Price Matching Guarantees and Collusion: Theory and Evidence from Germany

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Abstract. On May 27, 2015, the Shell network of gas stations in Germany introduced a Price Matching Guarantee (PMG) available to its card-carrying members. In the ensuing weeks, a series of attempts at tacit collusion took place, typically with stations increasing prices at around 12 noon by 3 cents. In this paper, we argue that the juxtaposition of these two events is not a mere coincidence. We first present a theoretical model to argue that a PMG can be a collusion enacting practice. We then test various predictions of our theoretical model. Our source of identification is geographical variation in the presence of Shell stations (the chain that enacted the PMG) as well consumer demographics. Our empirical tests are consistent with the theoretical predictions, showing effects that are both statistically and economically significant.

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1. Introduction

On May 27, 2015, the Shell network of gas stations in Germany introduced a Price Matching Guarantee (PMG) available to its card-carrying members (specifically, members of its Clubsmart club). In the ensuing weeks, a series of attempts at (arguably) tacit collusion took place, typically with stations increasing prices at around 12 noon by 3 cents (and maintaining that price increase for much of the rest of the day). These were not mere "blips" in the daily price pattern: as we show below, they correspond to a relatively "permanent" price hike during the rest of the (high-demand) afternoon hours; and a higher average daily price than before the PMG was introduced.

In this paper, we argue that the juxtaposition of these two events (PMG and midday price increases) is not a mere coincidence. We do so in two steps: First we present a theoretical model to argue that a PMG can be a collusion-facilitating practice: not in the "conventional" sense, which centers on the stability of an agreement; but rather in the sense that it increases the likelihood an agreement is initiated. Intuitively, a low-price holdout receives lower profits when a PMG is in place: some of the price-sensitive customers who would otherwise purchase from such low-price holdout now purchase at a low price from the high-price seller. Consequently, a PMG decreases the opportunity cost of following an "invitation to collude."

Second, we test various predictions from our theoretical model. Previous research (Wilhelm, 2016) shows that the introduction of Shell's PMG was followed by higher prices. We find this evidence consistent with our theory (and provide similar evidence from our dataset); but we also admit that it is a relatively weak test: many confounding factors may explain the change in prices from before to after the introduction of the PMG. We propose a stronger test, one that takes advantage of the geographical variation in the presence of Shell stations (the chain that enacted the PMG) as well as geographical variation in consumer demographics (which we argue are a good proxy for the degree of customer loyalty). Our empirical tests are consistent with the theoretical predictions, showing effects that are both statistically and economically significant. For example, our base regression's point estimates imply that a one-standard-deviation change in the distance to the nearest Shell station is associated with a 54% increase in the likelihood of imitating the midday price increase initiated by the two leading chains (Shell and Aral).

As a robustness check that Shell's PMG is the mechanism explaining the effect of our proximity-to-Shell variable, we propose a simple placebo test. Specifically, we reestimate our base equations using distance to the nearest Aral station rather than distance to the nearest Shell station. Aral (affiliated with BP) and Shell are the two largest networks in Germany (by a long shot). With Shell, Aral was one of the two initiators of the midday pricing increase pattern. Differently from Shell, Aral did not offer any PMG. The coefficients of the revised regressions (with Aral distance) have the same sign as the base regressions (with Shell distance), but they are smaller in value and in statistical significance. These results are consistent with our narrative (Shell's PMG being a tacit-collusion booster) as well as simple strategic complementarity: the fact that Aral increases its prices makes it more likely that rivals will do so simply on account of strategic complementarity in prices.

■ **Related literature.** Interest in the PMG-collusion nexus is not new in the economics literature as well as in antitrust practice. In particular, in the *Ethyl* case the US Federal Trade Commission (FTC) put forward a case whereby Most-Favored-Customer and Meet-or-Release guarantees (together with a system of price announcements) helped sustain collusion in the market for antiknock compounds. Holt and Scheffman (1987), Schnitzer (1994), Pollak (2017), and others have developed formal models of collusion and discussed the extent to which PMG-type guarantees, which apparently favor the customer, may end up harming the consumer by making collusion more stable.

In addition to presenting data and a narrative of a more recent episode, this paper focuses on a different aspect of collusion: the emergence of tacit collusion, rather than the stability of a collusion agreement. Theoretical developments and anecdotal evidence suggests that there are many ways in which collusion can take place. This is particularly true for tacit collusion, when no direct communication between rivals takes place. The emergence of collusion is thus a topic of particular research interest.

At the conceptual level, the issue of the emergence of collusion is tackled by Harrington and Chen (2006). In their model of cartel birth and death, Harrington and Chen (2006) assume that, in a given period, if an industry is not cartelized then with probability $\kappa \in (0, 1)$ it has an opportunity to do so. They justify the assumption that $\kappa < 1$ by arguing that "cartelization requires having a set of managers willing to break the law or that feel they can communicate and trust each other or an opportunity arises to communicate without much risk of being caught." Our modeling approach — the assumption that there is a stochastic cost of engaging in collusion, bears some resemblance to their approach. Following Rotemberg and Saloner (1986), Harrington and Chen (2006) also show that incentive-compatibility conditions for full collusion fail during high-profitability periods; and this pattern contributes to explaining cross-section variation in rates of cartelization. Rather than industry cross section, our focus is on a specific industry — retail gasoline — in which the frequency of interaction suggests incentive compatibility is not the binding constraint to initiating and maintaining collusion.[1]

Recent work by Byrne and De Roos (2019) focuses on the emergence of tacit collusion in Perth, Australia. Unlike Germany, where prices can be changed at will, Australian gas stations must post their prices one day in advance. Byrne and De Roos (2019) show how, over time, the majority of gas stations coordinated on a weekly cycle with a large price increase on Thursdays. This agreement was achieved over a period of about 10 years by means of price leadership and experimentation by dominant firms. We too observe dominant firms as leaders in price leadership and experimentation. Different from Byrne and De Roos (2019), the time frame of convergence to midday price increases is remarkably shorter (a matter of weeks, not years). One justification

1. See also and Harrington and Myong-Hun (2009).

for the speedy convergence to the new pricing pattern, we argue, is the introduction of a PMG by Shell, one of the dominant firms.

Also related to our paper, Chilet (2017) studies the emergence of collusion in the Chilean retail pharmacy industry. He documents a pattern of gradual, staggered price increases that starts with a limited set of products and gradually spreads to other ones. He shows that "pharmacies raised first the prices of products in which they were more differentiated," adding that "collusion on differentiated products is safer due to smaller losses should the collusive scheme collapse." Relatedly, our theoretical model shows that the risks of failed collusion are lower when a PMG is in place.

We are not the first to examine the effect of Shell's 2015 PMG. Wilhelm (2016) finds that the PMG was followed by a 1.68 Euro cents per liter price increase (E5 gasoline). Dewenter and Schwalbe (2015) obtain similar results from a similar exercise. Our paper differs from these in that we provide a coherent argument for the PMG-collusion nexus, as well as an empirical identification strategy that takes us beyond simple correlation.[2]

Other than retail gasoline, a number of empirical studies address the impact of price-matching and related guarantees on prices. Arbatskaya et al. (1999) find PMGs in tire markets lead to a decrease in prices; Arbatskaya et al. (2006), however, argue that PMG lead to lower prices. Manez (2006) evaluates a price beating guarantee introduced in the mid-1990s by a supermarket in the UK. By observing prices in three supermarkets in South Coventry the author finds that the price beating guarantee leads to lower prices. Zhuo (2017) examines a PMG introduced by two US retailers and finds a 6% price increase after the introduction of the PMG. Hess and Gerstner (1991) show that grocery store prices are higher for products included in a PMG offer.

■ **Roadmap.** The rest of the paper is organized as follows. In Section 2 we present a theoretical model of the emergence of collusion. We argue that the introduction of a PMG increases the likelihood that collusion will emerge. In Section 3 we describe the German retail gasoline market and the events surrounding Shell's 2015 introduction of a PMG. In Section 4 we test our theoretical results taking advantage of spacial variation in pricing patterns. Section 5 concludes the paper.

2. Price-matching guarantees and tacit collusion: theory

In this section we consider a simple model of price-matching guarantees (PMG) and the emergence of collusion. The model sets the stage for the empirical analysis included in the next sections. Much of the economics literature on collusion assumes that firms understand well what equilibrium is being played. The emphasis is then placed on the conditions such that the equilibrium is stable. However, anecdotal ev-

2. Also, Pollak (2017) argues that a PMG with a markup holds the same potential to facilitate collusion as a PMG with exact matching.

idence from many industries, including retail gasoline, suggests that achieving tacit collusion is as complex as maintaining it. Accordingly, our focus is on the process of emergence of collusion.

In the tradition of Maskin and Tirole (1988), we assume that there are two sellers who alternate over time in setting prices: Firm 1 sets prices during odd periods and Firm 2 during even periods. In other words, firms commit to prices during two periods and prices are set in a staggered pattern. In each period, the firm choosing its price selects one of two different price levels: p_h and p_l (with $p_h > p_l$).

A crucial element we add with respect to the Maskin and Tirole (1988) alternating-moves game is that, before setting prices, each firm draws a value of its collusion cost c. The idea is that initiating a process of collusion implies a series of costs, including in particular antitrust penalties in case the agreement is discovered and deemed illegal.[3] We assume that c is i.i.d. across firms and periods and distributed according to the cumulative distribution function (cdf) $F(c)$.

