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Markets Take Breaks: Dynamic Price Competition with Opening Hours

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Markets Take Breaks: Dynamic Price Competition with Opening Hours*

Steffen Eibelshäuser[†] Sascha Wilhelm[‡]

July 28, 2017

Abstract

We develop a model of dynamic price competition in which the intraday interaction among retailers is paused at regular closing times and resumed the next day. In this non-stationary market environment, there exists a Nash equilibrium with repeating price cycles of deterministic length. The equilibrium is salient in the sense that it is a repeated version of the unique subgame perfect equilibrium of the daily stage game and, as such, does not require collusive behavior. We test and verify the equilibrium prediction as well as a number of additional model predictions using an extensive dataset on the German retail gasoline market. Furthermore, we perform a structural estimation of the model to evaluate several policy counterfactuals. At the estimates, regulatory interventions such as price setting restrictions or increased market transparency lead to higher average retail prices and harm consumer welfare.

Keywords: Spatial competition, Dynamic pricing, Edgeworth cycle, Gasoline

JEL Classification: D43; L11; L13; L81

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1 Introduction

A number of recent technological changes such as digital price tags and price comparison applications have accelerated the pace at which retailers can perform dynamic pricing. Digital price tags reduce menu costs close to zero while price comparison applications promote price transparency and increase the speed at which retailers can react to price changes by their competitors. As a result, retailers in many different industries change their prices more and more frequently. This development does not only encompass online retail but also brick-and-mortar stores. Both in the U.S. and in Europe, several supermarket chains and electronic retailers are currently experimenting with digital price tags and dynamic pricing strategies. It seems to be only a matter of time until multiple price changes per day are the norm rather than the exception.¹

With the pace of price competition increasing, it becomes ever more important to understand dynamic pricing *within* business days, not only across business days. Intraday price competition, however, is potentially different from interday price competition because of non-stationarities. When firms have distinct business hours, business days are finite and the exact closing times are common knowledge *ex ante*. The time left until the end of the business day might influence firms' pricing decisions, leading non-stationary strategies.

To fix intuition, suppose two firms compete in prices over the course of a day. In the evening, one of the two firms closes at a pre-specified time and reopens at another pre-specified time the next morning. The fact that one firm closes in the evening might influence its pricing decisions during the day. For example, the firm might not like to increase its price shortly before closing, so that pricing strategies become non-stationary. Anticipating that, the other firm might want to adjust its pricing decisions accordingly. By a backward induction argument, all pricing decisions might be influenced by the fact that the two firms have different business hours. Finally, the market structure changes fundamentally when one of the two firms closes. The remaining firm suddenly finds itself in a monopoly situation and probably wants to set the monopoly price during the night.

¹Sources for this paragraph: [Economist \(2016\): "Schumpeter: Flexible Figures"](#), [Bloomberg \(2015\): "Amazon Showrooming Forces Stores to Go Digital on Price Displays"](#), [The Wall Street Journal \(2015\): "Now Prices Can Change From Minute to Minute"](#) and [Frankfurter Allgemeine Zeitung \(2015\): "Die Preise werden smart"](#).

Since the classic [Maskin and Tirole \(1988\)](#) model of dynamic price competition, economic theorists have typically studied dynamic price competition in a *stationary* repeated game framework. These models feature a number of interesting equilibria, for example different equilibria with constant prices as well as equilibria with stochastic price cycles². However, these models are not particularly suited to analyze high-frequency intraday price competition when firms have business hours. As described, business hours introduce structural breaks in the competitive market structure that are not captured in traditional models. These market breaks lead to a non-stationary market environment, which may have a profound effect on intraday price competition.

In order to study dynamic price competition *within* business days, we develop a variation of the classic [Maskin and Tirole \(1988\)](#) model. Specifically, we introduce business days in which a *finitely* repeated game of sequential price competition is played. Business days, in turn, are repeated indefinitely. Furthermore, we incorporate a number of extensions such as differentiation among firms.

In the extended Maskin-Tirole model, one single business day can be interpreted as a stage game and the full model of repeated business days can be interpreted as the supergame. We identify a Nash equilibrium of the supergame in which the unique subgame perfect equilibrium of the stage game is played repeatedly. This equilibrium is salient in the sense that it is competitive and arises out of simple backward induction for a single business day. The equilibrium price path depends on the model parameters. For low degrees of differentiation, equilibrium prices move in cycles. For high degrees of differentiation, equilibrium prices are constant at oligopoly levels. Moreover, price patterns can cyclically change over time. For example, there can be constant oligopoly prices at night and price cycles during the day. In contrast to the original Maskin-Tirole model, price cycles are non-stochastic and repeat regularly. Furthermore, price cycles have a stable size that depends on the exact degree of differentiation.

