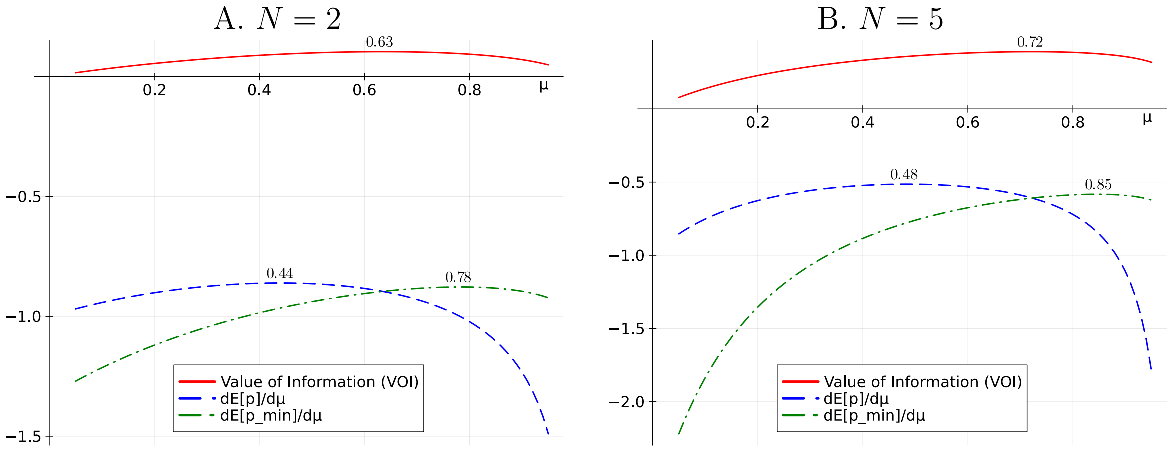
Furthermore, if the ex ante share of informed consumers is greater than $\hat{\mu}$, any downward shift in the clearinghouse access cost curve leads to a reduction in the VOI. Although a sufficiently large downward shift in the clearinghouse access cost curve could lead to a reduction in the VOI even if $\hat{\mu} > \mu_0$, observing a decrease in the VOI after MPD suggests that $\hat{\mu} < \mu_0$. As we show in Section 4, the VOI decreases after MPD, which is why we focus on predictions when $\hat{\mu} < \mu_0$ from here onward.

Prediction 3. *If $\hat{\mu} < \mu_0$, a marginal downward shift of the clearinghouse access cost curve decreases the VOI.*

Figure 2 plots the VOI and the effect on prices of marginally increasing the share of informed consumers by the share of ex ante informed consumers. As we show in Appendix

[9]For $\hat{\mu} < \mu_0$, the slope of the VOI is negative, making the curve steeper the smaller the slope is.

Figure 2: VOI and marginal price effect by share of informed consumers



Notes: The figure shows simulations of the VOI and the change in $E[p]$ and $E[p_{min}]$ for a marginal increase in μ by the share of informed consumers. We use $v = 1$ in all simulations. Panel A uses $N = 2$, and Panel B uses $N = 5$. Appendix Figure A2 shows that the share of informed consumers maximizing the VOI and the partial derivatives of $E[p]$ and $E[p_{min}$ with respect to μ are independent of v and increase in N.

Figure A2, the share of informed consumers maximizing the marginal price effect curves is independent of v and increases in N.

An increase in the share of informed consumers always decreases the expected price and the expected minimum price. Furthermore, if μ_0 is greater than $\hat{\mu}$, a marginal increase in μ decreases $E[p]$ more the higher is μ_0. Finally, if $\hat{\mu} < \mu_0$, a marginal increase in μ decreases the VOI more the higher is μ_0.

Prediction 4. *If $\hat{\mu} < \mu_0$, a marginal increase in the share of informed consumers decreases $E[p]$ and the VOI to a greater extent the higher μ_0 is.*

When studying MPD empirically, we cannot separately test the last two predictions since we do not observe the change in μ. A lower μ_0 leads to a higher price decrease because it results in a larger change in μ but also lowers prices less for a given change in μ. Since the two predictions go in opposite directions, studying them jointly does not reveal whether the data are consistent with the model. However, if we can establish that the data are consistent with the model by testing other predictions, the two untestable predictions offer useful insights into the mechanisms behind the price effect of MPD.

Another implication from Figure 2 is that if μ_0 is greater than $\hat{\mu}$, a given downward shift of the clearinghouse access cost curve should decrease $E[p]$ more than $E[p_{min}]$. We can test this prediction empirically without observing μ because we can compare $E[p]$ and $E[p_{min}]$ in the same market, i.e., for the same change in μ.

Prediction 5. *If $\hat{\mu} < \mu_0$, a marginal downward shift of the clearinghouse access cost curve decreases $E[p]$ more than $E[p_{min}]$.*

Next, we turn our attention to how the number of sellers mediates the effect of MPD on prices. As becomes immediately clear and is shown by Tappata (2009), a higher number of sellers increases the VOI, and so for a given distribution of clearinghouse access costs, a higher N increases the equilibrium share of informed consumers.

Understanding the way N affects how a marginal downward shift in the clearinghouse access costs changes the equilibrium share of informed consumers is more complicated. Appendix Figure A1 shows that the VOI curves become steeper the higher is the number of sellers. A higher number of sellers therefore means that a downward shift in the clearinghouse access costs increases the equilibrium share of informed consumers more.

Prediction 6. *The presence of more sellers leads to a larger increase in μ^* resulting from a marginal downward shift of the clearinghouse access cost curve.*

Figure A2 shows that the higher the number of sellers, the smaller is the decrease in $E[p]$ and $E[p_{min}]$ resulting from a marginal increase in μ.

Prediction 7. *The presence of more sellers leads to a smaller decrease in $E[p]$ and $E[p_{min}]$ resulting from a marginal increase in μ.*

Since we cannot observe the change in μ resulting from MPD, we can estimate only how the the price effect of MPD varies with the number of sellers. The presence of more sellers leads to a larger increase in μ, which leads to a stronger decrease in prices. At the same time, the presence of more sellers leads to a smaller price decrease resulting from a marginal increase in μ. The price effect of MPD could therefore be increasing or decreasing in the number of sellers.

Thus far, we have discussed only a marginal decrease in clearinghouse access costs. Depending on how the MPD policy is designed, it can lead to a more-than-marginal shift in the clearinghouse access cost distribution. It is straightforward to see from Figure 1 that a larger downward shift in the clearinghouse access cost curve leads to a larger increase in the equilibrium share of informed consumers.

Prediction 8. *The more mandatory price disclosure decreases clearinghouse access costs for all consumers, the more it increases μ^* and decreases prices.*

2.4 Mapping predictions to empirics

The simulation-based predictions highlight how MPD, represented by a downward shift of the clearinghouse access cost curve, affects prices and how this price effect is mediated by the ex ante share of informed consumers and the number of sellers.

Prediction 1 suggests that the lower the clearinghouse access cost curve, the higher is the equilibrium share of informed consumers. Although our data do not allow us to estimate the change in the share of informed consumers induced by MPD, we can estimate the relative share of informed consumers between fuel types, where consumers of gasoline and diesel differ in their clearinghouse access costs.

Prediction 3 suggests that the change in the VOI after MPD reveals whether μ_0 is smaller or larger than $\hat{\mu}$. Since we can estimate the market-level VOI before and after MPD, we can assess whether μ_0 is smaller or larger than $\hat{\mu}$.

Once we have this result in hand, Prediction 5 hypothesizes a differential impact of MPD on $E[p]$ and $E[p_{min}]$. We can test this empirically by estimating the effect of MPD on the market-level average price and minimum price in the empirical application.

Finally, according to Prediction 8, a greater reduction in clearinghouse access costs leads to a larger price decrease. We test this by studying local follow-on information treatments, which presumably further reduce clearinghouse access costs.

Together, Predictions 2 and 4 imply that the price effect of MPD could increase or decrease in μ_0. Similarly, Predictions 6 and 7 imply that the price effect of MPD could increase or decrease in N. In other applications with data on μ before and after MPD, testing these predictions separately is possible. Furthermore, if we can establish the suitability of the model using the testable predictions, these untestable predictions reveal useful information about the mechanism through which MPD affects prices.

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 fuel stations also sell other products, we focus on fuel sales only.

The two main fuel products are diesel and gasoline. Consumers cannot substitute between these without switching cars. In our analysis, we focus on gasoline with an octane rating of 95 and an ethanol share of 5% (also referred to as *E5*), as well as on diesel, which were used in 56% and 29%, respectively, of passenger vehicles with combustion engines in Germany in 2013.[10]

On the demand side, diesel and gasoline drivers differ in how much they drive. Diesel drivers 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.

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

Buying a diesel vehicle is considered a fixed cost investment to lower marginal costs. 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 because taxes on diesel are lower. Drivers who expect to drive longer distances can therefore self-select into paying more upfront for a diesel vehicle to save on fuel costs later on. For the same reason, on average, the returns to being informed are higher for drivers of diesel than for drivers of gasoline vehicles.

One could still argue that since diesel vehicles are often used for business purpose, diesel drivers may actually be less prone to search for lower prices. This is unlikely to be a concern in our case. As of January 2013, while 12.6 million diesel passenger vehicles were in circulation in Germany, just 4.6 million vehicles, including both those with gasoline and those with diesel engines, were in use for commercial purpose. This means that at least 63% of diesel vehicles are owned and operated by private individuals (Kraftfahrt-Bundesamt, 2013). Among the remaining 37% of diesel vehicles used for business purposes, 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, that many diesel vehicles are used for commercial purposes does not invalidate our observation that diesel drivers are on average more price sensitive than gasoline drivers.[11]

On the supply side, the retail fuel market in Germany is vertically organized. In the upstream market, crude oil is refined into retail products. These are sold and distributed to the downstream market, where fuel stations sell the retail products to drivers. According to the German Federal Cartel Office (2011) (GFCO), 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 sellers 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 learn the prices of all potential sellers, a driver would need to drive to all stations.[12]

A market investigation ending in 2011 led the GFCO to determine that prices in regional fuel markets were 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

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

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

called for an increase in price transparency in the downstream market. In 2012, the German parliament passed a law stipulating the creation of the market transparency unit for petrol under the management of the GFCO, and on 12 September 2013, the MTU began operating. 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 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 app providing fuel prices in Germany under MPD.

3.3.1 Prices, retail margins and fuel station characteristics

Our primary data set contains station-level *E5* gasoline and diesel prices on weekdays at 5 pm between 12 April 2013 and 31 August 2014 in Germany.[13] Throughout most of our analyses, we use the station-level gross retail price, which includes taxes and duties, as an outcome variable. To estimate heterogeneity in the treatment effect, we add station characteristics such as information on the brand, address and geographic coordinates to our data set.

To illustrate how MPD affects sellers, 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.[14] Although these retail margins contain costs of different types, such as refining and 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 from *before* the introduction of MPD. At that time, to the best of our knowledge, two smartphone apps existed that allowed their users to self-report station-level fuel prices. Although the usage of these apps was low in comparison to the usage of the more than 40 apps available after the introduction of MPD and the publicity that came with it, the pre-MPD apps contain rich price information. We use price data for the pre-MPD period supplied by one of the apps collecting self-reported prices. This data

[13]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. Although the stylized model does not feature price cycles, Cason, Friedman, and Hopkins (2020) show for experimental markets with features similar to those of the Varian (1980), Burdett and Judd (1983) and Stahl (1989) models that the observed pricing patterns feature price cycles. After prices over time are collapsed, the mixed strategy equilibrium distribution in the theoretical search models does well at explaining the observed price distribution.

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

set comprises 17 million price reports for more than $13,500$ stations between 1 January and 12 September 2013. Although the MTU started operations on 12 September 2013, we have access only to its data from 1 October 2013 onward. Since our self-reported pre-MPD data only run until 12 September 2013, the period in between is not analyzed.

