Price Matching Guarantees and Collusion: Theory and Evidence from Germany

Luís Cabral
New York University and *CEPR*

Niklas Dürr
CEER (Zentrum für Europäische Wirtschaftsforschung)

Dominik Schober
University of Mannheim and *CEER (Zentrum für Europäische Wirtschaftsforschung)*

Oliver Woll
CEER (Zentrum für Europäische Wirtschaftsforschung)

July 2018

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 from 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.

Cabral: Paganelli-Bull Professor of Economics and International Business, Stern School of Business, New York University; and Research Fellow, CEPR; luis.cabral@nyu.edu. Dürr: dürr@zew.de Schober: schober@zew.de. Woll: woll@zew.de. The usual disclaimer applies.

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 tacklend 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 that 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 (2016) 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 (2016) 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 (2016), the time frame of convergence to midday price increases is remarkably shorter (a matter of weeks, not years). One justification 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).

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

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 (2107) 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 6 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 evidence 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

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

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: 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

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.

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.

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]

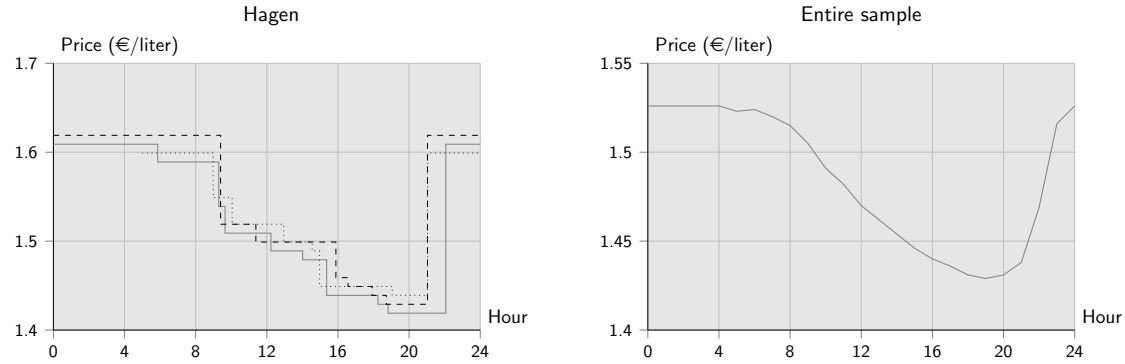
Proposition 3. *Suppose that*

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

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

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



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 9 provides a listing for North Rhine-Westphalia, the region of Germany on which our empirical analysis will be focused.

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 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.

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 2
Daily traffic and search patterns

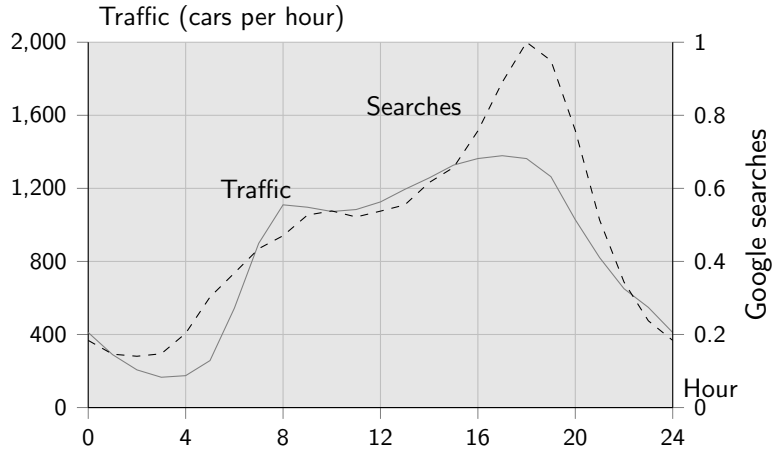
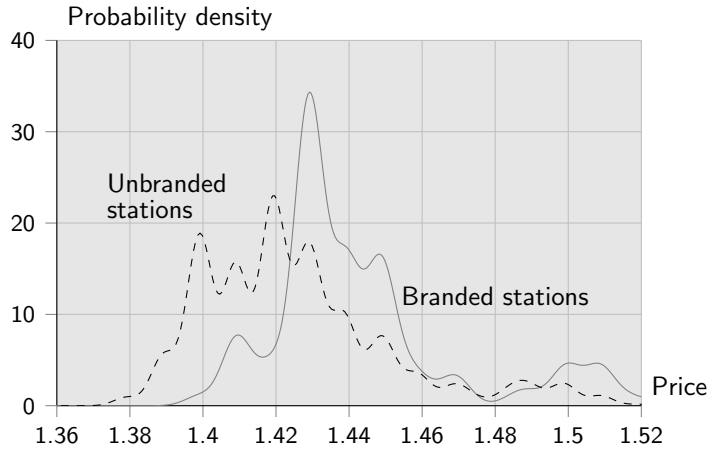