Most retail businesses with business hours are not fast enough (yet) to serve as a test for our model. However, we found one particularly suited market that is ahead of its time in terms of digitization of pricing: the German retail gasoline

²[Maskin and Tirole \(1988\)](#) coin their equilibrium price cycles *Edgeworth cycles*. In an Edgeworth cycle, retailers sequentially undercut each others' prices until a threshold price is reached. From there, one retailer drastically raises its price and the remaining retailers follow up by starting a new undercutting process. The resulting price pattern has a saw tooth shape with many small price decreases and few large price increases.

market. Using detailed price data from June 2014 to May 2017 as well as station-specific data such as business hours and geographic coordinates, we confirm the model’s key predictions: During the day, when all firms are operating and spatial differentiation is lowest, prices move in cycles of fairly stable size and cycles repeat every day. During the night, when some firms are closed and spatial differentiation among the remaining operating firms increases, prices are constant and the price level is higher the fewer firms are operating. In particular, the number of price cycles goes hand in hand the number of daily price adjustments: the more price adjustments, the more price cycles. Starting with one daily price cycle in December 2013, the German retail gasoline market has evolved to two daily cycles in June 2015 and to three daily cycles in April 2017.

Finally, we perform a structural estimation of the model to evaluate a number of policy counterfactuals that have been proposed to counteract fluctuating retail prices. Interestingly, we find that, in the fitted model, regulatory interventions such as increased price transparency or restrictions on price adjustments lead to higher average retail prices and harm consumer welfare. We conclude that regulation of highly dynamic markets should be done with great care to avoid counterintuitive and undesirable outcomes.

The rest of the paper is organized as follows. [Section 2](#) presents the literature most closely related to this paper. [Section 3](#) sets up the price competition model and derives a number of testable predictions. [Section 4](#) presents the dataset on the German retail gasoline market, tests the predictions of the model and conducts a structural estimation. [Section 5](#) conducts a welfare analysis and evaluates several policy counterfactuals. Finally, [section 6](#) addresses potential concerns and [section 7](#) concludes the paper. Additional details on the theoretical and empirical analyses are deferred to [appendix A](#) and [appendix B](#), respectively.

2 Related Literature

The present paper relates to the theoretical literature on dynamic price competition and price cycles and the empirical literature on retail gasoline markets. This section briefly reviews the academic literature most closely related to our paper. Readers interested in a broader literature review may consult [Noel \(2011\)](#) for a comprehensive survey on Edgeworth cycles and [Houde \(2010\)](#) as well as [Eckert](#)

(2013) for surveys on empirical studies of retail gasoline markets.

2.1 Dynamic Price Competition and Price Cycles

Edgeworth (1925) was the first to formulate the idea that dynamic price competition might yield equilibrium prices very different from those obtained from static models. In critique of the classic Bertrand (1883) model of static price competition, Edgeworth introduced dynamics and capacity constraints to argue that firms will not set prices equal to marginal costs. Instead, he argued that prices will cycle. Firms will undercut each other until one firm relents and raises its price, before mutual undercutting starts over.

The first to provide a formal analysis of dynamic price competition were Maskin and Tirole (1988). Instead of capacity constraints, they consider an infinitely repeated game of price competition in which two firms set prices alternatingly. For sufficiently low discounting, they find two different types of Markov perfect equilibria, both featuring strictly positive profits for firms. First, they find equilibria with constant prices up to the monopoly level and, second, they find equilibria with price cycles which they coin *Edgeworth cycles*.

Since then, the classic Maskin-Tirole model has been extended in various directions. Lau (2001) shows that firms in Bertrand competition choose to act sequentially even under endogenous timing and that Edgeworth cycles continue to exist under endogenous timing. Eckert (2003) shows that Edgeworth cycles continue to exist when firms differ in size. Noel (2008) numerically confirms that Edgeworth cycles continue to exist when marginal costs fluctuate, when mild capacity constraints are present, when products are slightly differentiated and when there are three firms. Wills-Johnson and Bloch (2010) show that Edgeworth cycles continue to exist in a simple Hotelling model with sufficiently mild spatial differentiation. Finally, Wallner (1999) considers a *finitely* repeated version of the classic Maskin-Tirole model and finds that constant price equilibria are ruled out by the finite time horizon and only Edgeworth cycles remain as Markov perfect equilibria.

We depart from the implicit stationarity assumption present in all models mentioned and analyze a variation of the Maskin-Tirole model with business days and non-stationary pricing strategies. In contrast to previous studies, our model is intended to study high-frequency price competition occurring *within* business

days. Furthermore, we incorporate a number of generalizations such as differentiation, N firms, discounting, differing firm sizes and different policy restriction on price setting. Our model yields a rich set of predictions, both confirming and complementing the results of the previous literature.