Among the multiple equilibria of the alternating-moves infinite game, we consider the following. If the first time firm i sets p_h is followed by firm j setting p_h as well, then a collusion equilibrium ensues, that is, $p = p_h$ in every subsequent period. If, however, a switch from p_l to p_h is followed by p_l by the other firm, then firms set p_l in every subsequent period. The idea is that, contrary to the common assumption in the repeated-game literature, players are not aware of what equilibrium is being played. Uncertainty and asymmetric information regarding the value of c is a natural way of modeling this situation of strategic uncertainty.

Let V_i^c be firm value (measured at the beginning of a price-setting period) along the collusion path (that is, when both firms set p_h), where $i = 1, 2$ denotes firm identity. Let V_i^b be firm value given that the rival switched to p_h in the previous period but the focal firm has not done so in the past. Let V_i^a be firm value before any price increase has taken place. Finally, let V_i^d be firm value along the "punishment" path, that is, when firms set p_l indefinitely. We assume the value of the discount factor δ is sufficiently high that the selected subgame equilibria are indeed equilibria.

The focus of our analysis will be on the values of ϕ_i, the probability that firm i responds to p_h being set by the rival (for the first time) with p_h; and β_i, the probability that firm i initiates collusion (that is, sets p_h for the first time). In each period, firms use a threshold strategy and select p_h as a function of c. Since c is distributed according to $F(c)$, this strategy results in the above-mentioned switch probabilities β_i and ϕ_i. The values of β_i (begin collusion process) and ϕ_i (follow up rival's invitation to collude) stochastically determine the emergence of collusion: the higher the values of β_i, ϕ_i ($i = 1, 2$), the sooner the collusion subgame emerges.

We are left to consider period payoffs. Let $\pi_i(p_j, p_k)$, where $i = 1, 2$ denotes the firm; p_j the price set by firm i, where $j = h, l$; and p_k the price set by the rival firm, where $k = h, l$. These profit values are derived from the following demand system:

3. In their model of cartel birth and death, Harrington and Chen (2006) assume that a cartel is discovered and convicted with probability $\sigma \in [0, 1]$; and that, if discoverdx, then each firm incurs a penalty of $F/(1 - \delta)$ (so that F is the per-period penalty).

Consumers, who buy one unit each period from one of the two sellers and form a total mass of 2, are divided into three segments: A measure $2\,\alpha$ of consumers is loyal, α to each of the sellers. These consumers purchase from their preferred seller in all cases. A measure $2\,(1-\alpha)$ purchases from the seller setting the lowest price; and, if both sellers set the same price, then $(1-\alpha)$ purchases from each of the sellers. For simplicity, we assume zero costs.

The above assumptions induce the following set of period payoffs as a function of firm prices:

$$\begin{aligned}\pi_i(p_h,p_h) &= p_h\\ \pi_i(p_h,p_l) &= \alpha\,p_h\\ \pi_i(p_l,p_h) &= (2-\alpha)\,p_l\\ \pi_i(p_l,p_l) &= p_l\end{aligned}$$

Suppose however that Firm 1 offers a price-matching guarantee (PMG) unilaterally. Suppose moreover that only a fraction λ of consumers benefit from the PMG.[4] Finally, for simplicity suppose that club membership is independent of other buyer characteristics. If Firm 1 sets p_h and Firm 2 sets p_l, then a fraction λ of the α measure of Firm 1 loyal buyers now pay p_l instead of p_h; and a fraction λ of the searchers who would buy from Firm 1 under equal prices now buy from Firm 1 at the price set by Firm 2, that is, p_l. It follows that period payoffs as a function of firm prices are now given by:

$$\begin{aligned}\pi_i(p_h,p_h) &= p_h\\ \pi_2(p_h,p_l) &= \alpha\,p_h\\ \pi_1(p_l,p_h) &= (2-\alpha)\,p_l\\ \pi_i(p_l,p_l) &= p_l\\ \pi_1(p_h,p_l) &= \alpha\,(1-\lambda)\,p_h+\alpha\,\lambda\,p_l+(1-\alpha)\,\lambda\,p_l\\ &= \alpha\,(1-\lambda)\,p_h+\lambda\,p_l\\ \pi_2(p_l,p_h) &= \alpha\,p_l+(1-\alpha)\,(2-\lambda)\,p_l\end{aligned}$$

Note that payoffs are as before except in the case when Firm 1 (who offers a PMG) sets p_h and Firm 2 sets p_l. Note also that, if $\lambda=0$, then the above payoffs correspond to the case when no PMG is in place: a PMG is only effective to the extent that there are consumer who can benefit from it. Accordingly, we assume that $0<\lambda<1$.

An equilibrium is determined by the firms' strategies to initiate collusion (probability β_i); and follow-up a rival's invitation to collude (probability ϕ_i). We consider separately the cases when no price-matching guarantee is in place and the case when it is.

Our first results states that the likelihood that an invitation to collude is heeded increase when a PMG is in place.

4. This can be either because the offer is limited to certain consumers (e.g., club members) or because benefiting from the PMG requires buyers to actively request it, which only some do.

Proposition 1. *A price increase by firm i is more likely to be followed by a collusion subgame under a PMG regime than under a no-PMG regime.*

As mentioned earlier, the intuition is that the opportunity cost of increasing price is lower under a PMG regime. Specifically, if Firm 1 increase price, Firm 2 makes less by keeping a low price under a PMG than it would under no-PMG.

Our next result takes advantage of the structure of product market payoffs to derive specific comparative statics. These comparative statics will allow us to perform sharp empirical tests of our theory.

Proposition 2. *The probability that a price increase by firm i is followed by collusion is increasing in λ and decreasing in $\alpha\,\lambda$.*

Propositions 1 and 2 only provide an incomplete characterization of equilibrium (they're limited to the values of ϕ_i). A complete characterization of β_i and ϕ_i requires specific assumptions regarding the distribution $F(c)$. Our final theoretical result provides sufficient conditions on $F(c)$ such that collusion emerges in equilibrium if and only if a PMG is in place. Specifically, suppose that $F(c)$ corresponds to a mass point at c.[5]

Proposition 3. *Suppose that*

$$\frac{p_h - p_l}{1-\delta} - (1-\alpha)\,p_l < c < \frac{p_h - p_l}{1-\delta} - (1-\alpha)\,(1-\lambda)\,p_l \tag{1}$$

$$p_h < \max\left\{\frac{1}{\alpha}, \frac{\lambda + (1-\alpha)}{1-\alpha\,(1-\lambda)}\right\} p_l \tag{2}$$

Then there exists an interval S of values of c such that, if $c \in S$, then collusion takes place if and only if a PMG is in place.

We should mention that (1)–(2) defines a non-empty set of values. For example, suppose that $p_h = 5$, $p_h = 4$, $\alpha = .5$, $\lambda = .5$, and $\delta = .9$. Then any value $c \in [8,9]$ satisfies the first set of conditions; and the second set of conditions is satisfied with slack.

3. The German retail gasoline market

There are a total of 14,567 gas stations in Germany. A significant fraction of these correspond to the two largest chains: Aral (a subsidiary of BP) and Shell. The remaining retailers are a combination of vertically integrated and vertically separated, branded and non-branded, stations. Table 6 provides a listing for North Rhine-Westphalia, the region of Germany on which our empirical analysis will be focused.

5. Strictly speaking, the assumption that c is equal to a specific point violates our assumption that $F(c)$ has full support and is continuously differentiable. However, our results are based on strict inequalities. We can therefore assume that c is, for example, normally distributed with μ equal to the desired value and an arbitrarily small variance.

Figure 1
May 25, 2015 gasoline prices

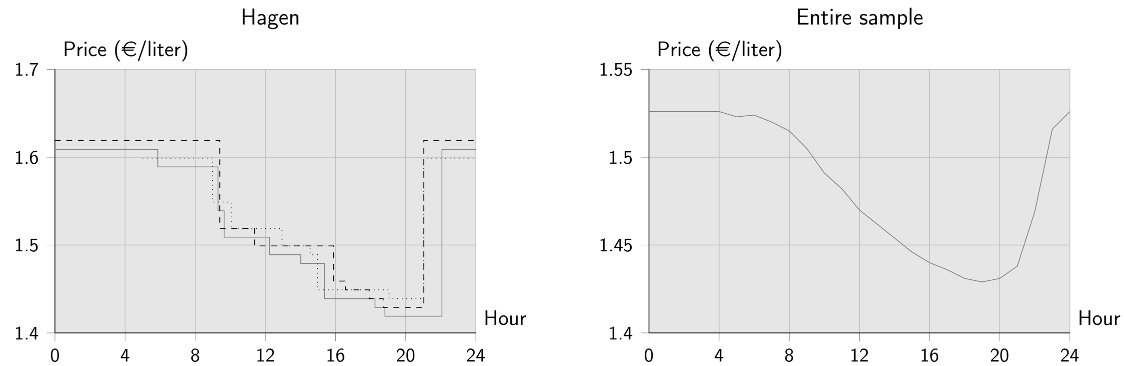
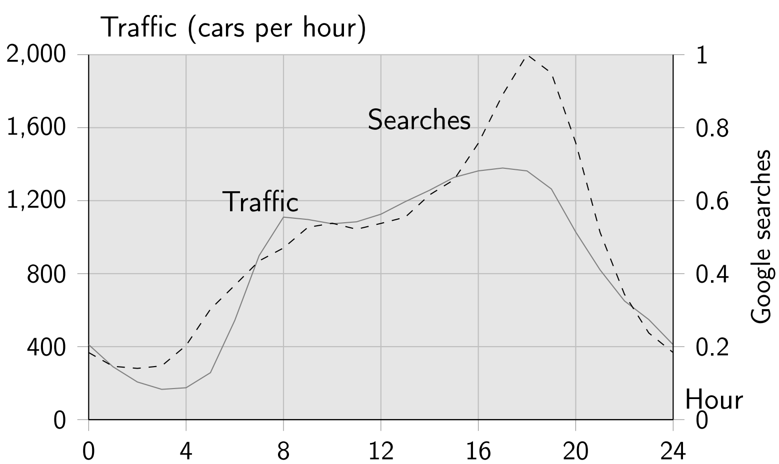