Figure 3
May 25, 2015, 5pm price kernel density



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 Prime 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 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 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 of the ten closest gasoline stations. Shell excluded from the comparison set some unbranded gas stations. 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 Aral's increases took place at 12:02, Shell's at 12:01).

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.[7]

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 regularly increasing prices at around noon. Although we present data for two specific days and for one of more than nineteen 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 point. The left panels show the distribution

7. Shell made other (unsuccessful attempts) at increasing prices in their daily sequence, one at 11am, one at 4pm.

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

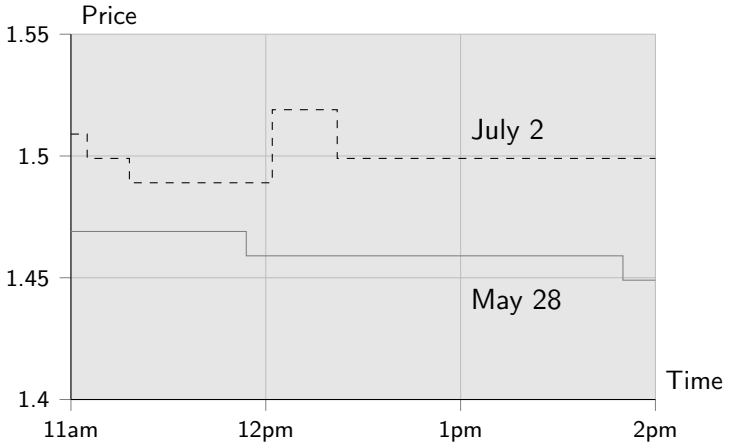
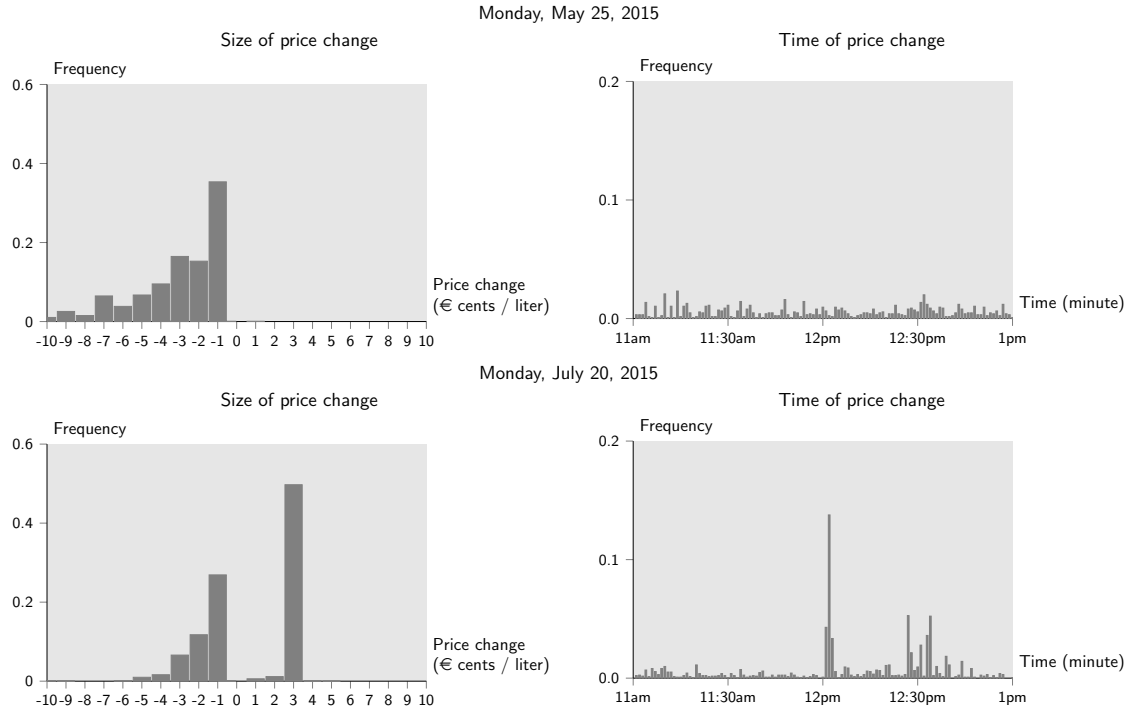