2.2 Retail Gasoline Markets

A number of retail gasoline markets around the world have long been known to support dynamic price competition in different forms. For example, early signs of Edgeworth price cycles have already been reported in parts of the U.S. and Canada from the 1960s onwards, for example in the descriptive studies of [Allvine and Patterson \(1974\)](#), [Slade \(1987, 1992\)](#) and [Castanias and Johnson \(1993\)](#). Subsequent studies also found price cycles in retail gasoline markets in Australia ([de Roos and Katayama, 2013](#)) and Norway ([Foros and Steen, 2013](#)) as well as in further cities in the U.S. ([Hosken et al., 2008](#); [Woods, 2014](#)) and Canada ([Noel, 2007b](#); [Eckert and West, 2004](#)). But all these studies rely on daily or weekly data and the corresponding cycles have a typical duration between one week and several months. Due to lack of detailed high-frequency data, none of these studies is able to analyze intraday price patterns. In contrast, our dataset contains prices at German gasoline stations *at all times* for over two years. Therefore, we are able to conduct a detailed long-range analysis of intraday price competition.

This paper complements other studies that have recently been conducted on the German retail gasoline market. [Dewenter et al. \(2016\)](#) examine price levels before and after the German price transparency initiative and compare them to price levels in other European countries. They find that the price levels in Germany have actually increased in the course of the price transparency initiative. [Boehnke \(2014\)](#) suggests that gasoline price patterns in Germany stem from discrimination between different types of consumers, whereas we do not find any significant correlation between prices and demand proxies. [Neukirch and Wein \(2016\)](#) provide a detailed descriptive analysis of the market and conjecture that collusive behavior among the largest gasoline retailers might drive price patterns. In contrast, we show that collusion is not necessary and that a model of dynamic price competition alone is sufficient to generate the price patterns observed in the German market. Furthermore, we provide evidence that there is actually a high degree of competition among gasoline retailers, which has also been found by [Frondel et al.](#)

(2016).

The closest paper to ours in terms of structural analysis is probably [Atkinson \(2009\)](#). This study uses a relatively detailed dataset that contains prices of 27 gasoline stations in Guelph (Ontario, Canada) observed eight times per day on 103 days in 2005. Atkinson reports large price increases followed by gradual undercutting in cycles with typical length of about one week. Furthermore, he tests several structural implications of the Maskin-Tirole model and finds clear evidence of classic Edgeworth price cycles. In contrast to Atkinson, our focus lies on *intraday* price competition fast enough so that business hours matter. Furthermore, our analysis goes further in that we also conduct a structural estimation to evaluate policy counterfactuals.

3 Model

This section develops and solves a model of dynamic *intraday* price competition. Starting from the classic price competition model by [Maskin and Tirole \(1988\)](#), we successively incorporate two main modifications: business hours and spatial differentiation. The full model is intended to capture cyclical changes in the competitive market structure in the following sense. During the day when all firms are open, spatial differentiation is lowest and competition is most intense. During the night when a number of firms are closed, spatial differentiation among the remaining operating firms is higher and competition is less intense. Moreover, the transition between different competition intensities is perfectly predictable because business hours are common knowledge. In equilibrium, firms optimizing their pricing strategies will take into account that the competitive environment changes at pre-specified times.

3.1 Starting Point: Maskin and Tirole (1988)

In the Maskin-Tirole model, there are two firms, each producing a homogeneous product at zero marginal cost. The two firms compete on price to maximize profits. Time runs in discrete periods $t \in \mathbb{N}$ and firms alternate to set their prices. In odd periods, firm 1 sets its price and firm 2's price is locked in, and vice versa in

even periods.³ Each period, firms face demand $d(p)$, which goes to the firm with the lowest price. In case of equal prices, demand is split evenly. Firms choose prices from a finite price grid $\mathcal{P} = \{0, \varepsilon, 2\varepsilon, \dots, \bar{P}\}$ with price tick $\varepsilon > 0$, where \bar{P} is assumed to be the largest multiple of ε for which demand is nonnegative.⁴ Price setting is costless and future payoffs are discounted by a factor $\beta \in (0, 1)$. The entire setup including all parameters is common knowledge and there is no uncertainty.

Maskin and Tirole (1988) solve this dynamic game for equilibria in Markov strategies, in which any firm's pricing decision may only depend on the current price commitment of the other firm. They find an abundance of Markov perfect equilibria and prove that all equilibria fall in one of two categories. One category comprises equilibria with constant equilibrium prices at or below the monopoly price level. These collusive equilibria can be sustained by threatening a price war if one firm undercuts the collusive price. The other category comprises equilibria with cycling prices coined *Edgeworth cycles*. In an Edgeworth cycle, firms mutually undercut each other's prices until a low price level close to marginal costs is reached. Then, firms play a war of attrition and randomize between staying at the low price level and relenting to a very high price level. Once one of the firms relents to a high price level, undercutting starts over. The resulting price cycles have a stochastic length due to the stochastic play at the trough, as illustrated in figure 1.