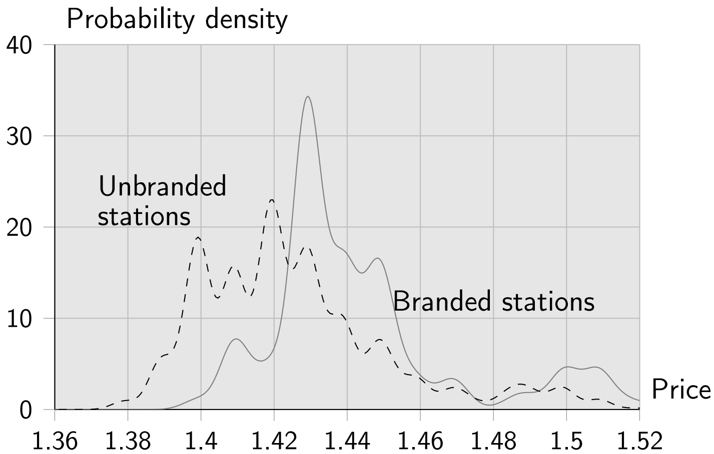
Figure 2
Daily traffic and search patterns



Unlike other countries, gas stations in Germany are allowed to change their prices at will. Typically, several price changes take place during the day. The left panel of Figure 1 shows a typical pattern on a typical day in Hagen, a representative German town. As can be seen, prices start at a high level. Throughout the day, a series of price decreases, highly correlated across firms, bring prices to a lowest level at around 5 or 6pm. Finally, by about 8pm prices are brought back to high levels. The pattern observed in Hagen is also present in other cities, leading to the overall pattern of average prices shown on the right panel of Figure 1.

Figure 2 shows indicators of traffic and price search throughout the day. Comparing these patterns to the daily pricing pattern shown in Figure 1, we observe a nearly perfect negative correlation between traffic (or search) and prices. This suggests that

Figure 3
May 25, 2015, 5pm price kernel density



a substantial portion of the daily price variation is related to demand shifts.[6] Additional price variation is explained by station brand name. Specifically, Figure 3 shows the kernel density of the price distribution, where stations are divided into branded and non-branded categories. As can be seen, there is some dispersion in prices, much of which is explained by the branded or unbranded nature of retailers.

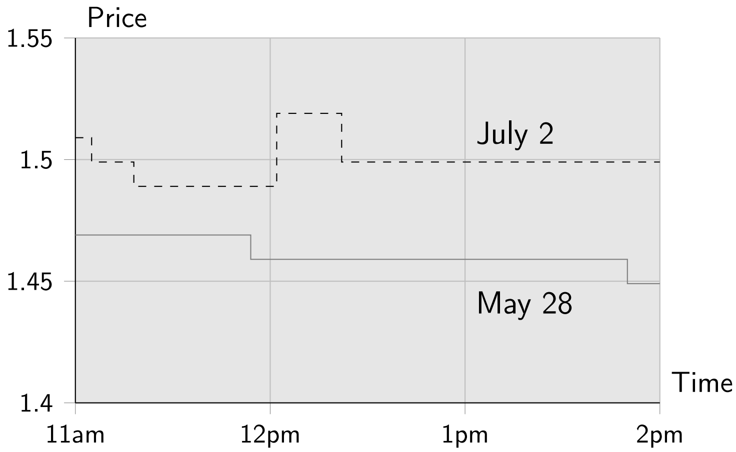
At this point, a note on the source of our price data may be in order. In 2008, the German Federal Cartel Office (Bundeskartellamt) conducted a comprehensive antitrust inquiry of the retail gasoline sector. The final report reflected a strong suspicion of tacit collusion in the sector. Partly as a result of this report, in 2012 the German parliament passed a law which effectively set up a market transparency unit for fuels. Since 2013, the Bundeskartellamt's Market Transparency Unit for Fuels has collected detailed retail fuel prices. Specifically, companies which operate gas stations are obliged to report price changes for the most commonly used types of fuel — Super E5, Super E10 and Diesel — in real time.

■ **Shell's price-matching guarantee.** On April 1, 2015, HEM, a small retailer with a market share of about 4%, offered a Price Matching Guarantee (PMG) to its customers. Customers can use price comparison software to find a lower price within a 5 km radius and generate a bar code that guarantees this lower price for a period of 30 minutes. The customer can then show the bar code to the HEM station cashier, who then scans it and charges the matched price. By comparison to other PMG (Hviid and Shaffer, 1999), this is a relatively hassle-free process.

On May 27, 2015, the Shell network of gas stations in Germany introduced a PMG similar to HEM's, with one important difference: it was only available to its card-carrying members (specifically, members of its Clubsmart club). Considering the

6. Boehnke (2017) argues that "high prices observed during the morning hours can be explained by fewer informed consumers traveling in the morning compared to the evening."

Figure 4
Gasoline prices at Shell's Osthaus strasse (Hagen) station on Thursday, May 28, 2015 and on Thursday, July 2, 2015



size of Shell's network of gas stations, as well as its market leadership role, we focus on Shell's PMG. Shell promised to automatically charge the cheapest price (plus a 2 cent markup) for diesel or unleaded gasoline at a set of nearby competing gasoline stations. Specifically, the set of "consulted" gas stations — that is, stations to which the PMG applies — is given by the ten nearest stations minus some unbranded ones. All in all, between 75 and 80% of the 10 closest gasoline stations are typically included in the price-matching set. Moreover, for Shell gas stations located along a highway, only the four adjacent gas stations (two each way) are considered. Finally, some Shell stations (about 5%) were excluded from the offer (according to Shell, because they use an old cash system that cannot be integrated into the policy).

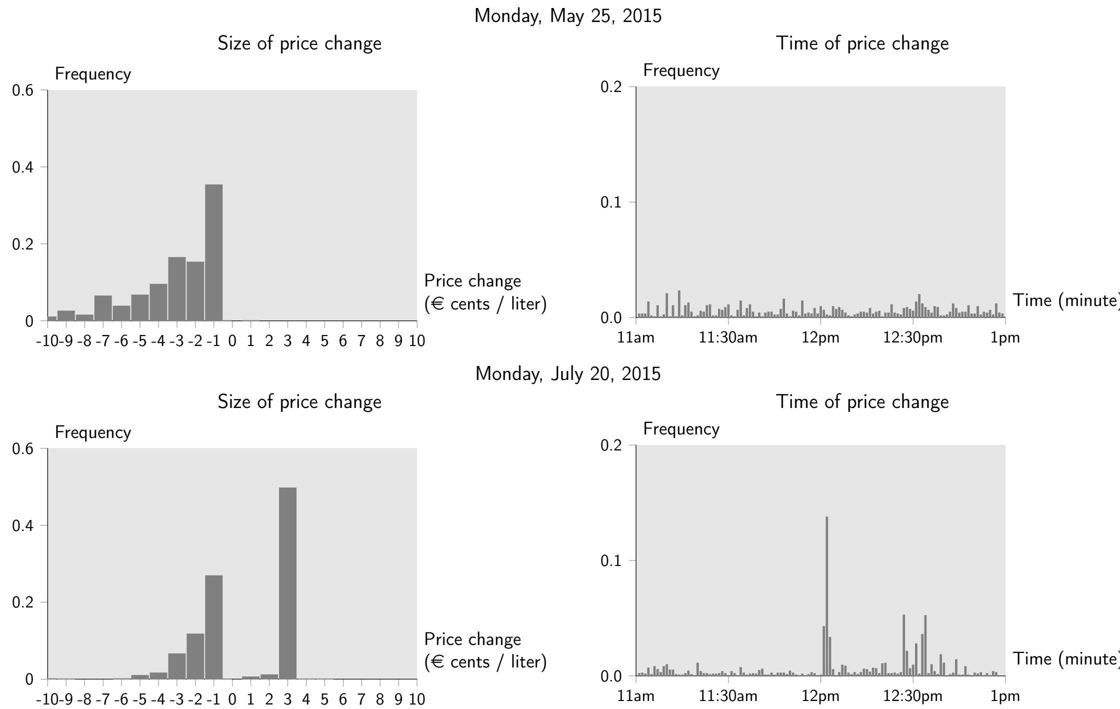
On June 24, 2015, Aral and Shell — the two largest retailers — changed their daily price pattern by introducing a series of price increases at around noon. Specifically, 150 of the 254 Aral stations increased price by 3 cents at 12:01. The move was followed by 168 of the 189 Shell stations within three hours. In the weeks that followed, almost all of the Aral and Shell stations adhered to a midday 3 cent price increase (most of Aral's increases took place at 12:02, Shell's at 12:01).[7]

This was a previously unseen pattern: as exemplified in Figure 1, before June 2015 prices declined throughout the day and only returned to their high levels after the evening rush hour had passed.[8]

Figure 4 shows the price path from 11am-2pm at a particular Shell station (Osthaus strasse, Hagen) on two different Thursdays: May 28, before the midday increases began taking place, and July 2, when a large fraction of gas stations were

7. Considering that we only have price information at the minute level, and considering that there may be a reporting lag, it's possible that these changes occurred at exactly noon.
8. Shell made other (unsuccessful) attempts during the fall holidays at increasing prices in their daily sequence, one at 11am, one at 4pm.