For most days in the pre-MPD period, we have prices for more than 80% of fuel stations.[15] If the reporting of prices was not random, selection could bias our estimation results. The most conceivable selection mechanism would be fuel stations themselves reporting prices to the apps when the prices were low to attract shoppers. At the same time, stations could refrain from posting prices when they are high to avoid discouraging consumers from driving to their fuel station and discovering the price. To alleviate this concern, we use weekly country-level average prices from the *Weekly Oil Bulletin* before and after MPD and show that our main results obtained with this measure are very similar to the baseline.

Another concern could be that the composition of fuel stations changed 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 did 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.[16] A detailed split of fuel stations by brand before and after the MPD introduction can be found in Table B1 of Appendix B.1. Overall, the composition of brands is very similar.

The largest share of the retail price for fuel 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.

Since January 2007, all fuel stations in France selling more than 500 m^3 of fuel per year have had 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 are regarded as of very high quality and have previously been used by Gautier and Saout (2015).

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

[15] The daily number of fuel stations with price reports and the number of daily price changes are reported in Figures B2 and B3 in Appendix B. We exclude from our analysis the observations from days after the launch of the MTU when the number of price changes relative to the number of changes the previous day drops by more than 40%. Since we observe the universe of price changes after the MTU's introduction and the average number of daily price changes is usually stable, we conclude that the price reports on these days were affected by technical difficulties. In total, this issue affects the data from ten days within the 15 months of data used from the MTU.

[16] Although we observe an increase in the number of stations between the pre- and post-MTU phases, this is attributable not to entry but to the change in data source. The number of fuel stations remained stable over this time period.

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

Table 1: Summary statistics

A. Station characteristics				
	D pre-MPD	D post-MPD	F pre-MPD	F post-MPD
Number of stations	13,782	14,606	8,740	9,224
Share of integrated stations	59%	57%		
Share of oligopoly stations	47%	46%		
Median # comp. (5 km catchment)	4	3	2	2
Share of local monopolists	15%	15%	18%	19%

B. Prices and margins				
	D pre-MPD at 5 pm	D post-MPD at 5 pm	F pre-MPD at 5 pm	F post-MPD at 5 pm
Mean price, gasoline	1.60	1.50	1.58	1.52
Mean retail margin, gasoline	0.08	0.05	0.11	0.10
Mean daily spread, gasoline	0.09	0.07	0.13	0.15
Mean price, diesel	1.41	1.33	1.38	1.31
Mean retail margin, diesel	0.11	0.09	0.11	0.10
Mean daily spread, diesel	0.09	0.08	0.13	0.13
Mean crude oil price, Rotterdam	0.61	0.55	0.61	0.55

Notes: “D pre-MPD” and “D post-MPD” refer to fuel stations in Germany before and after the introduction of MPD, respectively. “F pre-MPD” and “F post-MPD” refer to fuel stations in France before and after the introduction of MPD, respectively. The pre-MPD phase is from 1 January 2013 until 12 September 2013. The post-MPD phase is from 1 October 2013 until 31 December 2014. Prices are in euro per liter. The average daily spread is measured as the average of the difference between the retail margin at the 95^{th} and 5^{th} percentiles on each day.

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

3.3.2 Local radio reports

With Germany's 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 after the introduction of MPD, we exploit initial broadcasts of fuel price information 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 and contacted 60 radio stations that could potentially broadcast fuel prices. In 2014, four local radio stations broadcast local fuel prices (e.g., of the three lowest-price fuel stations in their reception area) more than once a day at some point, and we know the dates between which these broadcasts occur. 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, the salience of the information, and its usage over time.

First, we use data on search queries in 2015 from a major smartphone app displaying fuel prices to users in Germany. For each search query, there is a unique device ID, 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 fuel types.

Second, we analyze information from Google Trends on keywords surrounding the MTU. This tells us when public attention toward this authority is particularly high and so when salience of fuel 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

Let us begin the empirical analysis by presenting descriptive evidence on the price effect of mandatory price disclosure and its interplay with the stylized model in Section 2.

4.1 Price information uptake

In Section 3, we show that, on average, diesel car drivers drive twice as much as drivers of gasoline-powered vehicles. If we believe that the overall cost of being informed about prices (e.g., by using an app) does not differ across drivers, the per-liter clearinghouse access cost for diesel drivers is lower. Thus, in the context of the stylized model, we consider the clearinghouse access cost curve pre- and post-MPD to be lower for diesel drivers, with everything else held constant.[18] Prediction 1 states that this leads to a higher equilibrium share of informed diesel drivers pre- and post-MPD.

We can use data on price notifications by fuel type in the period before MPD as a proxy for differences in the information levels between fuel types. Intuitively, since fuel prices for price comparison apps before MPD were user reported, drivers who report more prices are also likely to use this price information more. To obtain a sense of the relative share of informed diesel and gasoline drivers before MPD, we adjust the daily number of diesel and gasoline price reports by the respective number of vehicles in circulation.[19] Figure 3 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 approximately 64% higher than that of gasoline notifications. Consistent with Prediction 1, this suggests that diesel drivers were, on average, more informed about prices than gasoline drivers prior to MPD.

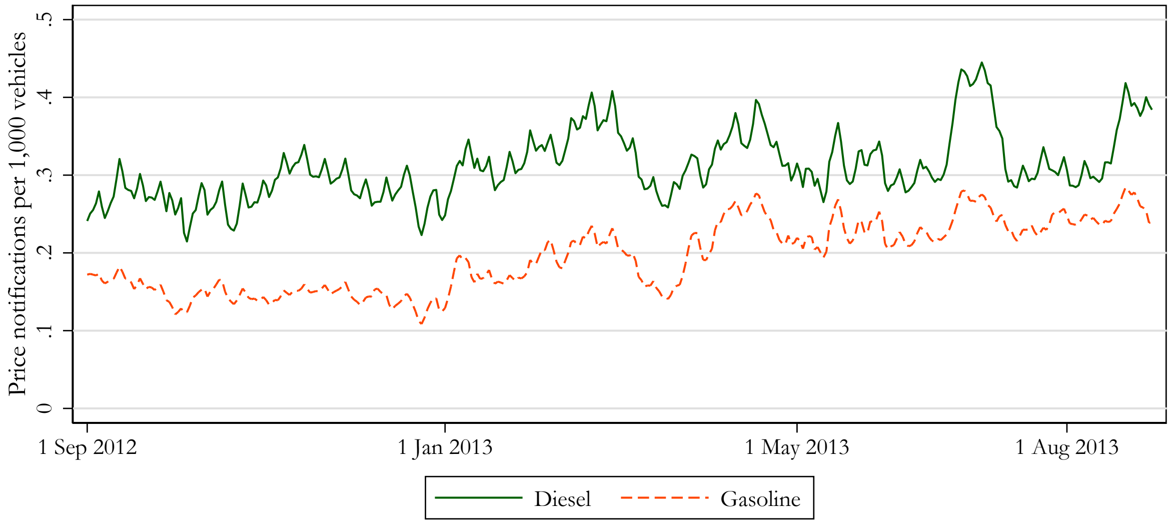
After the introduction of MPD, user reporting of prices became obsolete. Information on differences in app usage between drivers of vehicles of each fuel type can nevertheless provide evidence on their relative differences in information levels. To this end, we use data on search queries from a major app providing fuel prices in Germany in 2015. Figure 4 shows the number of daily unique users searching for gasoline and diesel prices per 1,000 vehicles of the particular fuel type in circulation. These data are 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 and consistent with Prediction 1, the share of searchers is higher among diesel than among gasoline drivers.

Next, we investigate the intensive margin of price search, namely, whether there are differences in the number of price searches per user. Figure 5 shows the average number

[18] An alternative that would lead to the same result would be to hold the clearinghouse access costs fixed and assume that υ is higher for diesel drivers because they buy more fuel every month. The drawback of this approach is that a unit would then become the monthly fuel consumption instead of a single liter of fuel. Our approach more closely maps to the empirical analysis we can perform.

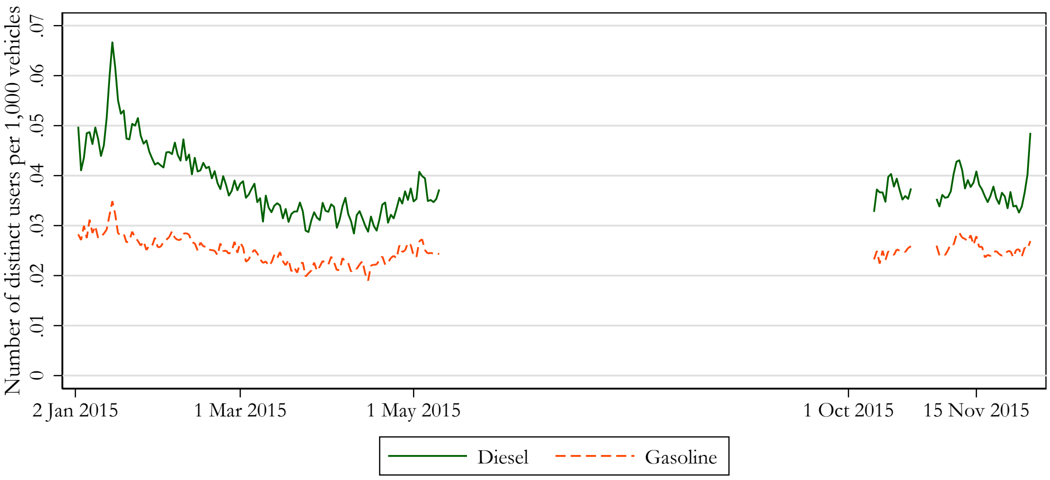
[19] From the count of price notifications, we drop all instances when *E5* gasoline, *E10* gasoline and diesel prices are reported in the same minute for the same station since these are likely prices self-reported by stations, not reported by motorists. Sixteen percent of all the price notifications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

Figure 3: Price notification patterns, pre-MPD (Germany)



Notes: The figure shows the daily number of price notifications by fuel type reported by individual users to a major German smartphone app per 1,000 diesel or gasoline vehicles in circulation. The data are 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.

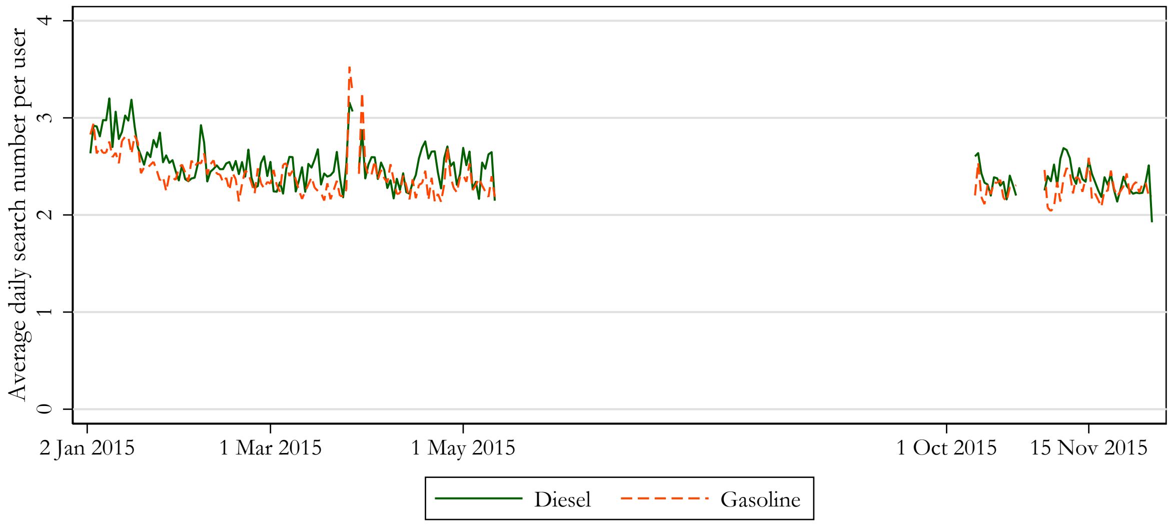
Figure 4: Unique daily price searchers by fuel type, post-MPD (Germany)



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

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

Figure 5: Average daily number of searches per user by fuel type, post-MPD (Germany)



Notes: The figure shows the daily number of price searches by fuel type on a major German smartphone app per 1,000 diesel or gasoline vehicles in circulation. The data are from 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.