Figure 5
Midday price changes



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 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 concentration around 12noon.[8]

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 into Shell & Aral (the leaders in the midday price increase pattern), typically change their prices at from 12:00 and 12:02 (almost 90% of the time), whereas the other stations almost always do so at around 12:30. Moreover, there is no significant difference in these distributions over time.[9] 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).

Figure 6 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 6 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 that increases price at midday, we expect station X's prices to be higher (by a simple strategic complementarity) 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 6 also shows a negative estimated coefficient for before-noon prices. It's as if gas station 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

8. 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.

9. This contrasts with Byrne and De Roos (2016), where one observes, over the years, significant differences in price-increase patterns.

Figure 6
Estimated coefficients from price equations (and 95% confidence interval)

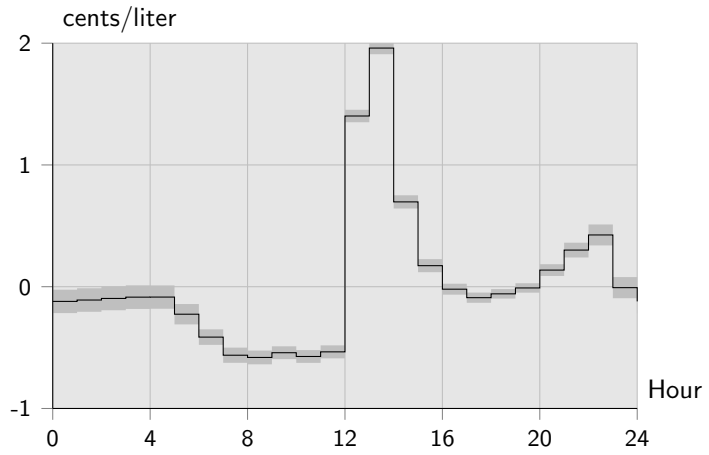
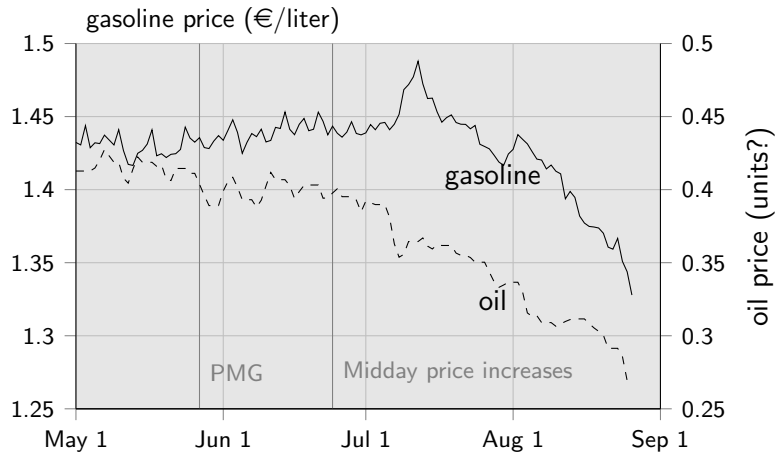


Figure 7
Oil price and 5PM gasoline price in 2015



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 7 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 in the previous section provides a narrative and 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