Figure 5
Midday price changes



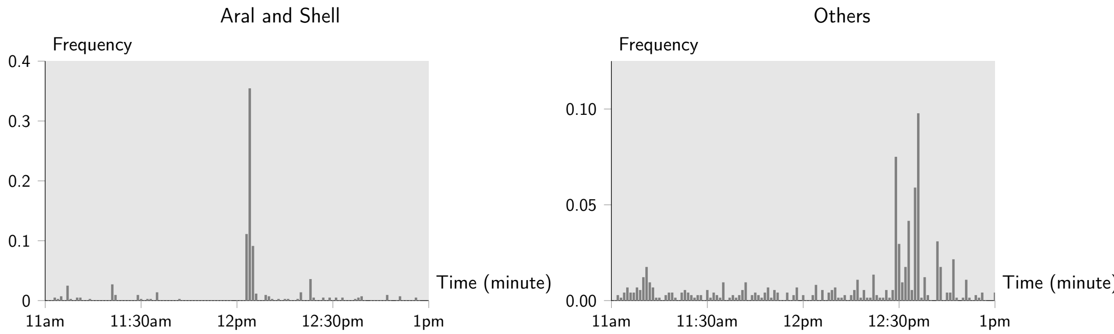
regularly increasing prices at around noon. Although we present data for two specific days and for one of more than fourteen thousand gas stations, the patterns exemplified by Figure 4 are fairly typical of the daily pricing pattern changes that took place in 2015.

The practice of midday price increases has several of the features of a coordination focal point (Schelling, 1960). Figure 5 illustrates this idea. The left panels show the distribution of price changes (in cents of €), whereas the right panels show the distribution of times at which a price change takes place (between 11am and 2pm). The top two panels correspond to Monday, May 25, 2015 (a typical day before midday price increases were introduced) and Monday, July 20 (a typical day after midday price increases were introduced).

The first difference that is noticeable between the top and bottom panels is that in the early period there are no price increases during the midday period, whereas in the late period most price changes from 11am-2pm are price increases. The second noticeable difference is that both distributions are considerably more concentrated in the later periods than in the earlier period. This is particularly the case for the price change distribution, which is highly concentrated in the € 3 cent value, but also in the time at which the price change takes place, where we find a significant

Figure 6

Time of midday price changes by station type



concentration around 12 noon.[9]

The focus of our analysis is on daily price patterns, not on intraday price patterns. That said, we might add that, once we split the sample by separating Shell & Aral (the leaders in the midday price increase pattern), we observe a high concentration of price changes in the 12:00–12:02 period (almost 90% of the observations), whereas the other stations almost always change price at around 12:30. Figure 6 allows us to dig deeper into the time distribution of price changes. The left panel corresponds to Aral and Shell stations, whereas the right panel corresponds to all other stations. As can be seen, Aral and Shell, the leaders in the midday price increase patter, concentrate their price changes around noon, whereas the remaining stations concentrate their price changes (typically a €3 cent increase) at around 12:30pm.

Finally, there is no significant difference in these distributions over time.[10] The main effect of time is, as we will see next, the degree to which stations increase price at all.

In the ensuing weeks after Aral's first move, we observe a gradual take-up of the midday-price-hike practice. In this regard, we can distinguish three broad groups: the initiators (the Aral and Shell chains); the early followers (a group of branded stations: ESSO, JET, TOTAL, Westfalen); and the late followers (mostly unbranded stations).

We argue that the midday price hikes were not just a "blip" in the daily price distribution; rather, they had a significant effect on average daily prices. To see this, we run a series of minute-by-minute price regressions where, on the right-hand side, we include time and station fixed effects; as well as a dummy indicating whether a midday price increase took place during that day at that particular gas station (specifically: was there a price increase from 11am-1pm).

9. Specifically, most measure is concentrated in the 12:01, 12:02 and 12:03 minutes. We don't know whether the deviations from 12noon correspond to explicit firm strategy or a lag in communicating the price change.

10. This contrasts with Byrne and De Roos (2019), where one observes, over the years, significant differences in price-increase patterns.

Figure 7

Estimated coefficients from price equations (and 95% confidence interval)

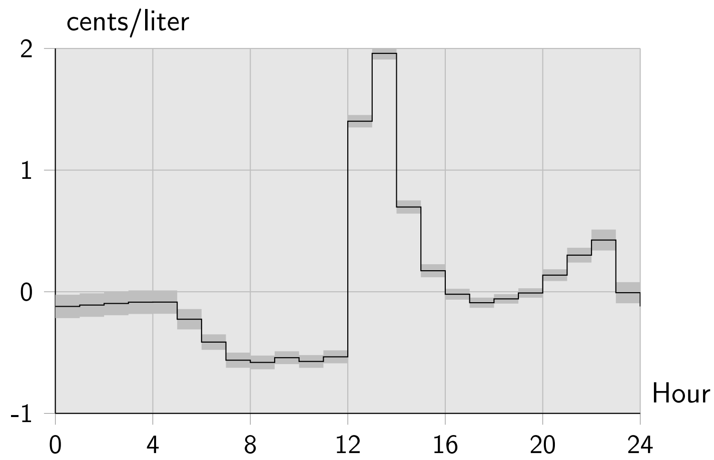


Figure 7 shows the estimated coefficient values of the price-hike dummy. The results suggest a relatively permanent effect of the midday price increase. Taking the integral of this estimated hike series from noon to the rest of the day we get an average of about 1 cent increase, which for a good with such low retail margins is quite significant. Moreover, we have reasons to believe the values shown in Figure 7 provide a strict lower bound on the actual average price increase associated with midday price increases. The reason is that, if station X is located nearby a station Y that increases price at midday, we expect station X's prices to be higher (by a simple strategic complementarity effect) even if station X does not increase prices at midday. If that is the case, then the coefficient of the price-hike dummy misses out the increase in price by station X; and underestimates the increase by station Y (to the extent that the price increase is measured by the difference with respect to firm X). We return to the issue of strategic complementarity later in the paper.

Finally, Figure 7 also shows a negative estimated coefficient for before-noon prices. It's as if gas stations anticipate that prices will be increased at noon and partly compensate for that by setting lower prices in the morning. However, we should mention again that the estimated coefficient provides a lower bound on the effect of midday price hikes. The negative coefficients are consistent with the effect of midday price increases being positive throughout the day.

Another way of judging whether the midday price hikes imply an overall average price increases is to plot the time series of retail prices. Figure 8 does just that. For reference, we also plot the oil price time series (right scale). Two vertical lines represent the date when Shell's PMG was introduced and the day of the first midday price hike. The data clearly suggests an increase in margins following the introduction of the PMG, in particular after the midday price hikes take effect.

We propose that the juxtaposition of these events (PMG, midday price hikes, average price increase) is not a mere coincidence. The theoretical model presented

Figure 8
Oil price and 5PM gasoline price in 2015

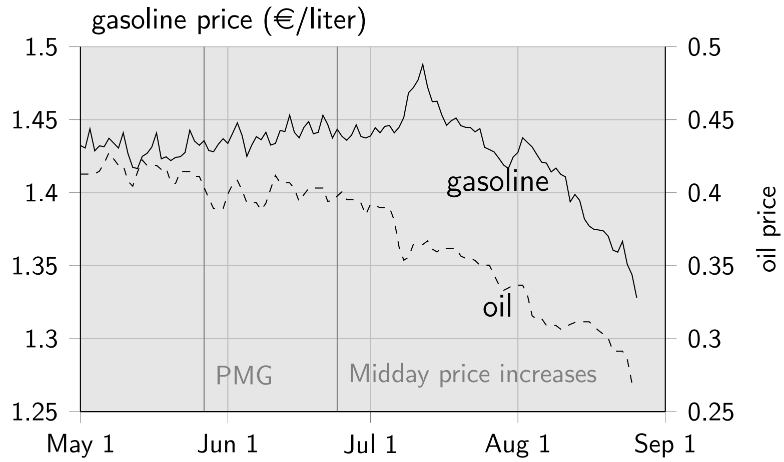
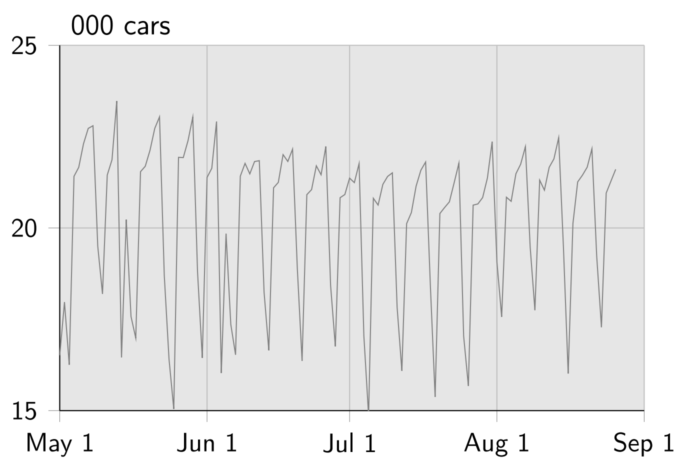