3.2 First Modification: Business Hours

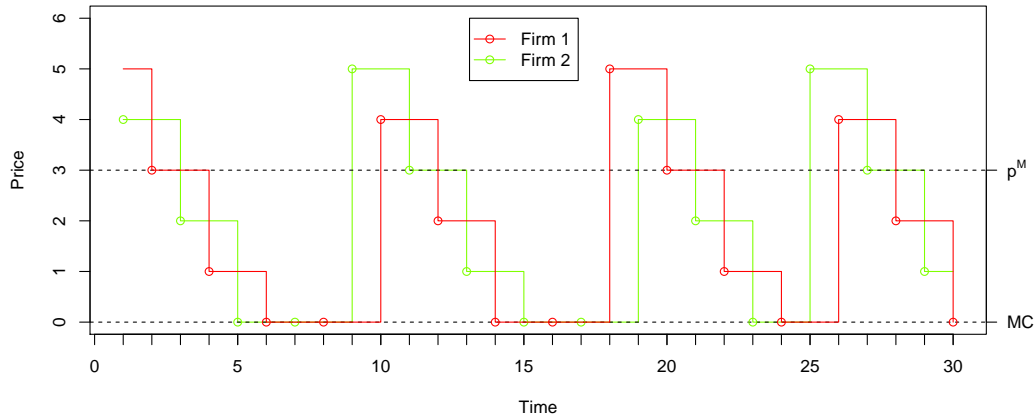
In order to reflect finite business hours that may interrupt intraday price competition, we depart from the original model and introduce business days. During business days, firms take turns competing on price as before. Between business

³For simplicity, the alternating order of moves is imposed exogenously. However, this assumption is less restrictive as it may appear at first glance. Maskin and Tirole (1988) themselves show that the alternating-move structure is robust to endogenous timing. In their model extension with endogenous timing, short-term commitments and null actions, firms *choose* to move sequentially after finite time with probability one. More generally, Lau (2001) shows that players endogenously choose to move sequentially in equilibrium in any dynamic game with strategic complementarities and short-term commitments. His results apply to price competition among firms because, first, price competition is a prime example for a game with strategic complementarities and, second, technological restrictions on monitoring and price setting provide natural commitments for firms to stick to chosen prices for some time.

⁴A discrete price grid ensures that best responses are well-defined. Moreover, discrete prices are realistic for most applications.

Figure 1: Edgeworth Cycles in the Maskin-Tirole Model

This figure depicts a simulation of an Edgeworth cycle. The corresponding equilibrium prices feature successive undercutting and stochastic resets. For this figure, we have used the same specification as [Maskin and Tirole \(1988\)](#): Demand is $d(p) = 6 - p$, the price grid is $\mathcal{P} = \{0, 1, \dots, 6\}$, marginal costs are $MC = 0$ and the monopoly price is $p^M = 3$.



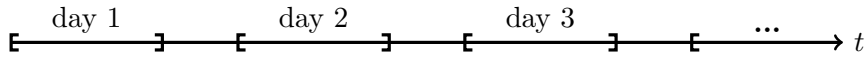
days, however, some firms close and temporarily exit the market. These structural breaks naturally split up firms' planning horizon into chunks. Business days are repeated indefinitely and there is discounting by $\beta \in (0, 1)$ between business days, but no discounting within business days.

3.2.1 Supergame

We interpret business days as the stage games of our new supergame of repeated price competition, as illustrated in [figure 2](#). In that sense, we extend the original Maskin-Tirole model by enriching its stage games. In the original model, a stage game consists of one single round of sequential price competition while a stage game in our extension consists of *multiple* rounds of sequential price competition.

Figure 2: The Supergame of Repeated Business Days

This figure depicts the supergame of repeated business days. Between business days, there are structural breaks in the sense that some (or all) firms are closed.

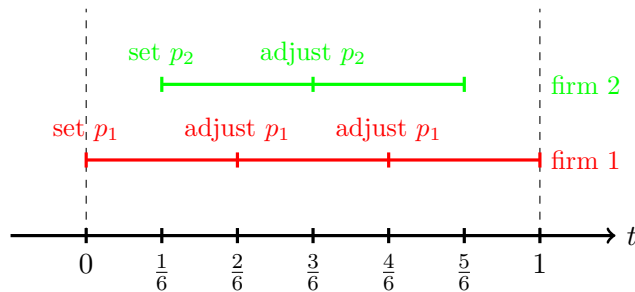


3.2.2 Stage Game

Specifically, we consider business days of length normalized to one. During a business day, firms enter and exit the market sequentially, mimicking differing business hours. Specifically, firm 1 enters the market one period before firm 2 and exits the market one period after firm 2. One can think of firm 1 as a retailer with long or even 24/7 business hours and firm 2 as a retailer with shorter business hours. Accordingly, firm 1 has one more move than firm 2, say $M + 1$ moves, and firm 2 has M moves. Figure 3 illustrates the timing of the game by means of a simple example. Demand is uniformly distributed throughout the business day so that demand between price setting times is scaled to $\frac{d(p)}{2M}$.