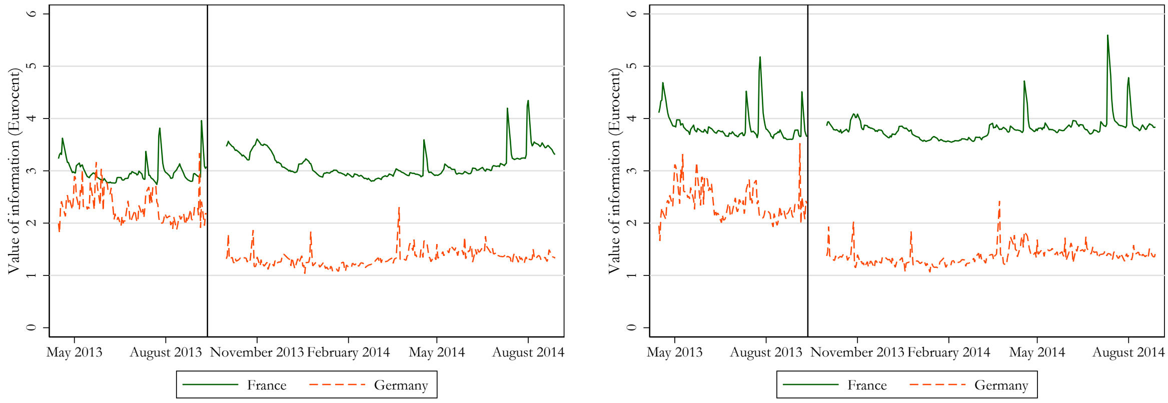
4.2 Mandatory price disclosure and the value of information

To analyze the effect of MPD on price dispersion, we construct overlapping markets of 5 km driving distance using the road network around a focal fuel station. For every market, we calculate the VOI as the difference between the average price and the minimum price at 5 pm on a particular day. This is the expected per-liter savings of a motorist who buys at the lowest price in the local market instead of at a randomly drawn price.

Figure 6 plots the average VOI in Germany and France before and after the introduction of MPD for gasoline and diesel. For both fuel types, MPD led to a decrease in the VOI, which, according to Prediction 3, suggests that the share of ex ante informed consumers is greater than $\hat{\mu}$.

Furthermore, the decrease in the VOI is larger for gasoline (with a lower μ_0) than diesel (with a higher μ_0). Recall that, according to Prediction 2, if $\hat{\mu} < \mu_0$, the lower is μ_0, the larger is the increase in the share of informed consumers following a decrease in the clearinghouse access costs, and hence the stronger is the decrease in VOI and prices. According to Prediction 4, the lower μ_0 is, the smaller is the decrease in the VOI and the average price. Therefore, if the VOI decreases to a greater extent the lower μ_0 is, the former effect dominates, and we should also expect a larger price decrease under MPD for gasoline than for diesel.

Figure 6: Effect of mandatory price disclosure on the value of information



(a) Gasoline **(b)** Diesel

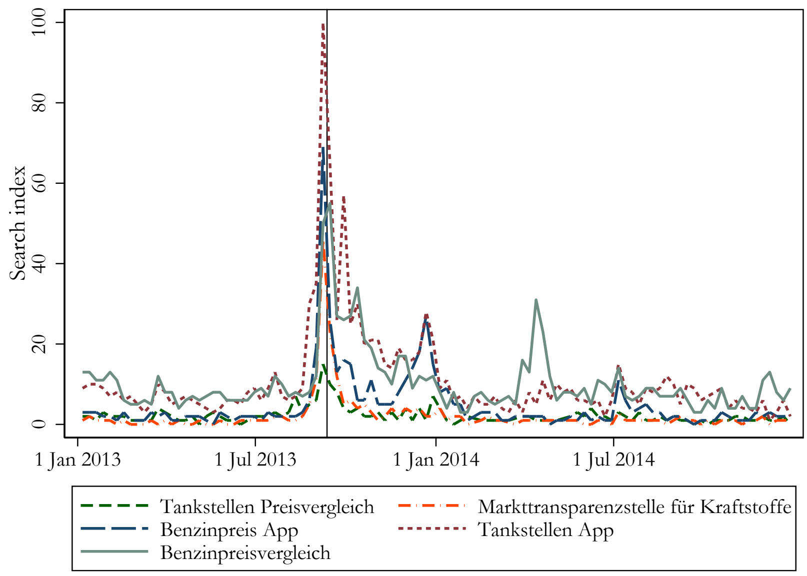
Notes: Panel (a) shows the value of information, defined as the difference between the within-market average and minimum price, for gasoline in Germany and France. Panel (b) shows the VOI for diesel in Germany and France. The vertical line represents the introduction of MPD in Germany.

4.3 Treatment intensity over time

Next, we analyze the treatment intensity and usage of price information over time. Figure 7 plots the search index for different keywords surrounding MPD, 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 with the most search queries. Searches for all keywords peaked in mid-September, when MPD began. Whereas searches for the market transparency unit itself declined again quickly, searches for "*Tankstellen App*" (fuel station app), "*Benzinpreis App*" (fuel price app), or "*Benzinpreisvergleich*" (fuel price comparison) remained high until mid-January 2014.

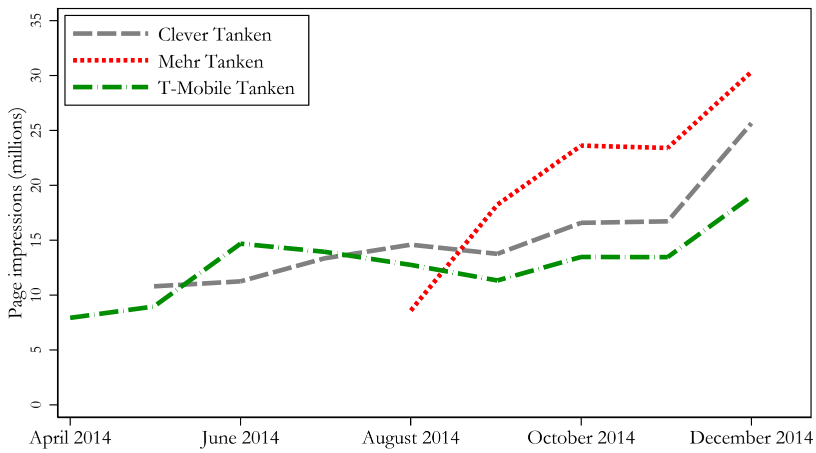
Figure 8 shows the evolution of monthly page impressions for three price comparison apps for which data are available starting from April 2014, which was after the period of high interest between September 2013 and January 2014 according to the Google search data. Using these trends to interpret the usage level of smartphone apps is difficult both because it is unclear how page impressions relate to the number of unique users and because these are just three out of 44 fuel price comparison apps registered in 2014. However, their continued usage between April and December 2014 does show that app usage did not stop shortly after the introduction of MPD.

Figure 7: 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 launch of the MTU.

Figure 8: Monthly page impressions

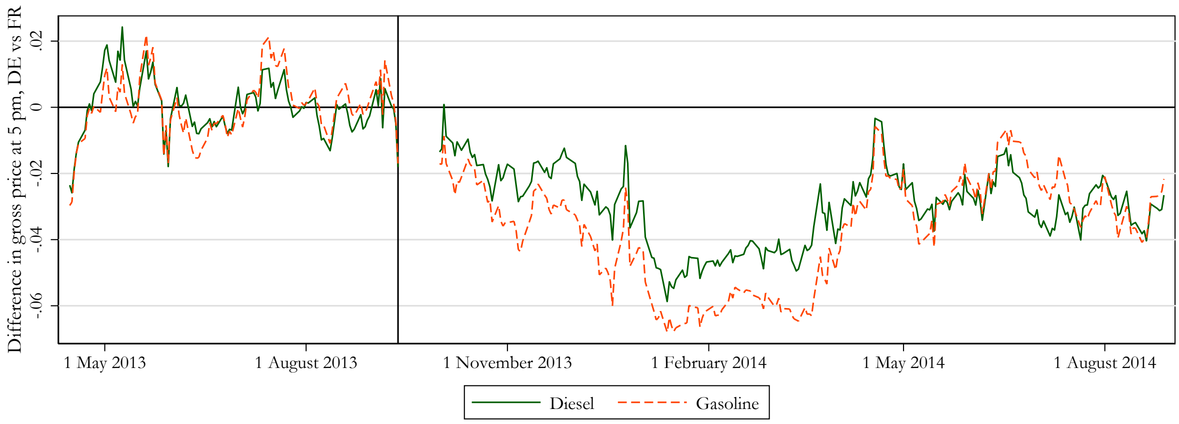


Notes: The figure shows the evolution of monthly page impressions for three popular mobile price comparison applications. Each line begins at the month when our data coverage for the particular app starts and ends at the end of our sample period, in December 2014.

4.4 Price effect of mandatory price disclosure

Finally, we turn to how mandatory price disclosure affects average diesel and gasoline prices over time. Figure 9 shows the evolution of gross prices in Germany relative to that of prices in 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, de-meaned by the average difference prior to MPD. The dashed line plots the same for gasoline.

Figure 9: De-meaned 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, de-meaned by the corresponding average difference prior to MPD. The dashed line shows the evolution of the analogous difference for gasoline. The vertical solid line marks the beginning of MPD.

Before MPD, the de-meaned price difference oscillated around zero for both fuel types. After MPD, prices fell more strongly for gasoline than for diesel. Given that the VOI fell more for gasoline, this is consistent with the stylized model.

The effect of MPD was strongest from January 2014 and weakened after May 2014. Thereafter, it stabilized at an economically significant level. This coincides with the public attention devoted to fuel price comparison apps shown in Figure 7. It suggests that public attention to the price information is key to exploiting the full potential of MPD.

5 Empirical Strategy

To unpack the mechanisms driving the price effect of MPD, we explore how it varies under different circumstances, such as between fuel types, with the number of competitors or when accompanied by a follow-on information campaign.

5.1 Identification strategy

Our main identification strategy relies on a synthetic difference-in-differences design in which we compare fuel prices at stations in Germany to those in France before and after MPD. Whenever this is infeasible, we use a traditional difference-in-differences approach.

SDID combines the advantages of difference-in-differences with those of synthetic control methods (see Arkhangelsky et al., 2021). 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 reweights units in the control group to make the pretrends 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 the pretreatment time periods. The SDID unit weights are designed to minimize the difference in pretrends of outcomes between the exposed and unexposed units. The SDID time weights are set to balance the time periods before and after the treatment for the control units and emphasize the pretreatment time periods most predictive of the post-treatment periods. In the second step, we estimate the treatment effect using the unit and time weights from the first step.[20] Standard errors are computed from 200 bootstrap draws.

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 MPD and $\hat{w}_i$ and $\hat{\tau}_t$ are the 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 MPD.[21]

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 with no missing weekly price observations.[22] These correspond to 47% of the

[20] In Appendix B, we show the geographic distribution of control stations that receive a disproportionately higher unit weight in the 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 the reweighting in SDID does not affect our results.

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

[22] We use 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.

stations in Germany and 94% of the stations in France.

This restriction raises two potential concerns: First, dropping 53% of the German stations in our data may lead to selection bias. Second, that we are missing at least one week of price data for 53% of the German stations is a reminder that the data for the pre-MPD period in Germany are a user-reported subsample of prices that could also suffer from selection bias. To address the first concern, we estimate the effect of MPD using regular difference-in-differences and the full, unbalanced panel with daily price observations. To deal with the second concern, we use the country-level weekly fuel prices for all countries in the European Union published by the European Commission in its *Weekly Oil Bulletin*. We use this alternative aggregate administrative data source that does not change around the time of MPD to estimate a difference-in-differences model where we treat Germany as the treatment group and all other countries in the European Union as the control group. Our results under both of these alternative strategies are robust and are reported in Appendix C.