Figure 9
Estimated daily car traffic

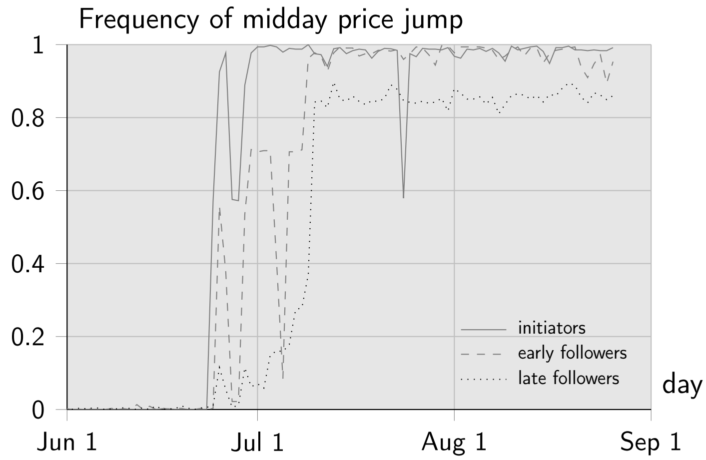


in the previous section provides a narrative and an intuition: a PMG lowers the net cost of engaging in collusion. Aware of the fact, Aral and Shell signal to each other and to the rest of the market their willingness to change the price daily pattern by increasing prices at midday, which in turn results in a significant increase in daily average price.

One natural alternative interpretation for Figure 8 is that price patterns are subject to seasonal changes. We perform a simple analysis of daily car traffic as a function of a time trend, a holiday dummy, and dummies for each day of the week. Figure 2 plots estimated daily car traffic. The results suggest strong weekend effects but otherwise low seasonal effects.

Naturally, there can be many other confounding factors interfering with our tacit

Figure 10
Emergence of collusion



collusion narrative. In the next section, we test various predictions from our theoretical model so as to strengthen our case. Our main source of identification is geographical variation in the presence of Shell stations (the chain that enacted the PMG) as well as in the density of Clubsmart members (drivers who can benefit from the PMG).

4. Results

We test a specific implication of our theory of PMG-facilitated collusion: Proposition 1 suggests that a price increase by Shell is more likely to be followed by a collusive price increase by a rival station if that station is part of the PMG regime initiated by Shell. Second, Proposition 2 predicts that, conditional on being part of a PMG scheme, the likelihood that an invitation to collude will be taken up is increasing in λ (the fraction of consumers who have access to the PMG) and decreasing in $\alpha\,\lambda$ (where α is the measure of loyal consumers, that is, consumers who do not shop and search for low prices).

In order to take advantage of cross-station heterogeneity as an identification strategy, we would need to obtain station-specific values of λ and α, as well as information as to whether they are part of the PMG regime, that is, whether they are part of the set of "consulted" gas stations. We do have information on whether a station is or is not "consulted" by Shell's PMG. However, we do not have station-specific information on λ and α. Instead, our strategy is to create variables to proxy the values of α and λ at the gas station level. Cabral et al. (2018) argue that searching for gasoline prices is largely done by means of one of several price-comparison apps. Moreover, anecdotal and statistical evidence shows that young drivers are particularly prone to download and use these price-comparison apps. We therefore propose the fraction of the population that is 30 years old or younger as a proxy for $1-\alpha$, the fraction of non-loyal consumers. We have demographic data at the ZIP code level. Therefore, for each station i we use the value of α in its ZIP code.[11]

A proxy for the value of λ is a little more problematic as we only have aggregate numbers regarding Clubsmart membership. We make the assumption that, other things equal, the closer a driver is located to a Shell station, the more likely the driver is a Clubsmart member. Accordingly, we measure the distance of each gas station i to the nearest Shell station as a measure of Clubsmart membership among station i's potential customers. We normalize values so that $\lambda = 1$ for Shell stations (zero distance to the nearest Shell station).

To summarize, the critical variables are defined as follows (for each gas station i):

- PMG_i: gas station i is part of Shell's PMG program (dummy variable)
- α_i: share of population aged over 30 in the zip code containing gas station i
- λ_i: $1 - d_i/D$, where d_i is distance to the nearest Shell station and $D = \max d_j$ over all stations j

Following our theoretical analysis, we wish to test the hypothesis that, conditional on being included in Shell's PMG offer, a gas station is more likely to follow the Shell "invitation" to collude the greater λ is and the lower α is. By accepting an invitation to collude we mean to engage in a pricing pattern characterized by a price increase around noon each day.

■ **Selection.** Our research design suffers from a potential selection problem. Shell's choice of which stations to include in its PMG offer is bound to be determined by strategic considerations. Presumably, Shell has a greater incentive to select those stations for which the PMG offer may have a greater effect in "softening" price competition. Specifically, Shell's close competitors are more likely to join Shell's invitation to collude than Shell's distant competitors. Moreover, Shell's benefit from listing a firm in its PMG program is also likely to be greater for close competitors than for distant competitors. If this is the case, then explaining a station's response to Shell's invitation to collude by the station's membership in Shell's PMG program is likely to provide biased estimates. Specifically, it is likely to overestimate the effect of Shell's PMG.

A Heckman (1979) selection model approach allows us to correct for this sample selection bias. In a first stage, we model the likelihood that a gas station is included in Shell's PMG list. Specifically, we consider the following selection equation:

$$\mathbb{P}(L_{it} = 1 | Z_{it} = z_{it}) = \Phi(\gamma\, Z_{it})$$

where L_{it} denotes that, at time t, station i is listed in the PMG program, Z is a vector of explanatory variables, γ a (transposed) vector of parameters, and the error

11. As an alternative, we also considered adding the demographic data in the neighboring ZIP codes, with weights inversely proportional to the distance from the station to the ZIP code's center of gravity. The results change very little.

is given by u. In a second stage, we model the likelihood that a gas station accepts Shell's "invitation" to increase prices. Specifically, we model the probability that a gas station increases price during the 11am-1pm time period, an event we denote by $N_{it} = 1$. We assume the probability of this event is given by

$$\mathbb{P}(N_{it} = 1 | X_{it} = x_{it}) = \Phi(\beta\, X_{it})$$

where X is a vector of explanatory variables, β a (transposed) vector of parameters, and the error is given by ϵ. Following Heckman (1979), we assume that u and ϵ are distributed according to a bi-variate normal, that is, $(u, \epsilon) \sim N(0, \sigma_u^2, \sigma_\epsilon^2, \rho_{u\epsilon})$. The correlation between the two errors, which we denote by $\rho_{u\epsilon}$, reflects the selection effect. Henceforth, we will term this coefficient ρ for notational convenience. If we properly control for it, then we are able to obtain unbiased coefficient estimates $\widehat{\beta}$. Specifically, Heckman (1979) shows that

$$\mathbb{P}(N_{it} = 1 | X_{it} = x_{it}, L_{it} = 1) = \mathbb{P}(N_{it} = 1 | X_{it} = x_{it}) + \rho\, \sigma_u\, \mu(\gamma\, Z_{it})$$

where μ is the Inverse Mill's Ratio (IMR) evaluated at $\gamma\, Z_{it}$, that is, $\phi(\gamma\, Z_{it})/\Phi(\gamma\, Z_{it})$.[12] In practical terms, we use $\mu(\gamma\, Z_{it})$ as an additional explanatory variable in our second-stage estimation and in the process estimate the value of ρ. The product of IMR times its coefficient serves to counterbalance the expected value bias in the second stage (collusion) equation's error term ϵ conditional on being listed. This reflects the idea that stations with large negative collusion equation errors are likely not to be listed, so the expected value of the collusion equation error will no longer be zero for some of the stations which are listed (for example, the ones close to Shell stations and with high margins). To the extent that the estimate differs from zero, we conclude that there is a sample-selection bias. And to the extent that the joint normality assumption holds, adding μ to the regression corrects for such selection bias.

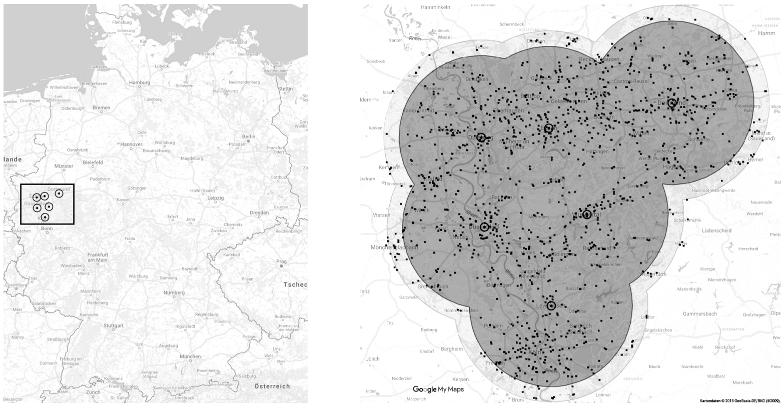
Our first-stage selection equation includes the following variables Z

- λ (proximity to Shell station)
- α (fraction of older population)
- Street type fixed effects.
- Station's brand nationwide market share
- Station's margin prior to the introduction of Shell's PMG (estimate of).