Figure 8
Estimated daily car traffic

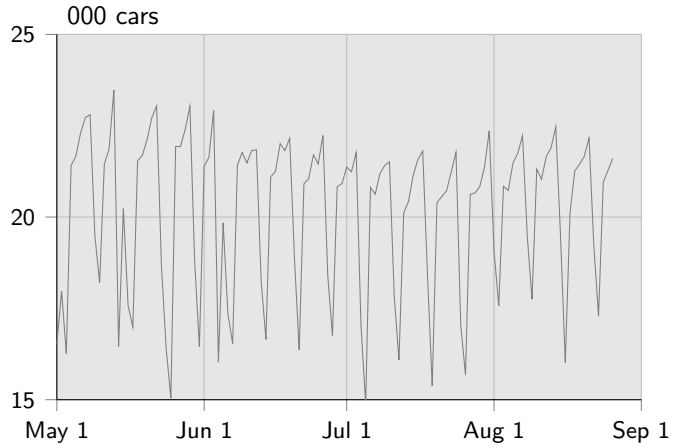
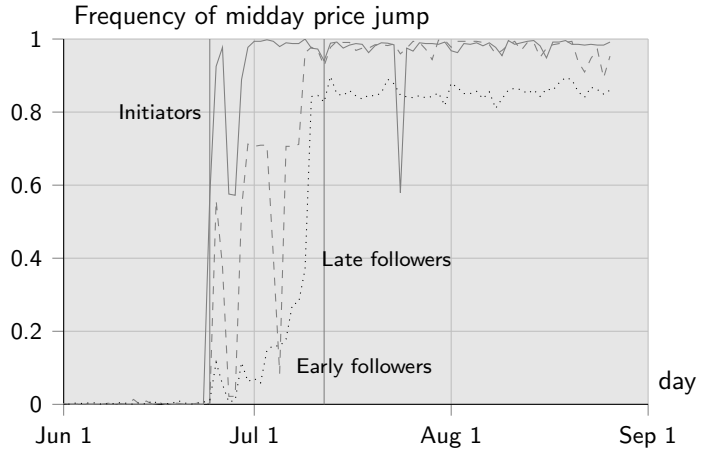


Figure 9
Emergence of collusion (solid vertical lines divide phases of transition process)



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 7 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 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

As mentioned in the previous section, the extent to which the Aral/Shell price hike was taken up by other gas stations varied across stations. It also varied over time. Figure 9 shows, for each day after June 1, the percentage of stations within each group that increased their prices any time from 11am-2pm. Two vertical lines separate the different phases: before June 24, when the first price hikes take place; between June 24 and July 12, a transition phase; and after July 12, when decisions of whether to increase prices at midday have been taken in a stable way (nearly 100% of the initiators and early followers, about 80% of the late followers).

Our empirical test focuses on the transition phase, a phase when there is considerable variation across stations. Specifically, we test a specific implication of our theory of PMG-facilitated collusion: Proposition 2 predicts that 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, which we do not have. 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.

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):

- α_i: share of population aged under 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

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 10 shows the section of Germany we consider for our empirical test.[10]

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

10. 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.

Figure 10
Catchment area: all gas stations in a 50k radius of Düsseldorf, Wuppertal, Gladbach, Duisburg, Essen, Dortmund, and Leverkusen