5.2 France as control group

We identify the effect of MPD using the evolution of fuel prices at fuel stations in France for comparison. Two assumptions must be met to identify the effect of MPD in our framework: The first is that no transitory shocks other than MPD itself affected fuel stations in France and Germany differently before and after the introduction of MPD. The second is that there were no spillovers from the treatment to the control group.

Our station fixed effects capture time-invariant differences between fuel stations in France and Germany. Our week fixed effects capture transitory shocks that affected French and German fuel stations equally. Given the two countries' similarity in size, wealth and geographic location and our narrow observation period, there should not have been any additional transitory demand and supply shocks that affected 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 in much the same way. Given the countries' 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 that customs, border controls and other regulatory hurdles do not restrict arbitrage possibilities between the two countries. To nevertheless ensure we eliminate any transitory shocks to input prices and 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.

A further benefit of our using fuel stations in France as a control group is that 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 should thus not have affected different French fuel stations differently over our observation period. In contrast to other countries, France, similarly to Germany, did not restrict its fuel stations in their price-setting behavior other than by imposing mandatory price disclosure.[23]

To test the robustness of the analysis to a more conservative interpretation of our identifying assumptions, we rerun our analysis for a subsample of the data around the France–Germany border, where economic conditions should be even more similar because of geographic proximity. First, we restrict our analysis to fuel stations that are 100 km to the left and right to the border. The fuel stations in the treatment and control groups are thus in the same economic area and exposed only to common transitory shocks. Second, to eliminate any potential spillover effects, we drop all fuel stations less than 20 km to the left and right of the border. We are left with a donut SDID comparing stations on both sides of the border that are geographically close but dropping stations that are potentially subject to spillover effects.

5.3 Role of prior information

To test the role of prior information, we estimate the effect of MPD separately for diesel and gasoline. A key advantage of this analysis is that the same stations sell the different fuel types. They therefore face the same number of local competitors and, more generally, the same supply-side conditions. To the extent that the differential reaction of consumers to MPD is not attributable to something other than ex ante information, we can learn how ex ante information impacts the effect of MPD through this comparison. Based on the stylized model and the descriptive evidence, we should expect a larger price effect of MPD in the gasoline market, where there are fewer ex ante informed consumers.

5.4 Treatment effect over time

Next, we set out to study the effect of MPD over time. We estimate the parameters of the following regression model:

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

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

where $ln(p_{it})$ is the logarithm of the monthly average fuel price at station i. β captures the effect of 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 include fuel station and month fixed effects.

This analysis allows us to understand whether the effect of MPD was short-lived around the time that it received public attention or rather was more persistent.

5.5 Market-level analysis

Prediction 5 indicates that MPD should have decreased the average price in a local market more than the minimum price. To test this prediction, we use the same overlapping 5 km driving-distance markets that we used to compute the VOI in Section 4.

We estimate the price effect of MPD on the average price and the minimum price using a difference-in-differences design that compares market-level prices in Germany and France. Each observation is the daily average price (minimum price) at 5 pm of a particular fuel type in a local market.

5.6 Supply-side factors

Although the stylized model makes no predictions on the role of supply-side factors that are empirically falsifiable with our data, it does highlight that supply-side factors play an important role in mediating the effect of MPD. For example, Predictions 6 and 7 show that the number of sellers shapes the price effects of MPD.

Although monopolists do not feature in the model, they are present in our application. A local monopolist does not face any competition from other stations, and so mandating price disclosure should not have an effect in such markets. In practice, we define a local monopolist as a station without a rival at a driving distance of up to 5 km.[24] Although it is reasonable to assume that a motorist who arrives at the station and whose only purpose is to buy fuel is not going to drive more than 5 km to the next station, this "local monopolist" may still very well face competition from other stations. For example, commuters who drive past this station and another station outside this radius on their daily route to work will consider both stations. Thus, we do not expect a null effect of MPD on stations without competitors within a 5 km driving distance.

[24] The empirical literature analyzing price dispersion in retail fuel markets defines geographic markets in different ways. For example, Chandra and Tappata (2011) consider 1 mile and 2 mile radiuses, while Barron, Taylor, and Umbeck (2004), Hosken, McMillan, and Taylor (2008) and Lewis (2008) consider a radius of 1.5 miles. Carranza, Clark, and Houde (2015) employ a clustering algorithm to create nonoverlapping markets.

To test the effect of MPD on local monopolists and the role of the number of sellers in mediating the price effects of MPD, we estimate how the effect of MPD varies with the number of local competitors.

Two further dimensions were key in the market investigation by the German Federal Cartel Office (2011) that preceded the introduction of MPD. First, there was the question of whether integrated competitors (i.e., firms that act as upstream suppliers of fuel and also operate refineries and downstream stations) harmed competition. Second, a subset of these vertically integrated competitors were identified as oligopolists wielding market power.[25] We therefore estimate whether the treatment effect varies if a station belongs to an integrated competitor or to an oligopolist.

5.7 Follow-on information campaigns

The descriptive evidence in Figure 9 suggests that the effect of MPD decreased over time. This decrease coincided with a decline in Google searches for MPD-related terms and presumably of public attention to the policy. Prediction 8 suggests that higher treatment intensity leads to larger MPD-induced price decreases. To test whether follow-on information campaigns can strengthen the treatment effect, we exploit the fact that some local radio stations started broadcasting local fuel prices over the air after the introduction of MPD.

We limit the burden on data collection by restricting our analysis of radio reports to those aired by stations in the state of Bavaria.[26] As described in Section 3, we identify four radio stations with segments recurring at least daily in which they broadcast the prices at the cheapest fuel stations in the reception area. Two of these radio stations were already broadcasting the lowest fuel prices among those called in by their listeners before MPD started. We exclude all fuel stations in these stations' reception areas from the analysis, as they were treated throughout the observation period. The two remaining radio stations are Radio Arabella, which started broadcasting fuel price segments on 25 April 2014, and Extra-Radio, which started its corresponding broadcasts on 2 February 2014.

Figure 10 shows the reception areas of Radio Arabella and Extra-Radio. For each fuel station, we know whether, on a particular day, it was within the reception area of a radio station broadcasting prices.

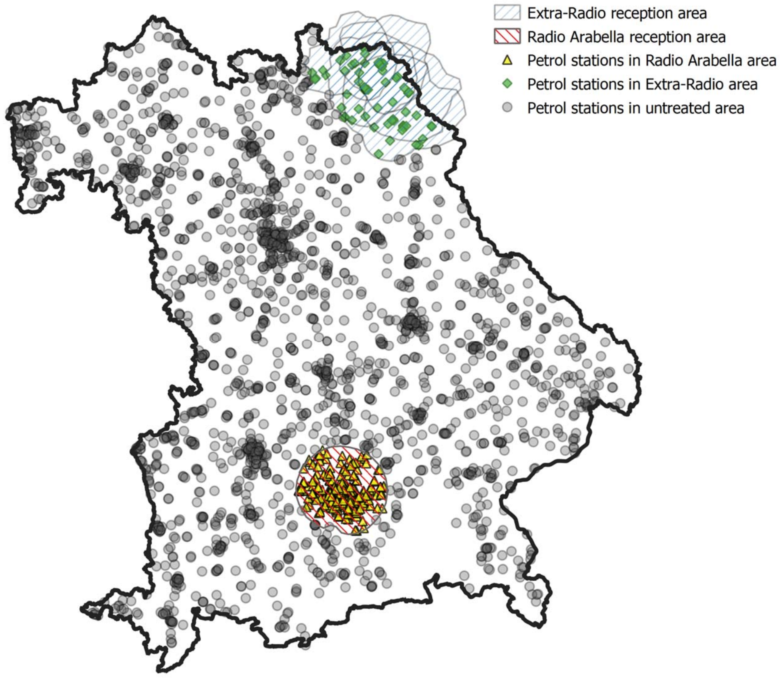
We estimate the parameters of the following regression model:

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

[25] These are BP, ConocoPhillips, ExxonMobil, Shell and Total.

[26] The fuel stations in the treatment and control groups for this exercise are therefore also all in Bavaria.

Figure 10: Radio reception areas and fuel stations in Bavaria



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 is fuel station fixed effects, and γ_t is date fixed effects.

Since our analysis is restricted to Bavaria, we can rule out that fuel stations in the control group were affected by reports by radio stations we did not survey. We restrict our analysis to the period October 2013 until September 2014, the twelve months after the beginning of MPD.

A potential threat to identification could be that radio stations anticipated a trend that would create local demand for reports about fuel prices and also affected fuel prices. This seems unlikely. After multiple interviews with program directors, we learned that the decision to broadcast fuel prices was based not on a market analysis but on the fit of such a segment within the station's existing programming.

In our treatment group, we consider radio reports about fuel prices from Extra-Radio, which broadcasts in and around Hof, a city in northeastern Bavaria close to the Czech border, and Radio Arabella, a radio station broadcasting in and around Munich. Whereas Extra-Radio broadcast 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 its reports went on until at least 2019.

To account for treatment effect heterogeneity, we estimate the regression model for both radio stations separately. In each regression, we exclude fuel stations within the reception area of the other radio station from the control group.

6 Results

This section presents the results of our empirical analysis. Our aim is to shed light on the mechanisms by which mandatory price disclosure affects prices.

6.1 MPD effect by fuel type

Table 2 shows the average effect of mandatory price disclosure by fuel type. Columns (1) and (2) present 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) present results where the sample is restricted to fuel stations 20 to 100 km from the France–Germany border.[27]

Consistent with the descriptive results in Section 4, the main takeaway is that MPD is successful at decreasing prices and that its effectiveness is higher for gasoline than for diesel. Since we observe a larger decrease in the VOI for gasoline, Predictions 2 and 4 suggest that we should also see a larger price effect of MPD for gasoline. This is because with a lower share of ex ante informed consumers, MPD increases the share of informed consumers by more than it would had the share of ex ante informed consumers been large already. Since the same fuel stations offer both diesel and gasoline, supply-side characteristics cannot explain these differences in the effect of MPD across the two fuel types.

An unobservable dimension along which the gasoline and diesel markets differ could be the usefulness of the information provided by MPD. It seems plausible that, since diesel drivers drive more, MPD is more useful to them and therefore reduces their clearinghouse access costs more. However, if this were the case, we should see a larger price effect of MPD for diesel than for gasoline. If anything, we are therefore underestimating the role that the ex ante share of informed consumers plays.

We report the effect of MPD on retail margins in Table C5 of Appendix C.5. We find that MPD decreases gasoline margins by approximately 3 eurocents and diesel margins by approximately 2 eurocents. For reference, according to the industry data provider Energie Informationsdienst (EID), gross margins were on average 10.7 eurocents for gasoline and 11.0 eurocents for diesel in the twelve-month period ending in August 2013.

To test the robustness of our results, we run additional checks whose results we summarize in Appendix C. First, we use the full, unbalanced sample of gasoline stations

[27]The results are robust to changes to the distance thresholds. We provide estimates from exercises with alternative thresholds in Appendix C.3.