In order to estimate a station's pre-PMG market share, we compute the actual value of its margin at noon (price minus oil price) and regress this on the following variables: weekday dummy, school holiday dummy, brand dummies, and intensity of competition. Regarding the latter variable, we use the number of competitors per capita. As an alternative, we use the corresponding variable in a gas station's greater

12. The Mills ratio is frequently denoted by λ, but considering we already use λ in our theoretical model we use μ for the Mills ratio instead. σ_u is the standard deviation of the first stage error included for normalization purposes.

Figure 11
Catchment area: all gas stations in a 50k radius of Düsseldorf, Wuppertal, Gladbach, Duisburg, Essen, Dortmund, and Leverkusen



environment (outer "donut") as an instrument for the value in the station's immediate vicinity ("donut hole") as well as inhabitants (Bresnahan and Reiss (1991), Cabral et al. (2018)). Specifically, we use the number of competitors in a greater environment (three to seven kilometers) to predict the actual local competition proxy (based on the number of stations less than three kilometers away). However, this correction does not change our estimation results in any stage of estimation. For this reason, in what follows we present results based on non-instrumented measures of local competition.

■ **Price increase equation.** Our second-stage regression (probability of a midday price increase) includes the following variables X

- λ (proximity to Shell station)
- α (fraction of older population) times λ
- PMG. Price-Matching-Guarantee dummy: station is included in Shell's offer.
- Interaction of PMG and λ.
- Interaction of PMG and $\alpha\lambda$.
- Number of local competitors.
- Inverse Mills Ratio (μ) from selection equation
- Brand fixed effects.

We are particularly interested in the coefficients attached to PMG$\times\lambda$ and PMG$\times\alpha\lambda$. Propositions 1 and 2 predict that the coefficient on PMG$\times\lambda$ is positive (closer stations more likely to benefit from PMG inclusion), whereas the coefficient on PMG$\times\alpha\lambda$ is negative (for a given value of λ, the benefit from PMG inclusion is lower when there are more older consumers).

Table 1
Summary statistics

	N	Mean	St Dev	Min	Max
Midday jump	57,922	0.82	0.38	0.00	1.00
PMG consulted	57,922	0.78	0.42	0.00	1.00
λ	57,922	0.80	0.12	0.00	1.00
$\lambda \times \alpha$	57,922	0.32	0.17	0.00	0.62
PMG consulted $\times\lambda$	57,922	0.62	0.35	0.00	1.00
PMG consulted $\times\lambda \times \alpha$	57,922	0.25	0.20	0.00	0.97
# competitors	57,922	9.51	4.50	1.00	21.00
Inverse Mills	57,922	0.36	0.48	0.00	1.42
Closest neighbor day before	57,922	0.73	0.44	0.00	1.00
Second closest neighbor day before	57,922	0.65	0.48	0.00	1.00
Third closest neighbor day before	57,922	0.56	0.50	0.00	1.00

■ **Sample.** Although Shell's PMG was extended to the whole of Germany, our analysis focuses on a particular region of Germany. Specifically, our catchment area is defined as all gas stations in a 50k radius of Düsseldorf, Wuppertal, Gladbach, Duisburg, Essen, Dortmund, and Leverkusen. Figure 11 shows the section of Germany we consider for our empirical test.[13] Table 1 lists the summary statistics of the main variables we use in our regressions testing Proposition 2. As mentioned earlier, the α and λ observations are at the gas station level. In addition to these, we construct the dependent variable "midday price increase" at the day and gas station level. It is defined as 1 if and only if gas station i increases its price at any time from 11am-2pm during day t.

■ **Midday price increases.** Table 2 presents our base regressions, relating the dependent variable, "gas station i increased price in day t", to the variables PMG (station is included in Shell's offer list), λ (proximity to nearest Shell station), α (fraction of older people in zip code containing gas station i), and interactions thereof. Our sample corresponds to the entire period in our sample after Shell's PMG is introduced.

As mentioned earlier, we are particularly interested in the coefficients attached to PMG $\times\lambda$ and PMG $\times \alpha \times \lambda$. Propositions 1 and 2 predict that the coefficient on PMG $\times\lambda$ is positive (closer stations more likely to benefit from PMG inclusion), whereas the coefficient on PMG $\times \alpha \times \lambda$ is negative (for a given value of λ, the benefit

13. The shaded area in the periphery corresponds to stations not included in the main regressions but used as a reference for the stations in the core area.

Table 2
Base results

	Dependent variable: midday price increase			
Estimation method:	OLS	Probit	OLS	Probit
Station included in Shell's offer (PMG)	.4541*** (.1114)	1.1437*** (.4302)	.3807*** (.1172)	1.6412** (.6442)
Proximity to Shell (λ)	-.4238*** (.1352)	-1.3290*** (.4073)	-.5731*** (.1369)	-2.4051*** (.5021)
Share of older population (α) $\times\lambda$	.2559*** (..0963)	.8335*** (.2927)	.2367** (.0982)	.8571** (.3631)
PMG $\times\lambda$	.4153*** (.1342)	1.2840*** (.4090)	.4765*** (.1374)	1.9056*** (.5165)
PMG $\times\alpha\times\lambda$	-.2526*** (.0937)	-.8289*** (.2848)	-.2322** (.0971)	-.8310** (.3688)
# competitors	.0008 (.0010)	.0037 (.0046)	-.0054*** (.0012)	-.0237*** (.0065)
Inverse Mills Ratio	-.0862 (.0595)	-.3745* (.2079)	-.0249 (.0627)	-.0772 (.2730)
Closest neighbor day before			.2014*** (.0122)	.9018*** (.0503)
Second closest neighbor day before			.0830*** (.0103)	.4352*** (.0482)
Third closest neighbor day before			.0722*** (.0103)	.4014*** (.0517)
Constant	.4318*** (.1291)	.7310* (.4307)	.2580* (.1410)	.0359 (.6406)
(pseudo) R^2	.2093	.2140	.3071	.3370
N	57,922	57,859	57,922	57,859

Notes: Robust standard errors (clustered at station level) in parentheses.
Star levels: 10, 5 and 1%.
All regressions exclude Shell and include brand fixed effects.

from PMG inclusion is lower when there are more old, loyal consumers). Note that the theoretical model implies a greater propensity to engage in collusion both by the firm offering a PMG (Shell in our case) and the other firms. However, in principle the effect is likely to differ across these two sets of gas stations. Accordingly, we exclude the Shell observations from our regressions (and thereby obtain more conservative estimates). Finally, all regressions in Table 2 include brand fixed effects and street type fixed effects.[14]

The first regression is a linear probability model. The coefficients of interest, PMG $\times \lambda$ and PMG $\times\, \alpha \times \lambda$, are estimated with statistical precision and have the signs predicted by Propositions 1 and 2. To get an idea of the magnitude of our estimates, we note that as λ varies by one standard deviation (.13), the effect of being included in Shell's PMG offer amounts to a 5.4% increase in the probability of a midday price increase. In absolute terms, keeping in mind that the maximum distance to a Shell station equals 8.68 kilometers, each kilometer closer a Shell station will increase the probability of accepting Shell's collusive offer by 4.78%. Instead of evaluating at $\alpha = 0$ and $PMG = 1$, evaluating at sample means $\alpha = 0.40$ and $PMG = 0.78$ the probability increases become 3.19% and 2.82%, respectively. In contrast, the effects of a standard deviation variation of 9.37% in α are smaller. Evaluated at the mean values of $\lambda = 0.80$ and $PMG = 0.78$, there is a probability change of 1.48%. For the most extreme assumptions of $\lambda = PMG = 1$, the increase is given by 2.37%. Considering the PMG variable and all of its interactions, the overall effect of introducing a PMG is to increase the probability of a midday price increase by 70.55%, with variables evaluated at the mean values of $\lambda = 0.80$ and $\alpha = 0.40$. The PMG offer achieves maximum possible effectiveness with maximum proximity and minimum proportion of loyal customers, $\lambda = 1$ and $\alpha = 0$, with the probability then rising to 86.94%. The effects are of similar size for the other regressions. This illustrates that the effects of the PMG clause are considerable, whereas the effects of a variation of loyal customer shares are rather modest. [15]

The second regression in Table 2 repeats the first but using a probit model rather than a linear probability model. As can be seen, the coefficients have the same sign and similar levels of statistical significance as the OLS regressions.

■ **Learning.** Figure 10 shows a gradual adoption of the midday price increase strat-

14. Our results remain essentially the same if we include Shell stations in our sample.

15. The impact of the IMR on the probability to follow Shell's invitation to the collusive midday price increase is negative, as expected. The IMR represents a hazard rate for the listing decision that decreases when the explanatory variables of the first stage selection equation have a positive impact on the probability of being listed (e.g. λ and station's margin). Conversely, the IMR has a negative coefficient in the second stage collusion equation if stations are in closer competition (e.g. high λ and margin) and thus the probability of accepting the invitation to the midday price increase is a priori greater (not of being listed). In other words, a priori closeness and market power might have played a (moderate) role in coordination. However, including the learning variables in columns 3 and 4 takes away nearly all explanatory power from the IMR, suggesting that learning (through close neighbors) dominated the pure listing selection effect.

egy. This suggests that the process of midday price increases may be one of learning — namely learning from neighbors — rather than the result of incentives created by Shell's PMG. To investigate this possibility, we consider an alternative set of regressions where an indicator of midday price increase of the three closest neighboring stations in the previous day is added as an explanatory variable. The results are shown in the third and fourth columns of Table 2. Looking at the third column (linear probability model), the variable "closest neighbor day before" suggests that if the closest station increased price at noon the day before then the focal station is 20.14% more likely to do the same during the current period. The past actions of the second and third-closest stations are related with a 8 and 7% increase in probability of a midday price increase. It is noteworthy that the explained variance (pseudo R^2) increases substantially. The coefficients of the probit regression (fourth column) have the same sign and are also estimated with statistical precision. We also note that the coefficients of PMG $\times\lambda$ and PMG $\times\, \alpha \times \lambda$ are fairly similar in size and statistical significance. In other words, the introduction of learning does not change the result of our test of Propositions 1 and 2.