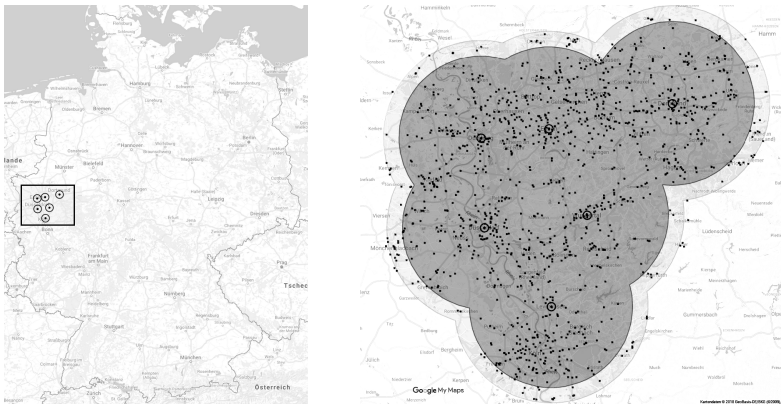


Table 1
Summary statistics

	N	Mean	St Dev	Min	Max
Price at 12pm	71895	1.46	0. 05	1.29	1.80
Traffic volume at 12pm (in '000)	71895	1.10	9.14	0.00	6.13
School holidays	71895	0.37	0.48	0.00	1.00
Oil price per liter	71895	0.37	0.04	0.27	0.43
Car density	71895	504.81	51.21	430.00	599.00
Aral	71895	0.22	0.42	0.00	1.00
Shell	71895	0.17	0.37	0.00	1.00
# of Competitors (3 km)	71895	9.57	4.52	1.00	22.00
# of Competitors (7 km)	71895	32.21	13.05	0.00	65.00
Midday price increase	71895	0.83	0.38	0.00	1.00
Card membership proxy (λ)	71895	0.84	0.13	0.25	1.00
Loyal card members proxy ($\alpha\,\lambda$)	71895	0.78	0.12	0.24	0.96

Table 2
Base regressions

	Dependent variable: midday price increase during June 24-July 12			
Sample:	OLS	OLS (excluding Shell)	Probit	Probit (excluding Shell)
Card membership proxy (λ)	3.0185*** (0.9901)	4.2192*** (1.2438)	7.7407*** (2.5611)	10.6283*** (3.1595)
Loyal card members proxy ($\alpha\,\lambda$)	-2.8878*** (1.0600)	-4.7557*** (1.3366)	-7.4107*** (2.7394)	-11.9811*** (3.3978)
Constant	0.2938*** (0.0708)	0.6947*** (0.0833)	-0.5258*** (0.1799)	0.4916** (0.2119)
N	19,985	16,658	19,985	16,658

Notes: Robust standard errors (clustered at station level) in parentheses. Star levels: 10, 5 and 1%.

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.

Table 2 presents our base regressions, relating the dependent variable, "gas station i increase priced in day t", to our proxies for λ (distance from i to the nearest Shell station) and $\alpha\,\lambda$ (λ times the fraction of young people in zip code containing gas station i). Our sample corresponds to the transition period market in Figure 9, that is, the period from June 24-July 12 (when there is greater variability across gas stations regarding midday price increases).

The first two models in Table 2 correspond to OLS regression. The first one includes all of the observations (during the transition period). By contrast, the second regression excludes Shell station observations. The idea is that Shell's PMG induces a fundamental asymmetry between Shell stations and competing stations, which in principle might be reflected in pricing behavior as well.

Proposition 2 predicts a positive λ coefficient and a negative $\alpha\,\lambda$ coefficient. Regardless of which regression we consider (in Table 2), the estimated coefficients have the sign predicted by Proposition 2. Moreover, they are identified with high statistical precision (p values lower than 1%).

The size of the estimated coefficients is quite large, suggesting that our narrative of what's driving midday price increases has bite. Specifically, as λ varies by one standard deviation (.13), the probability of a midday price increase during first phase (excluding Shell) increases by 54% (sample average of 83%). Moreover, as $\alpha\,\lambda$ varies by one standard deviation (.12), the probability of a price increase during first phase (excluding Shell) increases by 56% (sample average of 83%).

These are very large effects, which in turn suggests that a linear probability model may not provide the best approximation. Accordingly, the second set of columns of Table 2 display the results of the corresponding probit regressions. As can be seen, the coefficients have the same sign and level of statistical significance as the OLS regressions.

Table 3
Base regressions including various controls (type of street, day of week, school holidays, time trend and oil price)

	Dependent variable: midday price increase during June 24-July 12			
Sample:	OLS	OLS (excluding Shell)	Probit	Probit (excluding Shell)
Card membership proxy (λ)	3.4229*** (1.0080)	4.6143*** (1.2628)	9.9562*** (2.9511)	12.8435*** (3.5287)
Loyal card members proxy ($\alpha\,\lambda$)	-3.3123*** (1.0804)	-5.1491*** (1.3565)	-9.6620*** (3.1582)	-14.3359*** (3.7927)
Constant	-3.1406*** (0.2730)	-2.6414*** (0.3126)	-10.3421*** (0.8077)	-8.7389*** (0.8780)
N	19,985	16,658	19,985	16,658

Notes: Robust standard errors (clustered at station level) in parentheses. Star levels: 10, 5 and 1%.