Table 2: Effect of MPD on log gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.027***	-0.018***	-0.030***	-0.019***
	(0.0004)	(0.0004)	(0.0011)	(0.0014)
95% confidence interval	[-0.028, -0.027]	[-0.018, -0.017]	[-0.032, -0.027]	[-0.022, -0.016]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	647,500	768,550	50,400	56,500

Notes: Columns (1) and (2) present 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 km from the France–Germany border. The observation period is from 15 April 2013 to 31 March 2014. Standard errors are computed from 200 bootstrap draws and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

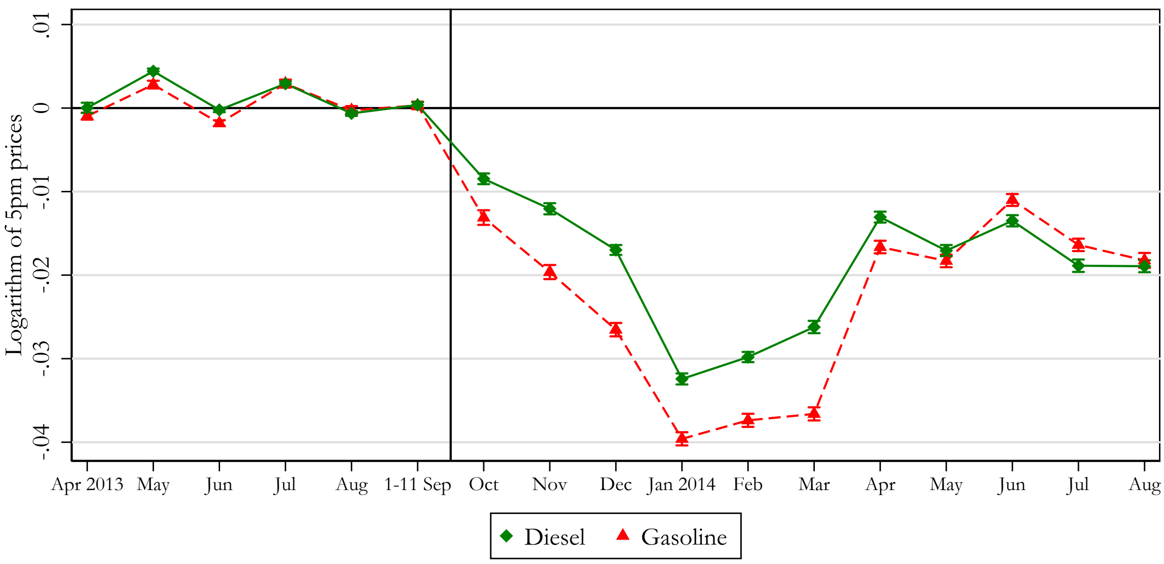
and a regular difference-in-differences estimator. Second, we estimate the donut SDID using alternative distance thresholds. Third, we control for an interaction of the crude oil price and a country dummy to allow for differential pass-through of crude oil shocks in each country. Fourth, we use country-level 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 the control group to estimate the effect of MPD for diesel and gasoline. Our results hold across all of these alternative specifications.

6.2 MPD effect over time

Figure 11 shows how the effect of mandatory price disclosure evolved over time. Fuel prices started dropping in the first month after the introduction of MPD. This coincides with the strong public interest in this policy exemplified in Figure 7. The effect intensified over time and was stronger for gasoline than for diesel.

The largest effect of MPD can be observed at January 2014, after which it dropped by approximately half. The decrease in the treatment effect was more pronounced for gasoline than for diesel. This coincides with the sharp drop in public attention to mandatory price disclosure shown by the evolution of Google queries in Figure 7. Thereafter, the effect of MPD stayed at a smaller but stable level. This is in line with evidence of stable and continuous use of price comparison apps after April 2014. The MPD-induced price effect stabilized at approximately the same percentage-point value for diesel and gasoline. As the price level of gasoline is higher than that of diesel, the long-term price effect in eurocents is stronger for gasoline than for diesel.

Figure 11: Time-varying effect of MPD on log gross prices



Notes: The figure shows the time-varying monthly treatment effects of MPD on log weekly prices for gasoline and diesel between April 2013 and August 2014 and includes 95% confidence intervals based on standard errors computed from 200 bootstrap draws. The vertical solid line marks the beginning of MPD.

6.3 MPD effect at the market level

Table 3 shows the results from the market-level analysis using overlapping 5 km driving-distance markets. Each observation is the market-level average or minimum price in Germany or France on a particular day.

The outcome variable in Columns (1) and (3) is the average price for gasoline and diesel, respectively. The outcome variable in Columns (2) and (4) is the respective minimum prices. Consistent with Prediction 5, MPD decreases the average price in a local market more than the minimum price.

Beyond lending support to the model, this finding also has distributional consequences. It means that MPD benefits previously uninformed consumers more than previously informed consumers through two channels: First, it turns uninformed consumers into informed consumers, who purchase at the minimum rather than the average posted price post-MPD. Second, it reduces the price paid by consumers who remain uninformed more than that paid by those who are always informed.

6.4 MPD effect under different supply-side conditions

Table 4 shows how the effect of MPD varies for gasoline and diesel between fuel stations that differ along supply-side conditions. Columns (1) and (4) show how the effect of MPD varies between stations with a different number of competitors within a 5 km radius. Whereas stations that do not have a competitor within a 5 km radius still lower

Table 3: Effect of MPD on log market-level prices

	Gasoline		Diesel	
	(1)	(2)	(3)	(4)
Outcome variable:	Average	Minimum	Average	Minimum
MPD	-0.030***	-0.024***	-0.024***	-0.018***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	5,320,971	5,320,971	5,408,420	5,408,420
Adjusted R^2	0.855	0.810	0.805	0.784

Notes: Columns (1) and (3) present estimates of the effect of MPD on log daily average prices for gasoline and diesel, respectively, at the market level in Germany and France. Columns (2) and (4) present estimates of the effect of MPD on log daily market-level minimum prices. Standard errors clustered at the market level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

their price in response to MPD, this effect intensifies the more local competitors there are. Although it may at first seem surprising that stations without a nearby competitor are affected by MPD, it makes sense since such stations also compete with other stations that are further away but passed by many of the same drivers on the same route (e.g., during their daily commute).

We also investigate the role of vertical integration and of oligopoly. We find no statistically significant difference in the effect of MPD between vertically integrated and nonintegrated stations. However, we do find a stronger effect of MPD on the subset of stations that the German Federal Cartel Office (2011) classified as vertically integrated oligopolists. Though small in magnitude (approximately 10% of the overall treatment effect), this is an encouraging finding for this particular policy measure, as its aim was to rein in some of the market power allegedly held by these oligopolists.

6.5 Effect of follow-on radio reports

In Table 5, we report the results from a regression of the logarithm of prices on our indicators for stations in the reception areas for local radio reports about fuel prices. Columns (1) and (2) present the results of the effect of reports by Extra-Radio and Radio Arabella on gasoline prices. Columns (3) and (4) present the corresponding results for diesel.

We find that whereas reports by Radio Arabella lead to lower fuel prices, this is not the case for Extra-Radio. There are several plausible explanations for why this is the case. First, Radio Arabella has a listenership of approximately $100,000$ listeners on average per hour and reaches 14% of the population above age 14 in and around Munich,

Table 4: Effect of MPD under different supply-side conditions

	Gasoline	Diesel	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)	(5)	(6)
MPD	-0.022***	-0.020***	-0.024***	-0.022***	-0.023***	-0.021***
	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
MPD×1 Rival	-0.000	-0.000				
	(0.0004)	(0.0005)				
MPD×2 Rivals	-0.001**	-0.001**				
	(0.0004)	(0.0005)				
MPD×3 Rivals	-0.002***	-0.002***				
	(0.0004)	(0.0005)				
MPD×4 Rivals	-0.001***	-0.001**				
	(0.0004)	(0.0005)				
MPD×5+ Rivals	-0.003***	-0.002***				
	(0.0003)	(0.0004)				
MPD×Integrated			0.000	0.000		
			(0.0002)	(0.0002)		
MPD×Oligopolist					-0.001***	-0.002***
					(0.0002)	(0.0002)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	6,256,791	7,141,675	6,256,791	7,141,675	6,256,791	7,141,675

Columns (1) and (2) present estimates of the effect of MPD on log weekly prices for gasoline and diesel, respectively, interacted with the number of competitors in a 5 km radius around the focal station. Columns (3) and (4) present the results for the interaction of MPD with an indicator for whether a station is integrated. Columns (5) and (6) present the results for the interaction of MPD with an indicator for whether the station belongs to an oligopolist. The observation period is from 15 April 2013 to 31 March 2014. Standard errors are clustered at the station level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Effect of radio reports on log 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***
	(0.0026)	(0.0004)	(0.0024)	(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 with those at other fuel stations in Bavaria before and after the beginning of the radio reports. Columns (2) and (4) do the same for the stations in the reception areas of Radio Arabella. Standard errors clustered at the fuel station level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

while Extra-Radio has approximately $10,000$ listeners on average per hour and reaches 9% of the population above age 14 in and around Hof (Kantar, 2018).[28] Whereas Radio Arabella is the most listened-to local radio station in the Bavarian capital, Extra-Radio is the second most listened-to radio station in Hof.

Second, the reception area of Extra-Radio lies on the border of the Czech Republic, where fuel is approximately 20 eurocents cheaper. Radio reports about the cheapest fuel station on the German side of the border might therefore be less relevant for price-sensitive consumers.

A second finding is that the price effect on diesel is larger than that on gasoline. Through the lens of the stylized model, this should be the case when the effect of a larger price decrease from a marginal increase in μ in markets with a higher μ_0 (Prediction 4) is quantitatively more important than the effect of a larger increase in the share of informed consumers in response to a marginal decrease in clearinghouse access costs (Prediction 2).

Overall, we find that follow-on radio reports can intensify the treatment effect and lead to a further decrease in prices.

7 Discussion and policy implications

When and how can mandatory price disclosure policies be used to lower prices? We synthesize the results from our analysis with findings in the literature to identify key

[28]The average listenership per hour refers to weekdays between 6 am and 6 pm.

factors that determine the effect of MPD. We begin by discussing factors that may help assess whether MPD is likely to benefit consumers in a particular setting. Then, we discuss how the design of MPD can help make it successful.

Prior consumer information. The larger price effect of MPD for gasoline than for diesel suggests that the effect of increasing price transparency is larger in populations that are relatively less informed ex ante. This seems quite logical if one considers the need for at least some consumers to be uninformed for the price information to turn uninformed consumers into informed ones. The more uninformed consumers there are, the more consumers can potentially be converted into informed consumers by MPD. There is one important qualification: although the presence of uninformed consumers is a prerequisite for MPD to benefit consumers, it is not sufficient for this to occur. As we discuss below, it is also important to gauge whether previously uninformed consumers will take advantage of this new information.

Prior seller information. Though Green and Porter (1984) show theoretically that collusion can be stable even under imperfect observability of the actions of rivals, improving this observability makes the need for low-price punishment phases rarer and therefore increases prices. Empirically, Albæk, Møllgaard, and Overgaard (1997) show how an increase in price transparency among producers in the Danish ready-mix concrete industry facilitated price coordination and led to higher prices. Byrne and de Roos (2019) show that (tacit) coordination occurs in retail fuel markets, and Luco (2019) finds that prices in the Chilean retail fuel market increased after MPD.

Despite the negative findings in other settings, we find that MPD in Germany decreased prices. A major difference between our setting and the Danish ready-mix concrete industry or the Chilean retail fuel market is that price transparency in Germany was already very high before MPD. The German Federal Cartel Office (2011) notes that price transparency pre-MPD was highly asymmetric: Whereas consumers and independent fuel stations had to incur high search costs to learn about prices, the vertically integrated oligopolists had employees at their own fuel stations and at franchisee stations report local competitor prices to the oligopolists multiple times per day. This suggests that the limited risk of increasing price transparency for sellers was a crucial success factor in the German setting.

A flip-side implication of this could be that there are benefits to limiting price transparency on the seller side. Here, a cautionary tale is offered by Byrne et al. (2023). They show that when the *Informed Sources* antitrust case in the Australian retail gasoline market led to one player's being excluded from the price information sharing facility (whereas its prices were still observable by the other players), the asymmetric information sharing let the excluded player credibly commit to higher prices and increased equilibrium prices and profits.

Supply-side factors. Our empirical results show that supply-side factors play a key role in mediating the effect of MPD. Although we find that even local monopolists reduced their prices in response to MPD since they compete with other stations further away but on drivers' same route, we find that, the more local competitors there are, the higher is the price reduction in response to MPD. Relatedly, Fischer, Martin, and Schmidt-Dengler (2023) find that entry by a new station in a local retail fuel market decreases prices, especially at the lower end of the local price distribution.[29]

Another key finding is that oligopolist stations reduced their prices more than other stations. To the extent that the former enjoyed higher margins pre-MPD, this seems plausible since a price decrease requires a margin for the station to absorb this decrease without incurring losses. An obvious takeaway is that for MPD to lead to price decreases, there needs to be supracompetitive prices pre-MPD. More importantly, however, it seems that using MPD to lower prices works better in markets with more competitors.