■ **Placebo test: distance to nearest Aral.** One potential problem with our estimation is that we use a proxy for the value of λ, not the actual value of λ. Proximity to a Shell station might be proxying for many things other than the measure of Clubsmart members. A second potential problem with our base estimations is the interpretation we give to the coefficient estimate on PMG $\times\lambda$. As mentioned earlier, Proposition 2 implies a positive coefficient. In other words, a positive coefficient may be interpreted in light of a model where Aral and Shell initiate a process of tacit collusion; and other stations follow the leaders' "invitation to tacit collusion" especially if their customer base includes many beneficiaries from Shell's PMG (which we proxy by distance to the nearest Shell station). However, a positive λ coefficient may also be interpreted in the context of static oligopoly competition. If station i increases its price, strategic complementarity suggests that station j is also likely to increase price, especially if station j is located close to station i (and thus competes for the same customers).

One way to tease out these two interpretations is to replicate our base regressions with an alternative variable: distance to the nearest Aral station rather than distance to the nearest Shell station. The idea is that, while both Aral and Shell were leaders in the midday price increase process, only Shell offered a PMG. The effect described in Proposition 2 should therefore be measured by the distance to the nearest Shell station but not to the nearest Aral station. To the extent that there is a residual effect of distance to Aral we might ascribe it primarily to strategic complementarity rather than the combined effect of a PMG and collusion.

Table 3 reports the results of this placebo test. It includes the same regressions as Table 2, with the difference that Aral substitutes for Shell. As we compare the results, we notice that, generally speaking, the relevant coefficients are lower in size and estimated with considerably lower precision. In fact, in none of the regressions performed is the coefficient of the main variable of interest, PMG$\times\lambda$, statistically

Table 3
Placebo test

	Dependent variable: midday price			
Estimation method	OLS	Probit	OLS	Probit
Station included in Shell's offer (PMG)	.2436 (.1655)	2.5627*** (.5167)	.3572** (.1800)	3.8407*** (.6916)
Proximity to Aral (λ')	.2521** (.1151)	.7070** (.3234)	.0183 (.1169)	-.2090 (.4034)
Share of older population (α) $\times\lambda'$	.2516* (.1369)	1.0184* (.5222)	.1181 (.1838)	.7751 (.7636)
PMG $\times\lambda$	-.0712 (.1423)	.0038 (.4525)	-.1752 (.1604)	-.2675 (.6235)
PMG $\times\alpha\times\lambda$	-.3296** (.1559)	-1.3143** (.5917)	-.1944 (.2185)	-1.1341 (.9077)
# competitors	-.0022* (.0012)	-.0075* (.0042)	-.0083*** (.0016)	-.0319*** (.0068)
Inverse Mills Ratio	.0771 (.0638)	.2314 (.2060)	.1487** (.0673)	.5839** (.2655)
Closest neighbor day before			.2796*** (.0159)	1.0136*** (.0555)
Second closest neighbor day before			.1094*** (.0140)	.4509*** (.0523)
Third closest neighbor day before			.0936*** (.0139)	.4253*** (.0571)
Constant	-.2522* (.1344)	-1.2805*** (.4028)	-.4556*** (.1396)	-2.2546*** (.5331)
(pseudo) R^2	.1587	.1377	.3013	.2878
N	42,258	42,258	42,258	42,258

Notes: Robust standard errors (clustered at station level) in parentheses.
Star levels: 10, 5 and 1%.
All regressions exclude Aral and include brand fixed effects.

Table 4
Price equations

	Dependent variable: price at specific times of the day				
	12 pm	12:30	1 pm	1:30	2 pm
λ	-0.0108** (0.0044)	-0.0199*** (0.0046)	-0.0215*** (0.0044)	-0.0224*** (0.0045)	-0.0193*** (0.0045)
$\alpha\,\lambda$	0.0081* (0.0045)	0.0073* (0.0043)	0.0061 (0.0043)	0.0076* (0.0043)	0.0083** (0.0042)
$\lambda\,d$	0.0001 (0.0014)	0.0129*** (0.0017)	0.0223*** (0.0015)	0.0246*** (0.0014)	0.0196*** (0.0013)
$\alpha\,\lambda\,d$	-0.0086*** (0.0023)	-0.0094*** (0.0031)	-0.0081*** (0.0024)	-0.0103*** (0.0022)	-0.0102*** (0.0020)
Constant	1.1757*** (0.0038)	1.2034*** (0.0053)	1.2202*** (0.0042)	1.2209*** (0.0040)	1.2027*** (0.0040)
R^2	0.4535	0.3492	0.3461	0.3462	0.3451
N	131,701	131,701	131,701	131,701	131,701

Notes: $d = 1$ iff $t >$ June 24, 2015.
Robust standard errors (clustered at station level) in parentheses.
Regressions include controls for school holidays and crude oil price.
Star levels: 10, 5 and 1%.

significant at any conventional level. Moreover, in the preferred regressions where we include learning effects the coefficients of α and λ are not statistically significant — unlike the regressions for Shell. All in all, our Aral placebo tests suggest that the gross of the effect of our Shell-based λ variable is likely attributable to the effect of Shell's PMG, not to distance per se.

■ **Price equations.** The main goal of our analysis is to understand the nature and the unfolding of tacit collusion. The evidence suggests that tacit collusion took the place of a price hike at around noon; and that, following the leadership of Aral and Shell stations, other retailers followed suit, especially if they were close to PMG-granting Shell stations. Having established this pattern, a natural question to ask is whether the midday price increase had any effect on prices compared to the counterfactual of no midday price increases. Table 4 shows the results of a series of regressions with price as the dependent variable. Although the price increases take place at noon or shortly after noon, we are interested not only on noon prices but also at prices during the rest of the day. If the price increases only take place at noon and otherwise prices are at the levels they were prior to the midday price increase pattern, then the effect of midday price increases might be small. Moreover, it is possible that prices are lowered before noon so that the noon price increase is simply a return to the previous price level.

Specifically, we consider the determinants of prices at 30 minute intervals from 12 noon until 2pm. So as to estimate a differences equation that shows the impact of the PMG, we create a dummy variable d which takes the value 1 for dates after June 24, 2015. The relevant coefficients are therefore the interaction of d with λ and $\alpha\,\lambda$. The results suggest that, as λ varies from 0 to 1, the effect of the PMG is highest at 1:30pm (2.46 cents per liter). From Table 1, the average value of λ is given by 0.80. This means that, for the mean station, price at 1:30pm is $0.80 \times 0.0246 = 1.97$ cents per liter higher than it was before the introduction of the PMG. Also consistently with theory, we estimate negative coefficients of the variable $\alpha\,\lambda$ when interacted with the dummy d.

In sum, the price equation regressions complement those in the previous tables, suggesting that the practice of increasing prices by 3 cents at noon did have an effect on price levels by about 2 cents when compared to price levels prior to the introduction of a PMG. Interestingly, the condition for price adjustment contained in the Shell PMG offer is effective only if the difference with respect to the a competitor's price is greater than 2 cents. The PMG therefore only takes effect from a price increase of at least 3 cents.

■ **Robustness checks.** Table 5 considers two additional robustness checks. In our base regressions we clustered standard errors at the gas station level. While we believe this is a reasonable (and fairly standard) procedure, we also ran alternative regressions where standard errors are not clustered. Specifically, we re-ran the first regression in Table 2 with unclustered standard errors. The results, which can be found in the first column of Table 5, show that the choice of clustering method does change the estimated coefficients, rather it changes the level of standard errors. However, the central coefficients are estimated with precision both with and without clustered standard errors.

Most of the identification in our models comes from spatial variation across stations. In other words, except for the "learning" variables, the independent variables we consider are time-independent. An alternative way to estimate the effect of λ and $\alpha\,\lambda$ on midday price increases is then to consider as a dependent variable the fraction of days in which station i increases price (as opposed to the dummy variable "increased price in day t"). The second column of Table 5 presents the results from estimating the first model in Table 2 with a cross-section model. Despite this change in estimation procedure, our estimated coefficients remain fairly significant and with the signs predicted by Propositions 1 and 2.