5. Robustness checks and extensions

In this section, we consider a variety of robustness checks. The corresponding estimation tables may be found in the Appendix.

■ **Additional controls.** Our base regressions include exclusively λ and $\alpha\,\lambda$ as independent variables (in addition to a constant). We do have detailed information about each gas station. Moreover, as Figure 9 suggests, time played an important role in the degree of take-up of midday price increases. A natural robustness check is to add various time and station-level controls. Specifically, we re-estimate the same models as in Table 2 by adding controls for type of street, day of week, school holidays, time trend, and oil price.

Table 3 (in the Appendix) presents the results from the regressions with additional controls. As can be seen, the relevant coefficient estimates are very similar to those in the models without controls. Specifically, one of our central coefficient estimates, distance to Sell in the OLS regression excluding Shell stations, increases from from 4.2192 to 4.6143, a relatively small variation.

■ **Longer sample period.** The results listed in Table 2 correspond to the period June 24–July 12, the period when there was greatest variation across gas stations in terms of midday price behavior. Table 4 (in the Appendix) includes the corresponding regressions for a larger time period, June 24 to August 27. This larger period includes both a first transition phase, when there is greater heterogeneity across gas stations, and a second steady-state phase, when the dust has settled regarding gas stations' pricing behavior. However, to the extent that a fraction of the non-branded gas stations have not followed the invitation to engage in midday price increases, we might have additional data to explore the determinants of pricing behavior.

The results for the broader sample essentially confirm the results from the base regressions in terms of coefficient sign and statistical significance. Regarding coefficient size, we generally obtain lower values. Specifically, one of our central coefficient estimates, distance to Sell in the OLS regression excluding Shell stations, drops from 4.2192 to 2.2929. This

Table 4
Base regressions (longer time period)

	Dependent variable: midday price increase during June 24-August 27			
Sample:	OLS	OLS (excluding Shell)	Probit	Probit (excluding Shell)
Card membership proxy (λ)	1.6535*** (0.5652)	2.2929*** (0.7266)	8.4090*** (2.9847)	10.7503*** (3.5601)
Loyal card members proxy ($\alpha\,\lambda$)	-1.7023*** (0.6065)	-2.6376*** (0.7838)	-8.7230*** (3.1993)	-12.4354*** (3.8222)
Constant	-2.1133*** (0.1054)	-2.1039*** (0.1240)	-7.6053*** (0.4143)	-7.3207*** (0.4655)
N	71,895	59,989	71,895	59,989

Notes: Robust standard errors (clustered at station level) in parentheses. Star levels: 10, 5 and 1%.

Table 5
Base regressions (unclustered standard errors)

	Dependent variable: midday price increase during June 24-July 12			
Sample:	OLS	OLS (excluding Shell)	Probit	Probit (excluding Shell)
Card membership proxy (λ)	3.4229*** (0.3220)	4.6143*** (0.3893)	9.9562*** (0.9424)	12.8435*** (1.0906)
Loyal card members proxy ($\alpha\,\lambda$)	-3.3123*** (0.3451)	-5.1491*** (0.4182)	-9.6620*** (1.0086)	-14.3359*** (1.1723)
Constant	-3.1406*** (0.5239)	-2.6414*** (0.5897)	-10.3421*** (1.4972)	-8.7389*** (1.6338)
N	19,985	16,658	19,985	16,658

Notes: Robust standard errors in parentheses. Star levels: 10, 5 and 1%.

significant drop may be justified by the fact that, eventually, almost all stations join in the midday price increase routine, which in turn lowers the explanatory power of our λ variable. Basically, more than a robustness check, the regressions in Table 4 answer a different research question than those in Table 2. In the former case, the question is: what explains the eventual choice to engage in midday price increases; by contrast, in the latter case, the question is: during the transition phase, what explains the choice to follow the Aral and Shell's lead in engaging in midday price increases.

■ **Unclustered standard errors.** 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 regressions in Table 3 with unclustered standard errors. The results, which can be found in 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.