Figure 3: The Stage Game of One Single Business Day

This figure depicts the timing of moves in an exemplary business day with $M = 2$ moves for firm 2 and $M + 1 = 3$ moves for firm 1. Firms enter and exit the market sequentially and take turns setting their prices.



3.2.3 Equilibrium Concept

The supergame of repeated business days has plenty of Nash equilibria. For example, there are a number of collusive equilibria in which high price levels can be sustained due to punishment threats. These sorts of collusive equilibria are certainly important in a number of contexts. However, they are less important in large markets with many independent suppliers, for example in online markets or gasoline retail. In such markets, coordination and collusion are difficult to sustain. Therefore, we focus on competitive equilibria for the rest of this paper. Specifically, we characterize the stage game equilibria of an isolated business day. Stage game equilibria can always be supported as a Nash equilibrium of the supergame.

Each stage game is essentially a finitely repeated sequence of sequential price competition. The appropriate solution concept for finite-horizon sequential games is subgame perfect equilibrium. Subgame perfection eliminates non-credible threats and the corresponding equilibria satisfy the one-shot deviation principle. Furthermore, subgame perfect equilibria can easily be found by backward induction.

3.2.4 Equilibrium Characterization

Interestingly, if firms can change prices often enough and if the price grid is sufficiently large, all subgame perfect equilibria of the stage game feature price cycles. Subgame perfect equilibria with constant price path are ruled out by the finite time horizon. To see that, first note that collusion at the monopoly price or some other price above marginal costs cannot be sustained in any game with definite ending time. Second, subgame perfection eliminates Nash equilibria in which firms stick to marginal costs. That is because it is not credible for a firm to stick to pricing at marginal costs after the other firm has increased its price to a much higher level. Instead, it is optimal to follow the price increase and just undercut the competitor by one tick. In contrast to marginal cost pricing, marginal undercutting would yield strictly positive profits. Overall, equilibria with constant prices cannot occur.

The non-existence of constant price equilibria in finitely repeated games of sequential price competition has been proven formally by [Wallner \(1999\)](#). The result holds for arbitrary initial conditions and any finite time horizon, no matter how long. Interestingly, the solution to the finite horizon game does not require firms

to perform huge backward inductions. Instead, Wallner shows that it is sufficient for firms to only look a few steps ahead. Specifically, when undercutting firms approach marginal costs and consider raising prices again, they only need to evaluate their payoff in the next cycle compared to remaining at low prices.

On the other hand, the stage game is a finite extensive-form game, thus there surely *exists* a subgame perfect equilibrium. Put together, all subgame perfect equilibria of the stage game feature fluctuating prices, i.e. price cycles. Using an equilibrium of the stage game, we can trivially construct a Nash equilibrium of the supergame in which the stage game equilibrium is played repeatedly. The resulting equilibrium price path features cycles of stable size that repeat every day.

3.2.5 Equilibrium Illustration

We use standard backward induction to compute subgame perfect equilibria of the stage game. However, even for small price grids, two players and few moves, the game becomes large very quickly. Given the large number of decision nodes in the game tree, the corresponding equilibria are tedious to compute and to write down. Therefore, instead of writing down the equilibria of the model, we prefer to illustrate the equilibrium price paths in graphs.⁵

Consider the following baseline specification. There are $N = 2$ firms, each firm setting its price $M = 10$ times. Demand $d(p) = 2 - p$ is linear over $[0, 2]$ and zero otherwise, implying monopoly price $p^M = 1$. The tick size is given by $\varepsilon = 0.1$ such that the price grid reads $\mathcal{P} = \{0, 0.1, 0.2, \dots, 2\}$. All our subsequent results are robust to arbitrary specifications, as demonstrated in [appendix A.2](#).