■ **Additional placebo test: 2014 vs 2015.** Earlier we argued that the midday price increase period (and the Shell PMG period) were accompanied by significant increases in price-cost differences. For example, Figure 8 shows gasoline prices increasing during July 2015 just as oil prices decrease. Naturally, there can be many different factors besides the PMG underlying this pattern. One simple robustness test is to compare our 2015 period (when a PMG was in place) to the corresponding period in 2014 (when it was not). Are midday price increases a seasonal pattern? A natural robustness test of our empirical regressions is to redo the analysis in 2014, when no PMG was

Table 5

Robustness checks

Estimation method	OLS unclustered errors	OLS cross section
Station included in Shell's offer (PMG)	.4541*** (.0548)	0.5744*** (.1177)
Proximity to Shell (λ)	-.4238*** (.0387)	-0.3699*** (.1399)
Share of young population (α) $\times\lambda$	.2559*** (0.0276)	.2223** (.1048)
PMG$\times\lambda$	.4153*** (.0395)	0.3419** (.1385)
PMG$\times\alpha\times\lambda$	-.2526*** (.0285)	-.2246 (.1023)
# competitors	.0008** (.0004)	.0000 (.0011)
Inverse Mills Ratio	-.0862*** (.0220)	-.0424 (.0629)
Constant	.4318*** (.0544)	.2842** (.1248)
(pseudo) R^2	.2093	.6981
N	57,922	925

Notes: Robust standard errors (clustered at station level) in parentheses.
Star levels: 10, 5 and 1%.
All regressions exclude Shell and include brand fixed effects.

in place. This test turns out to be rather simple: there were no instances in 2014 when retail gasoline prices increased during the 11am-2pm period. As a result, no significant coefficients would be found if the regressions in Table 2 were ran on 2014 data.

5. Conclusion

As Harrington (2015) put it, "the focus of economic theory has been on characterizing the market conditions conducive to satisfying the stability condition." Specifically, a common result in this literature is that, if the discount factor is greater than some critical threshold δ', then grim-strategy collusion is feasible (see, e.g., Friedman, 1971).

This approach is helpful and useful in many different industries. However, considering the high frequency with which gas stations set prices, it's hard to believe no-deviation constraints play an important role in explaining when collusion takes place. We believe the conventional analysis of tacit collusion misses an important issue: by stressing whether collusion is *feasible*, it largely ignores the issue of whether collusion in *profitable*. To quote Harrington (2015), an important question is "when is it that firms want to replace competition with collusion."

In this paper we follow a route different from most of the previous literature. We assume no-deviation constraints are satisfied and instead look at conditions that favor the emergence of collusion. We argue, both theoretically and empirically, that price matching guarantees are one such condition that facilitates the emergence of tacit collusion.

Specifically, our empirical claim is two-fold: first, that there was an attempt at tacit collusion in the German gasoline retail market in June 2015; and second, that the introduction of a Price Matching Guarantee by Shell played a central role in implementing tacit collusion. As IO economists interested in competition and collusion, we are aware of Maslow's rule that "it is tempting, if the only tool you have is a hammer, to treat everything as if it were a nail." Nevertheless, we believe our paper makes a strong case for both of the above claims. First, the observed midday price increases have all the features of a focal-point equilibrium typical of tacit collusion outcomes: for example, the price increase is nearly always of 3 cents and almost always takes place at noon. Second by taking advantage of spacial differences in proximity to the nearest Shell station, we find strong evidence consistent with a causal relation from Shell's PMG and the emergence of tacit collusion.

Appendix

Proof of Proposition 1: Consider the problem faced by a firm responding to a rival who has just switched from p_l to p_h (for the first time). The value from responding with p_h is given by $\pi_i(p_h, p_h) - c + \delta\, V_i^c$, whereas the value from responding with p_l is given by $\pi_i(p_l, p_h) + \delta\, V_i^d$. It follows that Firm i accepts the invitation to switch to a collusion equilibrium if and only if $\pi_i(p_h, p_h) - c + \delta\, V_i^c > \pi_i(p_l, p_h) + \delta\, V_i^d$, which happens with probability ϕ_i given by

$$\phi_i = F\Big(\pi_i(p_h, p_h) - \pi_i(p_l, p_h) + \delta\, V_i^c - \delta\, V_i^d\Big) \tag{3}$$

Denote by $\widetilde{z}$ a generic variable under the no PMG regime; and by $\widehat{z}$ the corresponding variable under the PMG regime. Note that $\widetilde{V}_i^d = \widehat{V}_i^d = V^d$; and that $\widetilde{V}_i^c = \widehat{V}_i^c = V^c$. In other words, the value along the collusion or punishment subgames is independent of firm identity or PMG regime. Since $\widehat{\pi}_1(p_h, p_h) = \widetilde{\pi}_1(p_h, p_h)$ and $\widehat{\pi}_1(p_l, p_h) = \widetilde{\pi}_1(p_l, p_h)$, (3) implies that $\widehat{\phi}_1 = \widetilde{\phi}_1$. Moreover, since $\widehat{\pi}_2(p_h, p_h) = \widetilde{\pi}_2(p_h, p_h)$ and $\widehat{\pi}_2(p_l, p_h) < \widetilde{\pi}_2(p_l, p_h)$, (3) implies that $\widehat{\phi}_2 > \widetilde{\phi}_2$. ■

Proof of Proposition 2: From (3), the probability that firm i responds to p_h with p_h is increasing in $\pi_i(p_h, p_h) - \pi_i(p_l, p_h) + \delta\, V_i^c - \delta\, V_i^d$. Note that $V_i^c = p_h/(1-\delta)$ and $V_i^d = p_l/(1-\delta)$; that is, the punishment and collusion subgames imply a payoff which is independent of λ or α. By contrast, $\xi \equiv \pi_2(p_h, p_h) - \pi_2(p_l, p_h)$ is increasing in λ and decreasing in $\alpha\,\lambda$:

$$\begin{aligned} d\xi/d\lambda &= (1-\alpha)\,p_l > 0 \\ d\xi/d(\alpha\,\lambda) &= -p_l < 0 \end{aligned}$$

As to Firm 1, ϕ_1 is independent of α or λ. It follows that ϕ_i is increasing in λ and decreasing in $\alpha\,\lambda$, both strict inequalities for $i = 2$. ■

Proof of Proposition 3: We will prove that, if (1)–(2) holds, then $\widetilde{\beta}_i = \widetilde{\phi}_i = 0$, whereas $\widehat{\beta}_1 = \widehat{\phi}_2 = 1$ and $\widehat{\beta}_2 = \widehat{\phi}_1 = 0$. The condition that $\widehat{\phi}_2 = 1$ is equivalent to by

$$\begin{aligned} p_h - c + \delta\, p_h/(1-\delta) &> \alpha\, p_l + (1-\alpha)\,(2-\lambda)\,p_l + \delta\, p_l/(1-\delta) \\ c &< \Delta + p_l - \big(\alpha\, p_l + (1-\alpha)\,(2-\lambda)\,p_l\big) \\ c &< \Delta - (1-\alpha)\,(1-\lambda)\,p_l \end{aligned}$$

where

$$\Delta \equiv (p_h - p_l)/(1-\delta)$$

This corresponds to the second inequality in (1). The condition that $\widetilde{\phi}_2 = 0$ is equivalent to

$$\begin{aligned} p_h - c + \delta\, p_h/(1-\delta) &< (2-\alpha)\,p_l + \delta\, p_l/(1-\delta) \\ c &> \Delta + p_l - (2-\alpha)\,p_l \\ c &> \Delta - (1-\alpha)\,p_l \end{aligned} \tag{4}$$

This corresponds to the first inequality in (1). This condition also implies that $\widehat{\phi}_1 = \widetilde{\phi}_1 = 0$. In order to get $\widetilde{\beta}_i = 0$, as well as $\widehat{\beta}_2 = 0$, all we need to require is that $\widetilde{\pi}_i(p_h, p_l) < \widetilde{\pi}_i(p_l, p_l)$, that is

$$\alpha\, p_h < p_l$$

This corresponds to the first term on the right-hand side of(2). Finally, the condition that $\widehat{\beta}_1 = 1$ is equivalent to

$$\begin{aligned}
-c + \widehat{\pi}_1(p_h, p_l) + \delta\, p_h/(1-\delta) &\;>\; \widehat{\pi}_1(p_l, p_l) + \delta\, p_l/(1-\delta) \\
-c + \alpha\,(1-\lambda)\, p_h + \lambda\, p_l - p_h + p_h + \delta\, p_h/(1-\delta) &\;>\; p_l + \delta\, p_l/(1-\delta) \\
c &\;<\; \Delta - p_h + \alpha\,(1-\lambda)\, p_h + \lambda\, p_l \\
c &\;<\; \Delta - \big(1 - \alpha\,(1-\lambda)\big)\; p_h + \lambda\, p_l
\end{aligned}$$

So that this does not define an empty set, we require this upper bound on c to be greater than the lower bound defined by (4). This implies

$$\begin{aligned}
-\big(1 - \alpha\,(1-\lambda)\big)\; p_h &> -\lambda\, p_l - (1-\alpha)\, p_l \\
\big(1 - \alpha\,(1-\lambda)\big)\; p_h &< \lambda\, p_l + (1-\alpha)\, p_l \\
p_h &< \frac{\lambda + (1-\alpha)}{1 - \alpha\,(1-\lambda)}\; p_l
\end{aligned}$$

This corresponds to the second term on the right-hand side of (2). ■

Table 6
Types of gas stations in Germany

Brand	#	VI?	Notes
Aral	254	Yes	Subsidiary of BP
Shell	189	Yes	
STAR	99	Yes	
TOTAL	94	Yes	
JET	81	Yes	Brand of Phillips 66
ESSO	91	Yes	Subsidiary of ExxonMobil
Freie TS	53	No	
SB	38	No	Some supplied by Shell
OIL!	33	No	Subsidiary of Marquard & Bahls
BFT	35	No	Some supplied by Shell
Westfalen	23	No	Brand of Westfalen AG
Supermarkt TS	26		
Markant	26	No	Brand of Westfalen AG
HEM	18	No	Subsidiary of Oilinvest
AVIA	17	No	
PM24	11	No	Lessee for Aral, Shell

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