Table 6
Base regressions (cross section)

	Dependent variable: percentage days with midday price increase			
Sample:	first phase	OLS first phase, excluding Shell	entire period	Probit entire period, excluding Shell
Card membership proxy (λ)	3.6827*** (1.0244)	4.8961*** (1.2739)	1.6506*** (0.5868)	2.2777*** (0.7507)
Loyal card members proxy ($\alpha\,\lambda$)	-3.5812*** (1.0983)	-5.4517*** (1.3685)	-1.7022*** (0.6299)	-2.6267*** (0.8099)
Constant	0.1977*** (0.0712)	0.5897*** (0.0854)	0.7417*** (0.0345)	0.9151*** (0.0437)
N	1,169	980	1,169	980

Notes: Robust standard errors in parentheses. Star levels: 10, 5 and 1%.

■ **Cross-section vs panel regression.** Most of the identification in our models comes from spatial variation across stations. In other words, except for the regression in Table 3, 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"). Table 6 presents the results from these regressions. Basically, we re-estimate the same models as in Table 2 but we change the dependent variable. In the process, we switch from a panel to a cross-section regression and reduce the number of observations.

Despite these changes in estimation procedure, our estimated coefficients remain fairly similar. Specifically, one of our central coefficient estimates, distance to Sell in the OLS regression excluding Shell stations, increases from 4.6143 to 4.8961, a relatively small change.

■ **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 7 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 for our empirical test is to redo the analysis in 2014, when no PMG was 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.

■ **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 are given to the

Table 7
Placebo test: λ defined with respect to Aral rather than Shell

	Dependent variable: midday price increase during June 24-July 12			
Sample:	OLS	OLS (excluding Aral)	Probit	Probit (excluding Aral)
Card membership proxy (λ)	1.8538* (0.9575)	2.6683** (1.1298)	5.5263* (2.9239)	8.1983** (3.4793)
Loyal card members proxy ($\alpha\,\lambda$)	-1.1538 (1.0336)	-2.9241** (1.2191)	-3.4373 (3.1539)	-8.9795** (3.7558)
Constant	1.9242*** (0.1055)	3.1075*** (0.1167)	4.3334*** (0.2776)	6.6351*** (0.3304)
N	19,985	15,517	19,985	15,517

Notes: Robust standard errors (clustered at station level) in parentheses. Star levels: 10, 5 and 1%.

coefficient estimate on λ. 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 our these two interpretations is to replicate our base regressions with an alternative variable: distance to the nearest Aral station rather than 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 7 reports the results of this placebo test. As we compare the results to those in Table 2, we notice the relevant coefficients are lower and size and estimated with considerably lower precision. Specifically, one of our central coefficient estimates, distance to Shell (resp. Aral) in the OLS regression excluding Shell (resp. Aral) stations, drops from 4.6143 to 2.6683, a significant change, whereas the standard deviation of the estimate varies from 1.2438 to 1.1298, a relatively small change. Table 8 corresponds to the re-estimation of the models in Table 4, that is, the regressions based on the longer sample. In this case, the relevant same coefficient (distance to Shell/Aral) based on the subsample that excludes the Shell/Aral stations drops from 2.2929 (an estimate with a p value lower than 1%) to 1.0950 (an estimate which is not statistically different from zero).

All in all, our Aral placebo test suggest that the gross of the effect of our Shell-based λ variable is likely attributable to the effect of Shell's PMG.

Table 8
Placebo test: λ defined with respect to Aral rather than Shell (longer time period)

	Dependent variable: midday price increase during June 24-August 27			
Sample:	OLS	OLS (excluding Aral)	Probit	Probit (excluding Aral)
Card membership proxy (λ)	0.8975* (0.5006)	1.0950 (0.6937)	4.5703 (2.8093)	4.9980 (3.3609)
Loyal card members proxy ($\alpha\,\lambda$)	-0.6432 (0.5393)	-1.1633 (0.7511)	-3.4620 (3.0287)	-5.2942 (3.6344)
Constant	2.1440*** (0.0561)	2.8243*** (0.0599)	6.2668*** (0.2720)	8.2653*** (0.3477)
N	71,895	55,928	71,895	55,928

Notes: Robust standard errors (clustered at station level) in parentheses. Star levels: 10, 5 and 1%.