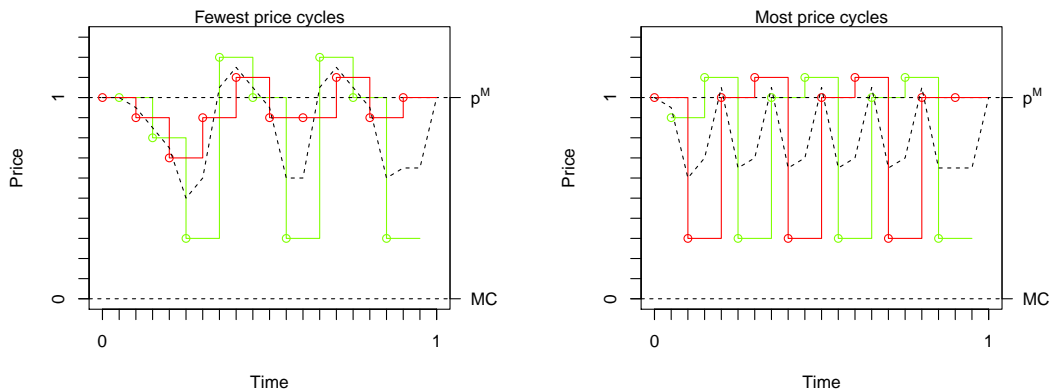
Equilibrium price cycles can take different forms and sizes. However, all price cycles are structurally similar in that they feature multiple rounds of undercutting and occasional large price increases. Starting at high price levels around the monopoly price, firms mutually undercut each other's prices once or multiple times. Finally, one of the two firms sets a *predatory price* low enough that the other firm refrains from further undercutting. Instead, the predatory price induces the other firm to set a *relenting price*, i.e. to raise its price back to some level close

⁵Equilibria are computed in *R* ([R Core Team, 2016](#)). The program code is available from the authors upon request.

to the monopoly price. Depending on the particular equilibrium, relenting can occur in one step or in two separate steps. After the price increase mutual undercutting starts over. Note that equilibrium price cycles may differ in duration and amplitude, but their length is non-stochastic, as illustrated in [figure 4](#).

Figure 4: Stage Game Equilibria

Note: This figure depicts two subgame perfect equilibria of a single business day. Firm 1 (red) starts the market at the monopoly price at time zero, firm 2 (green) enters the market one interval later. Price setting times of each firms are indicated with dots and average prices are shown as a dashed line (black). The equilibrium price paths feature price cycles: phases of mutual undercutting, ending with one firm setting a very low predatory price, inducing the other firm to raise its price, and undercutting starts over. Duration and amplitudes of cycles may vary across different equilibria, but the structure of all cycles is very similar.



Multiple equilibria arise in extensive-form games when players are indifferent between several actions at particular decision nodes. In the present game, indifference regularly arises at the end of a price cycle. After one firm has played a predatory price, the other firm is typically indifferent between a number of relenting prices because it does not get to serve demand at the relenting price anyway. The relenting firm only makes profit when it gets to undercut its competitor again a few moves later.

Note that, due to sequential entry and exit times, the business day always starts and ends at the monopoly price. At the beginning of the day, when firm 1 is the only firm active in the market, it prefers to set the monopoly price until firm 2

enters the market and price competition starts. Likewise, firm 1 prefers to set the monopoly price at the end of the day after firm 2 has exited the market again.

Due to the finite horizon and sequential market exit, stage games exhibit an *end-game effect*. Shortly before the end of the business day, the incentives for firm 2 to start a new cycle are limited because a new cycle would not pay off by the end of the day. Therefore, firm 2 typically prefers to end its business day at a very low price level and firm 1 only finds it profitable to raise its price after firm 2 has closed.

3.2.6 Transparency

Our model with an exogenously fixed number of price adjustments can be regarded as a reduced form model in which firms have already chosen their optimal number of price adjustments. In reality, price changes are connected to various costs such as menu costs, potential consumer dissatisfaction and costs for monitoring competitors' prices. If price adjustment costs decrease, for example due to increased transparency and thus decreased monitoring costs, we expect more price adjustments in the course of the day.

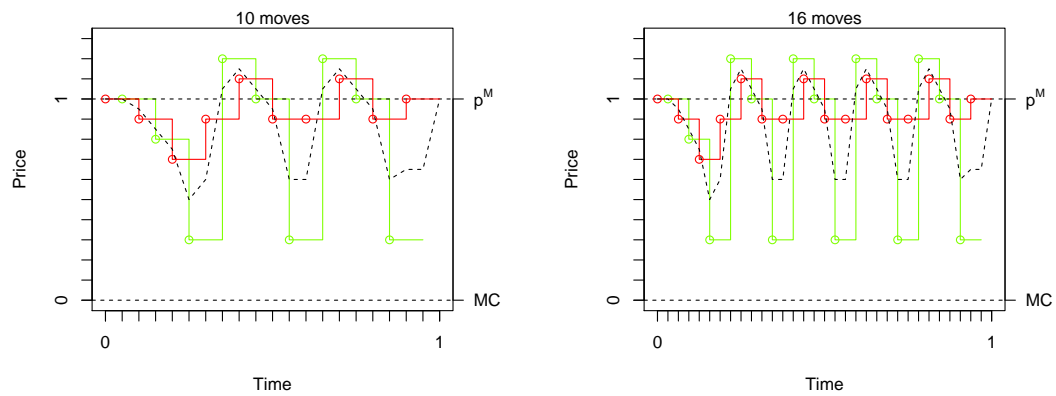
the number of price adjustments, in turn, determines the number of price cycles in equilibrium. The more price adjustments firms perform on a given business day, the more cycles occur in equilibrium. [Figure 5](#) illustrates the relationship between price adjustment activity and number of price cycles.