Price dispersion. A post-MPD increase in price dispersion, as measured by the VOI, is not a sign of failure of the policy. Although it might seem intuitive that the VOI should decrease if MPD is to lower prices, the stylized model shows that, at most levels of ex ante informed consumers, a marginal increase in the share of informed consumers leads to an increase in the VOI while at the same time decreasing the price paid by informed and uninformed consumers.

Information uptake. As noted by Byrne et al. (2023), a second remedy by the Australian Competition and Consumer Commission (ACCC) in the *Informed Sources* case was that the price information would have to be made available to third parties "on reasonable commercial terms." Byrne et al. (2023) note that there was no entry from price comparison apps through this channel. They explain that there already existed an incumbent price comparison app relying on consumer-reported prices but that even this app had very low adoption rates. Luco (2019) also reports that, in Chile, where MPD softened competition, consumer search after MPD remained low. On average, there were only 87 search requests within a 1 km radius of a station per month.

In contrast, adoption of price comparison apps in Germany was high. For the three apps for which we can report aggregate usage statistics in Figure 8 (out of the 44 apps and websites registered to connect to the MTU's database), there were more than 70 million monthly page impressions in December 2014. Information uptake appears to play an important role in the price effects of MPD. Before introducing MPD, policymakers could gauge consumers' willingness to use this information through surveys or their use of price comparison apps in other markets and check whether the conditions necessary for the adoption of the price information (e.g., widespread smartphone adoption, availability of mobile internet on driving routes) are fulfilled.

Low entry barriers for consumer apps. Whereas low expected adoption by

[29] Haucap, Heimeshoff, and Siekmann (2017) find that fuel stations with more local competitors tend to have more heterogeneous prices.

consumers might have deterred Australian app developers from creating fuel price comparison apps, another reason for such a dearth of new apps could be barriers to entry. The ACCC's mandate that *Informed Sources* make the data available "on reasonable commercial terms" suggests that app developers would have to pay for data access, allowing *Informed Sources* to create administrative barriers to entry. In contrast, the GFCO set up the MTU, which allows any app developer interested in diffusing this information to request registration. The only requirement is that applicants describe how the data will be used to inform consumers. Thereafter, developers can connect to the database via an API. In December 2013, three months after the start of MPD, there were 9 registered apps and websites. A year later, in December 2014, there were 44 registered apps and websites. Ten years later, in December 2023, there remain 43 registered apps and websites. Low barriers to entry for app developers thus appear to facilitate the creation of such apps.

Maintain attention. What else could policymakers do to encourage consumers to search? In Figure 11, we show that the MPD-induced price decrease was strongest a few months after the policy was launched and then prices stabilized at a lower level. This coincided with a drop in public attention to MPD. Our finding of a persistent long-term effect of MPD after attention to MPD was high in its initial phase is in line with what Byrne and de Roos (2022) dub "startup search costs". A large exogenous shock to consumers' search incentives (in their case a temporary increase in price dispersion) can lead to a persistent increase in price search even when this incentive subsides. In the case of MPD, this means that a temporary increase in attention to the availability of price comparison apps (e.g., through a temporary information campaign) can change habits and permanently increase such apps' usage beyond their counterfactual level had the information been made available without an information campaign.

Our results on the price effects of follow-on radio reports suggest that such information campaigns can have an impact on local prices and lead to a price decrease beyond the effect of simply making price data available. Taken together, these results indicate that information campaigns that remind consumers of the existence of price comparison apps or present them with the price information itself could lead to further permanent price decreases.

Limited price display. The price disclosure policies in Australia, Chile and Germany have the aim of diffusing information about all prices to consumers. Martin (Forthcoming) studies an alternative design used in Austria, where only the lowest 50% of fuel prices in a local market are displayed to consumers. He uses price data for Germany and a model with endogenous search and pricing to study what share of prices displayed to consumers leads to the lowest price level. He finds that showing all prices is not optimal for consumers and that showing only the lowest 20% of prices maximizes consumer welfare. Overall, he finds an inverse U-shaped relationship between price transparency and consumer welfare.

This inverse U-shaped relationship arises from two effects that can go in opposite directions: First, there is a *matching effect*, where consumers would like to be matched with the best station for them on the basis not only of price but also of other characteristics such as travel distance. Not showing the price at a particularly close station with a price just outside the range of the lowest-price stations can harm consumers. Second, there is an *attention effect*. Limiting the share of prices shown induces sellers to compete more intensely to be included in the displayed results. Whereas the exact share of prices that should be displayed to maximize consumer welfare will depend on the particular application and parameter values, the study holds an important message for policymakers. Limiting the share of prices displayed can magnify the effect of MPD on consumers beyond that of a full-information design.

8 Conclusion

The aim of the paper is to shed light on what factors lead mandatory price disclosure to be beneficial to consumers. We specify a stylized model featuring homogeneous good sellers and buyers who are uninformed about prices but can purchase access to an information clearinghouse. We use the model to simulate how market conditions mediate the effect of MPD.

We complement this with an empirical analysis of the introduction of MPD in the German retail fuel market. A key feature of the setting is that we have granular station-level prices from before and after the policy change and for a control country. Another key feature is that variation in fuel types, the number of sellers, and complementary information campaigns allow us to conduct a rich study of mechanisms.

We find that MPD in the German retail fuel market reduced price dispersion and the overall price level. It was particularly successful in markets with a lower share of ex ante informed consumers, in markets with a higher number of sellers, and when accompanied by complementary information campaigns.

Although our results, together with other findings in the literature, paint a much clearer picture of when we should expect MPD to benefit consumers, there is still much scope for future research. In particular, empirical applications in which there exist more direct measures of how MPD affects the share of informed consumers could help shed further light on the mechanisms underlying its effects.

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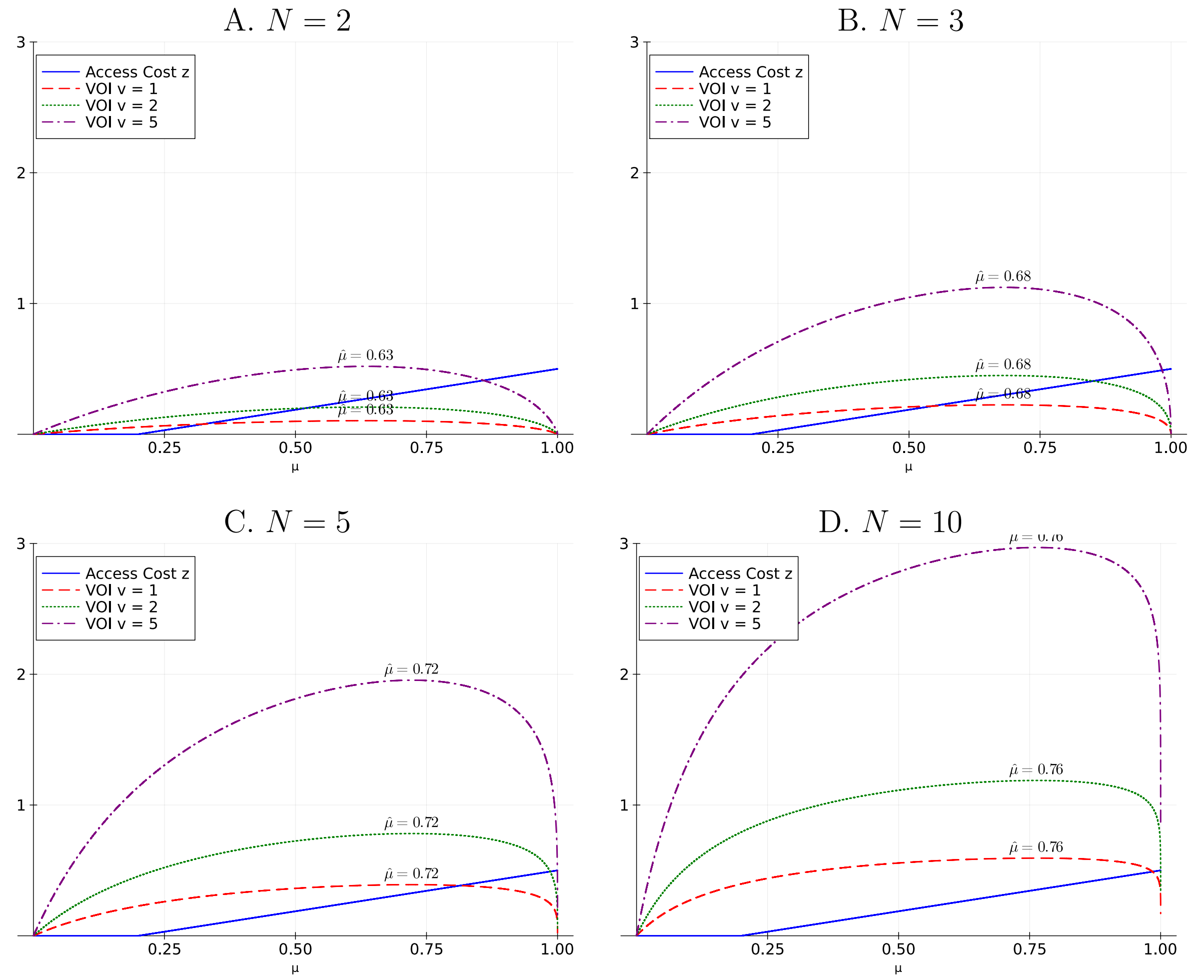
Appendix

A Appendix to Section 2: Theoretical Model

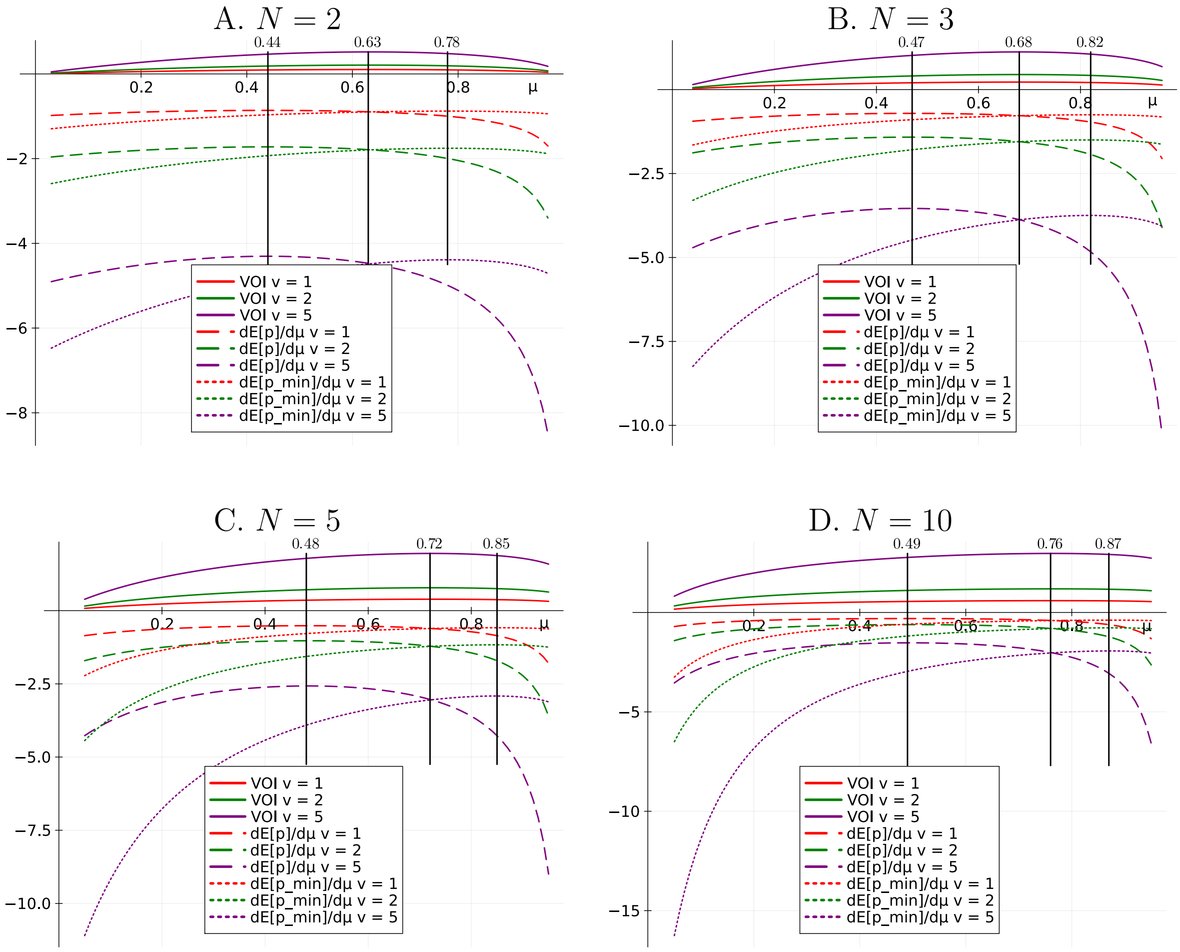
A.1 Further simulations

Figure A1: VOI and clearinghouse access costs by share of informed consumers



Notes: The figure shows simulations of the VOI and the clearinghouse access costs by the share of *informed* consumers. The clearinghouse access costs are for the marginal consumer if all consumers with lower costs purchase clearinghouse access. We use the following parameter values in the simulations: $v = 1$, $\lambda = 0.2$, and a uniform distribution of access costs between 0 and 1 for all *nonshoppers*. Panel A uses $N = 2$, Panel B uses $N = 3$, Panel C uses $N = 5$, and Panel D uses $N = 10$.