6. 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 prime 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 9
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

References

Arbatskaya, M., Hviid, M., and Shaffer, G. "On the Incidence and Variety of Low-Price Guarantees." Working Paper, Centre for Industrial Economics, Institute of Economics, University of Copenhagen (1999).

—. "On the use of low-price guarantees to discourage price cutting." *International Journal of Industrial Organization*, Vol. 24 (2006), pp. 1139–1156.

Boehnke, J. "Pricing Strategies and Competition: Evidence from the Austrian and German Retail Gasoline Markets." Working Paper, Harvard University (2017).

Byrne, D.P. and De Roos, N. "Learning to Coordinate: A Study in Retail Gasoline." Working Paper, University of Sidney (2016).

Cabral, L., Schober, D., and Woll, O. "Search and Equilibrium Prices: Theory and Evidence from Retail Diesel." Working Paper, NYU and ZEW (2018).

Chilet, J.A. "Gradually Rebuilding a Relationship: The Emergence of Collusion in Retail Pharmacies in Chile." Working Paper, University of Pennsylvania (2017).

Dewenter, R. and Schwalbe, U. "Preisgarantien im Kraftstoffmarkt." Working Paper (2015).

Friedman, J.W. "A Non-cooperative Equilibrium for Supergames." *Review of Economic Studies*, Vol. 38 (1971), pp. 1–12.

Harrington, J. "Thoughts on Why Certain Markets are More Susceptible to Collusion and Some Policy Suggestions for Dealing with Them." Background paper, OECD Global Forum on Competition (2015).

Harrington, J.E. and Chen, J. "Cartel Pricing Dynamics with Cost Variability and Endogenous Buyer Detection." *International Journal of Industrial Organization*, Vol. 24 (2006), pp. 1185–1212.

Harrington, J.E. and Myong-Hun, C. "Modeling the Birth and Death of Cartels with an Application to Evaluating Competition Policy." *Journal of the European Economic Association*, Vol. 7 (2009), pp. 1400–1435.

Hess, J.D. and Gerstner, E. "Price-Matching Policies: An Empirical Case." *Managerial and Decision Economics*, Vol. 12 (1991), pp. 305–315.

Holt, C.A. and Scheffman, D.T. "Facilitating Practices: The Effects of Advance Notice and Best-Price Policies." *The RAND Journal of Economics*, Vol. 18 (1987), pp. 187–197.

Hviid, M. and Shaffer, G. "Hassle Costs: The Achilles' Heel of Price-Matching Guarantees." *Journal of Economics & Management Strategy*, (1999), p. 489–521.

Manez, J.A. "Unbeatable Value Low-Price Guarantee: Collusive Mechanism or Advertising Strategy?" *Journal of Economics and Management Strategy*, Vol. 15 (2006), pp. 143–166.

Maskin, E. and Tirole, J. "A Theory of Dynamic Oligopoly, II: Price Competition, Kinked Demand Curves, and Edgeworth Cycles." *Econometrica*, Vol. 56 (1988), pp. 571–99.

Pollak, A. "Do Price-Matching Guarantees with Markups Facilitate Tacit Collusion? Theory and Experiment." Working paper, University of Cologne Working Paper Series in Economics No. 93 (2017).

Rotemberg, J.J. and Saloner, G. "A Supergame-Theoretic Model of Price Wars during Booms." *American Economic Review*, Vol. 76 (1986), pp. 390–407.

Schelling, T.C. *The Strategy of Conflict*. Harvard University Press, 1960.

Schnitzer, M. "Dynamic Duopoly with Best-Price Clauses." *The RAND Journal of Economics*, Vol. 25 (1994), pp. 186–196.

Wilhelm, S. "Price-Matching Strategies in the German Gasoline Retail Market." Working paper, Goethe University Frankfurt (2016).

Zhuo, R. "Do Low Price Guarantees Guarantee Low Prices? Evidence From Competition between Amazon and Big-Box Stores." *The Journal of Industrial Economics*, Vol. 65 (2107), pp. 719–738.