3.3 Second Modification: Differentiation

In reality, even in a market with a supposedly homogeneous good such as gasoline, firms are not identical. Instead, firms enjoy some form of differentiation, be it customer service, secondary products or geographical distance. In order to capture differentiation, we augment the baseline model by geographical locations for each firm and travel costs for consumers. The resulting spatial differentiation is, from a modeling perspective, equivalent to any other form of product differentiation. Therefore, the model extension with spatial differentiation can be interpreted to capture entire spectrum of differentiation.

Figure 5: Price Adjustment Activity

This figure depicts two different levels of price adjustment activity for one particular equilibrium price path of the stage game. The higher the activity, i.e. the more price adjustments per firm, the more cycles occur. Connecting price adjustment activity to price transparency, the model predicts an increasing number of price cycles with increasing transparency.



3.3.1 Demand Specification

Specifically, we assume that firm $i \in \{1, 2\}$ faces demand

$$D_i(p_i, p_{-i}) = d(p_i) \cdot w(p_i, p_{-i}),$$

where $d(p_i)$ is the market demand function from before and $w(p_i, p_{-i})$ is a weighting function. Since weights must always sum up to one, we have $w(p_1, p_2) = w(p_2, p_1)$.

In the perfect price competition case, the weighting function takes values from $\{0, 0.5, 1\}$, depending whether the firm i sets a higher price, equal price or lower price, respectively, compared to firm $-i$. With differentiation, the weighting function is generalized and may take on values from $[0, 1]$. It is derived from a model of spatial differentiation.

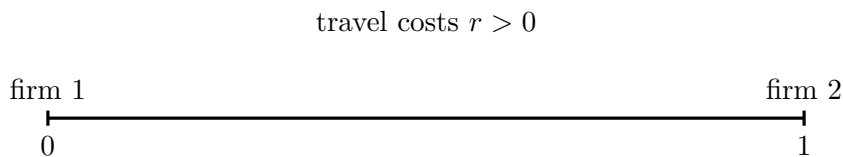
Specifically, we arrange firms at the endpoints of a [Hotelling \(1929\)](#) line of total length normalized to one, as illustrated in [figure 6](#). Consumers are uniformly on the line and face travel costs $r > 0$ per unit of distance. A consumer at location t buying at location x at price p faces utility

$$U_t(x, p) = -p - r \cdot |x - t|.$$

There is no outside option, so every consumer buys at her favorite firm. The mass of consumers buying at each firm serves as a weighting function for firms' demand functions. Accordingly, firms face demand given by the market demand function evaluated at their own price multiplied by the fraction of customers they attract.

Figure 6: Hotelling Line of Spatial Differentiation

This figure depicts the Hotelling line of spatial differentiation among firms. The fraction of consumers that each firm attracts serves as a weighting function for firms' demand functions.



3.3.2 Equilibrium Characterization and Illustration

With product differentiation, the firm offering at the lowest price does not automatically serve the entire demand. Instead, the other firm might still get to serve some residual demand of customers located closely enough. When differentiation is large enough, there exists a unique relenting price, balancing the immediate gains from staying close to the competitor's price and the future gains from a renewed price cycle. Accordingly, the subgame perfect equilibrium becomes *unique*. Furthermore, undercutting by more than one tick can become optimal when differentiation is present. That is because firms might need a sufficiently high price advantage over the competitor to steal a profitable fraction of customers. Finally, when differentiation becomes very large, the incentives to undercut are reduced, so that cycles get smaller and eventually convert to stable oligopoly prices converging to the monopoly price. Figure 7 illustrates the unique subgame perfect equilibrium price paths of the stage game for different levels of differentiation.

3.3.3 Brand Value and Firm Size

So far, differentiation among firms has been modeled as symmetric. However, we can easily extend the specification to capture asymmetric differentiation due to, for example, brand value. To that end, we define a new weighting function $\tilde{w}_i(p_i, p_{-i})$ for