Figure A2: VOI and marginal price effect by share of informed consumers



Notes: The figure shows simulations of the VOI and the change in $E[p]$ and $E[p_{min}]$ for a marginal increase in μ by the share of *informed* consumers. We use $\upsilon = 1$ in all simulations. Panel A uses $N = 2$, Panel B uses $N = 3$, Panel C uses $N = 5$, and Panel D uses $N = 10$.

B Appendix to Section 3: Institutional Setting

B.1 Retail margins and fuel station characteristics in Germany

Figure B1 shows the distribution of fuel stations in Germany over our sample period. Fuel stations are spread across the country and clustered around urban areas.

Figure B1: Distribution of fuel stations across Germany

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

Table B1 shows the share of stations in Germany by brand and the share of nonintegrated stations before and after the introduction of MPD. Overall, the brand composition before and after MPD is very similar.

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 actually do so. Whereas fuel stations in Germany changed their prices on average four times a day over our observation period, French fuel stations changed prices less than once a day.[30] Since we do not observe volume data, we cannot compute volume-weighted average fuel prices or retail margins over the day. We can 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, 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.

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

Table B1: 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
Nonintegrated	34.9	41

Notes: The "Pre-MPD" column shows the share of fuel stations by brand in the sample for Germany before the introduction of the MPD. The "Post-MPD" column shows the corresponding share after the introduction of MPD. We consider all fuel stations with at least one price entry in the sample before and after the launch of MPD, respectively.

We choose to use prices at 5 pm in our analysis, and we construct stations' 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 approximately 60% 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% of respondents buy fuel before 10 am.[31] 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 around 8 pm.[32] This suggests that consumers are aware of these price cycles and fuel during the low-price period in the late afternoon.[33] 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.

To construct retail margins based on prices at 5 pm, first, we subtract taxes and levies to compute net fuel prices. Second, we subtract daily market prices for refined oil at the port of Rotterdam to obtain a proxy for retail margins. In Germany, taxes and levies include a lump-sum energy tax, a value-added tax, and an oil storage levy per liter of fuel. In 2013 and 2014, the lump-sum energy tax was 65.45 eurocents per liter for gasoline and 47.04 for diesel. The oil storage levy was at 0.27 eurocents per liter for gasoline and 0.30 eurocents per liter for diesel. The value-added tax rate was 19%.[34] In

[31] The daily fueling patterns are described in detail in Figure B5 in Appendix B.1.

[32] This is consistent with the pricing patterns in the data described in Figure B6 in Appendix B.1.

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

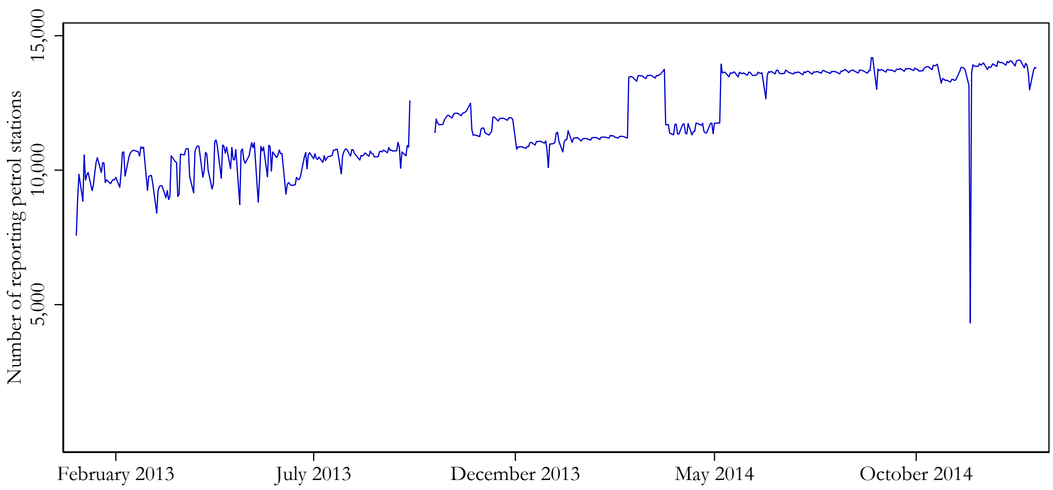
[34] See https://en2x.de/wp-content/uploads/2021/11/MWV_Mineraloelwirtschaftsverband-e.V.-

France, fuel products are subject to a lump-sum tax. In 2013 and 2014, the lump-sum tax was between 40 and 62 eurocents per liter, depending on the metropolitan region and fuel type.[35] In addition, the VAT rate in mainland France was 19.6% in 2013 and 20% in 2014. We exclude fuel stations located outside mainland France from our analysis.

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

Figure B2 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 MPD introduction. For most days in the pre-MPD period, we have prices for approximately $12,000$ fuel stations in our panel. This number stays approximately the same for the period after the introduction of MPD and increases only to approximately $13,500$ for the period from the end of February 2014, when the reporting issues of Total and Esso stopped.[36] 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 B2: 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 B3 shows fewer price changes per day in our data prior to MPD than after MPD was introduced. This is because whereas for the period after the introduction of MPD we observe the universe of price changes in Germany, for the period before MPD

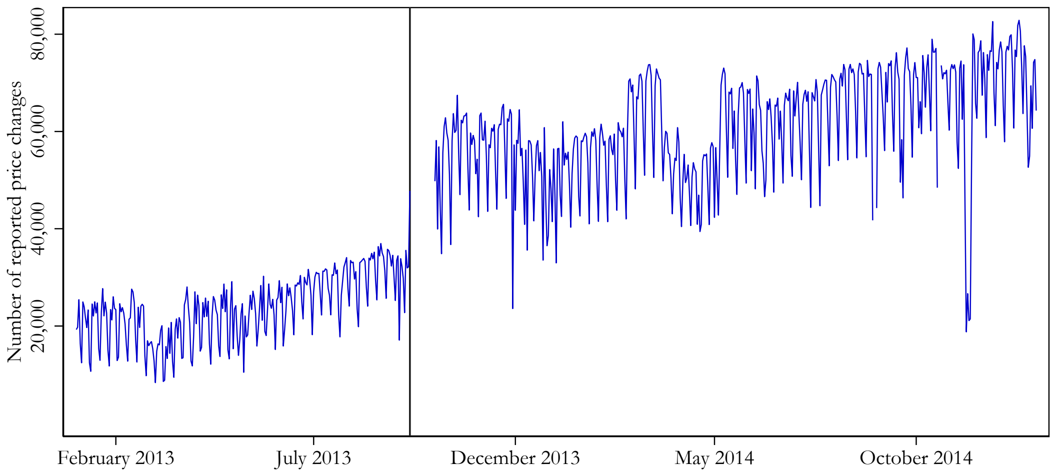
Jahresbericht-2020.pdf and https://www.ebv-oil.org/cms/cms2.asp?sid=77&nid=&cof=75.

[35]See https://www.douane.gouv.fr/la-douane/informations/bulletins-officiels-des-douanes.

[36]Total and Esso reported as normal in October 2013. Esso reported only a very limited number of prices between November 2013 and mid-February 2014. Total reported only a very limited number of prices between December 2013 and mid-February 2014. Both experienced reporting issues in April 2014, after which they returned to full reporting.

we observe only the subset of prices reported by users to the app.

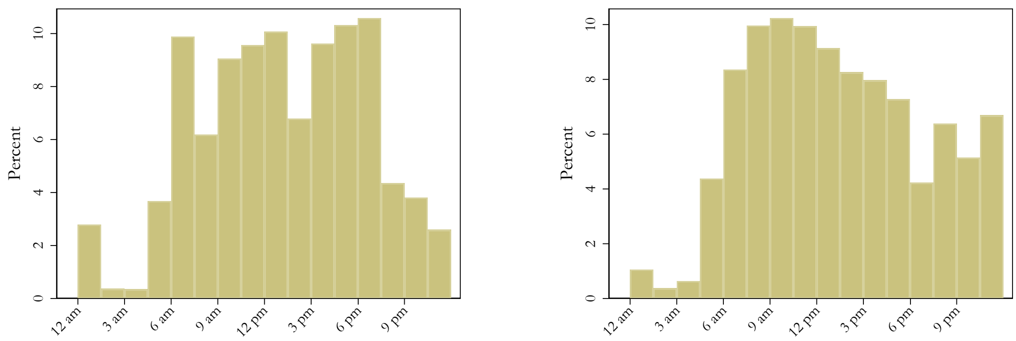
Figure B3: Number of daily price changes



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

Figure B4 shows the number of notifications of price changes over the day before and after the introduction of MPD. Whereas before MPD there was a notification every time a user of the app reported a price, under MPD there is a notification every time there is a price change.

Figure B4: Notification patterns over the day

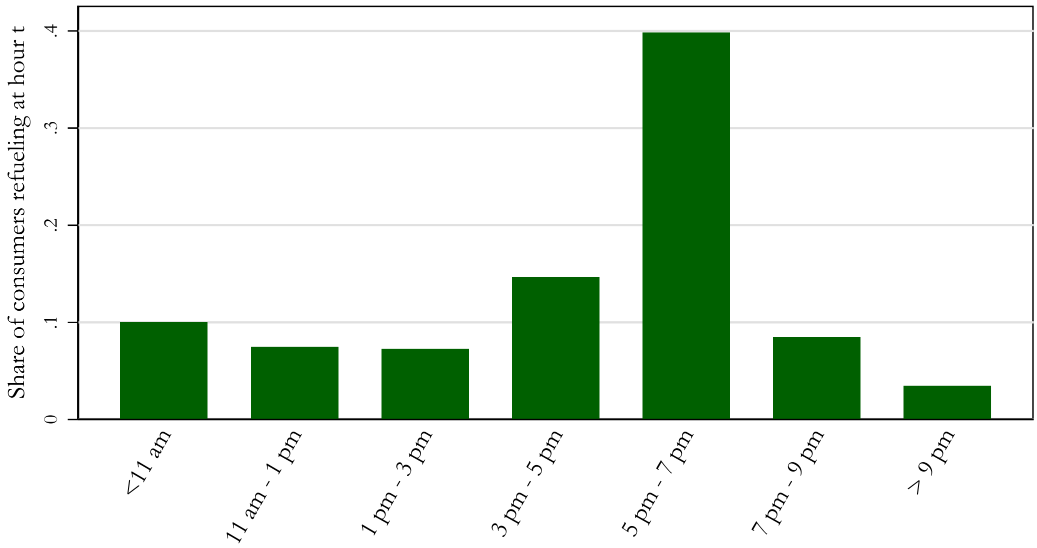


(a) Pre-MPD **(b)** Post-MPD

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

Figure B5 shows the hourly fueling 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.

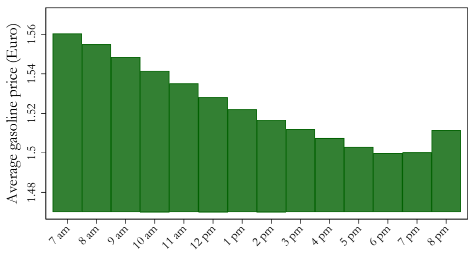
Figure B5: Daily fueling patterns



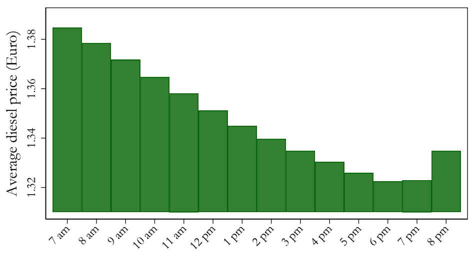
Notes: The figure shows the average fueling patterns of German motorists over the day. Data are based on a representative survey of drivers commissioned by the German Federal Ministry of Economic Affairs.

The fueling patterns are also consistent with the price patterns reported in Figure B6. Whereas gasoline and diesel prices are highest in the morning, they fall during the day until the early evening and start rising again around 8 pm.

Figure B6: 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.

C Appendix to Section 6: Results

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

Table C1: Effect of MPD on log gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.030***	-0.024***	-0.031***	-0.028***
	(0.0002)	(0.0002)	(0.0007)	(0.0005)
Date FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	4,128,744	4,727,297	359,372	389,625
Adjusted R^2	0.831	0.806	0.815	0.744

Notes: Columns (1) and (2) present 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) present the same estimates for a restricted sample of fuel stations 20 to 100 km from the France–Germany border. The observation periods is from 15 April 2013 to 31 March 2014. Standard errors are clustered at the fuel station level and are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1 Difference-in-differences analysis

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

$$Y_{it} = \beta_0 + \beta_1 MPD_{it} + \mu_i + \gamma_t + \epsilon_{it}, \tag{C1}$$

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 requirement has applied to all fuel stations in Germany since 1 October 2013. μ_i is fuel station fixed effects, and γ_t is date fixed effects.

Table C1 reports the effects of MPD estimated with Equation C1. The outcome variable in all columns is log 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 C1 are based on the full, unbalanced panel. Columns (3) and (4) report estimates when we use only data on stations located within 20 to 100 km of the France–Germany border.

Table C1 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 SDID results, remain larger for gasoline.

C.2 Daily average prices weighted by hour

We repeat the estimation of the parameters in Equation 1 using daily average prices weighted by the share of consumers refueling at that particular hour as reported in Figure

Table C2: Effect of MPD on log daily weighted average price

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.024***	-0.014***	-0.025***	-0.014***
	(0.0004)	(0.0004)	(0.0009)	(0.0013)
95% Confidence interval	[-0.025, -0.023]	[-0.015, -0.013]	[-0.027, -0.023]	[-0.016, -0.011]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	647,500	768,550	50,400	56,500

Notes: Columns (1) and (2) present 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) present the same estimates for a restricted sample of fuel stations 20 to 100 km from the France–Germany border. The observation period is from 15 April 2013 to 31 March 2014. We compute the daily average weighted price by weighting the hourly prices by the share of consumers refueling at a particular time as reported in Figure B5. Standard errors computed from 200 bootstrap draws are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B5.

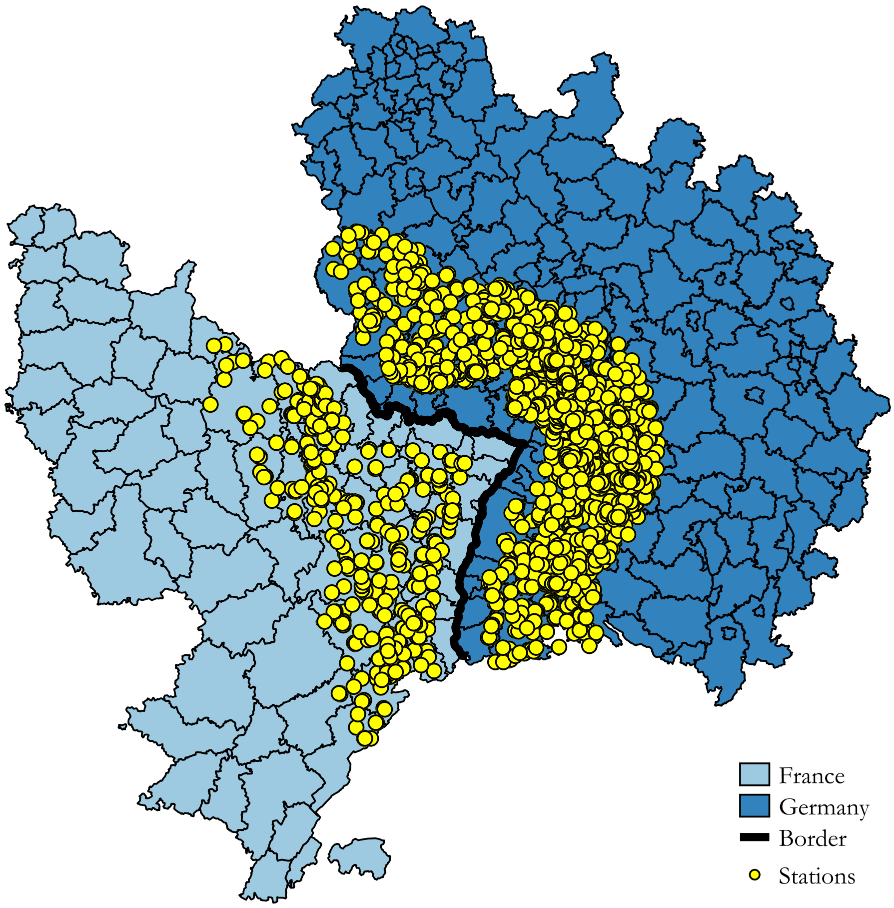
The results in Table C2 show that the differences in the effect of MPD between fuel types are not sensitive to our decision to use prices at 5 pm.

C.3 Donut SDID analysis

Figure C1 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 km of the France–Germany border. Fuel stations less than 20 km from the border are not considered because these could be in direct competition with each other and so spillovers of the treatment effect could occur, threatening the stable unit treatment value assumption. Each point in Figure C1 thus represents a fuel station in either France or Germany that is 20 to 100 km from the border.

In Table C3, we re-estimate the donut SDID regression for the analysis period 15 April 2013 until 31 March 2014 using different distances to the France–Germany border. We find that the results are robust to our changing the distance threshold and that the average effect of MPD is always larger for gasoline.

Figure C1: Fuel stations 20 to 100 km from the France–Germany border



Notes: The thick solid line represents the France–Germany border. Each point to the right of the border represents a fuel station in Germany that is 20 to 100 km from the border. Each point to the left of the border represents a fuel station in France that is 20 to 100 km from the border. These are the fuel stations considered in our donut SDID analysis, when they have no missing weekly price observations.

Table C3: Effect of MPD on log gross prices under alternative donuts

	Gasoline	Diesel	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)	(5)	(6)
MPD	-0.032***	-0.021***	-0.029***	-0.018***	-0.028***	-0.018***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
95% CI	[-0.034, -0.029]	[-0.026, -0.017]	[-0.033, -0.026]	[-0.022, -0.015]	[-0.031, -0.026]	[-0.021, -0.015]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Observations	9,550	11,900	21,200	25,250	37,950	43,600

Columns (1) and (2) present 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 km from the France–Germany border. Columns (3) and (4) present the same estimates for fuel stations 20 to 60 km from the border. Columns (5) and (6) present the same estimates for fuel stations 20 to 80 km from the border. The observation periods is from 15 April 2013 to 31 March 2014. Standard errors computed from 200 bootstrap draws are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.4 Estimation with control for crude oil price

As discussed in Section 5, the 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 MPD 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 MPD by directly allowing for differential pass-through of oil cost shocks between stations in Germany and France.

Table C4 shows the effect of MPD on the log gross weekly average gasoline and diesel price when we control for an indicator for 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 of the France–Germany border. The effects are estimated via SDID, and all columns use data from between 15 April 2013 and 31 March 2014. In addition to allowing for differential pass-through of input cost shocks between stations in Germany and France, we include fuel station and time fixed effects.

Columns (1) and (2) in Table C4 show that the introduction of mandatory price disclosure led to a decrease in weekly average prices of 2.7% for gasoline and 1.8% for diesel. When we restrict to the donut SDID sample, the corresponding estimates indicate a decline of 2.9% for gasoline and 1.9% for diesel. Overall, the magnitude of the MPD effect and its ranking with respect to the two fuel types remain robust to our allowing for differential pass-through of the crude oil price between stations in Germany and France.

Table C4: Effect of MPD on log gross prices

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-0.027***	-0.018***	-0.029***	-0.019***
	(0.0004)	(0.0005)	(0.0011)	(0.0014)
95% confidence interval	[-0.028, -0.026]	[-0.019, -0.017]	[-0.032, -0.027]	[-0.022, -0.016]
Germany × crude oil price	*Yes*	*Yes*	*Yes*	*Yes*
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	647,500	768,550	50,400	56,500

Notes: Columns (1) and (2) present 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) present the same estimates for a restricted sample of fuel stations 20 to 100 km from the France–Germany border. The observation period is from 15 April 2013 to 31 March 2014. We control for the interaction of an indicator for Germany with the crude oil price at the port of Rotterdam. Standard errors computed from 200 bootstrap draws are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.5 Effect of MPD on retail margins

Table C5 shows the effects of MPD on retail margins, as estimated with 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.

The results in Columns (1) and (2) show that mandatory price disclosure led to a decrease in weekly average retail margins of 3.4 and 1.8 eurocents for gasoline and diesel, respectively. In Columns (3) and (4), we restrict the analysis to stations within 20 to 100 km of the France–Germany border. Using this donut SDID, Columns (3) and (4) show that, after MPD, weekly average retail margins declined by 3.7 eurocents for gasoline and 2.0 eurocents for diesel. The effect of MPD is statistically and economically significant and is larger for gasoline.

Table C5: Effect of MPD on retail margins in eurocents

	Gasoline	Diesel	Gasoline	Diesel
	(1)	(2)	(3)	(4)
MPD	-3.346***	-1.786***	-3.661***	-2.043***
	(0.046)	(0.046)	(0.129)	(0.147)
95% confidence interval	[-3.431, -3.261]	[-1.878, -1.693]	[-3.937, -3.384]	[-2.351, -1.735]
Week FE	*Yes*	*Yes*	*Yes*	*Yes*
Station FE	*Yes*	*Yes*	*Yes*	*Yes*
Observations	647,500	768,550	50,400	56,500
Mean retail margin	8.21	10.70	8.36	11.14

Notes: Columns (1) and (2) present 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) present the same estimates for a restricted sample of fuel stations 20 to 100 km from the France–Germany border. The observation periods is from 15 April 2013 to 31 March 2014. Standard errors computed from 200 bootstrap draws are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

To test the validity of France as a counterfactual, we also estimate the effect of MPD on fuel prices in Germany using 26 other European countries as a control group.[37] To do so, we use information on country-level weekly average net gasoline and diesel prices as reported by the European Commission in its *Weekly Oil Bulletin*.

Table C6 shows the effects of MPD on the logarithm of net gasoline and diesel prices, as estimated with a difference-in-differences strategy. As in our main analysis, the estimation is based on data from between 15 April 2013 and 31 March 2014, and we include 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 C6 shows that, when we use other European countries as our control group, we find that MPD 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 our using this alternative control group.

[37] 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 C6: Effect of MPD on log 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) present 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 the control group. Columns (3) to (4) present additional interactions between the crude oil price and an indicator variable for each country. Robust standard errors are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$