$$D_i(p_i, p_{-i}) = d(p_i) \cdot \tilde{w}_i(p_i, p_{-i})$$

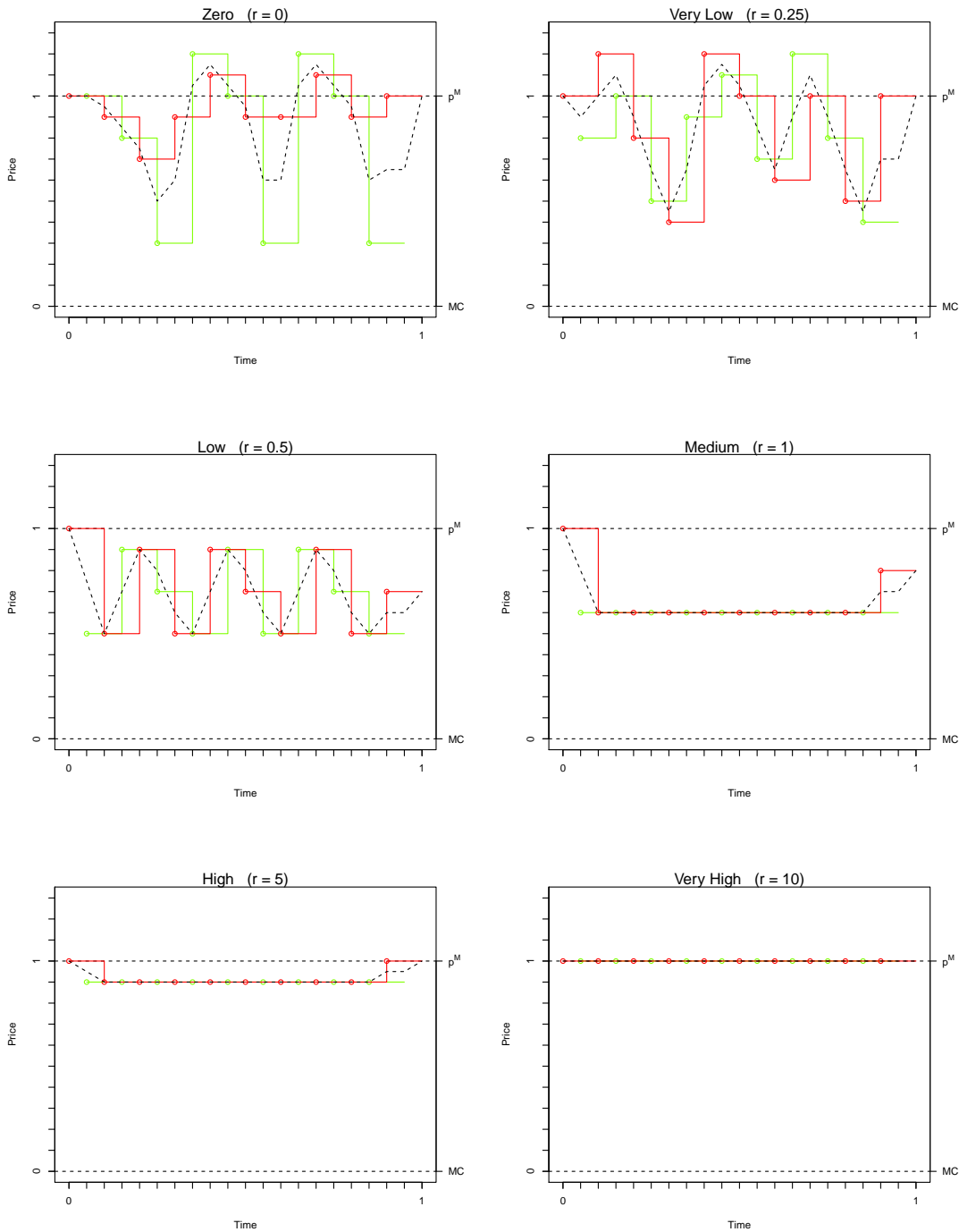
that adjusts both weights such that firm 1's original weight $w(p_1, p_2)$ is multiplied by a factor $x \in \mathbb{R}_+$. Then

$$\begin{aligned}\tilde{w}_1(p_1, p_2) &= \frac{x \cdot w(p_1, p_2)}{x \cdot w(p_1, p_2) + w(p_2, p_1)}, \\ \tilde{w}_2(p_2, p_1) &= \frac{w(p_2, p_1)}{x \cdot w(p_1, p_2) + w(p_2, p_1)}.\end{aligned}$$

If firm 1 enjoys a high brand value in the sense that it attracts a disproportionate fraction of customers, it has less incentives to undercut firm 2. That is because firm 1 already gets to serve a sizeable share of customers even if it is not strictly cheaper than firm 2. Moreover, firm 1 makes larger profits at high price levels

Figure 7: Differentiation

This figure depicts the equilibrium price paths of the stage game for six different levels of spatial differentiation. Under differentiation, firms with prices above the market price still get to serve residual demand of customers located closely enough. With mild differentiation, undercutting by more than one price tick can be optimal, so that cycles are amplified. With differentiation increasing further, the incentives to undercut are reduced, so that cycles get smaller and eventually convert to stable oligopoly prices converging to the monopoly price.



compared to firm 2 and therefore it has even larger incentives to set a high price. On the contrary, firm 2 has increased incentives to undercut firm 1 because it needs to be strictly cheaper in order to attract sufficient demand. As a result, firms with high brand value are more likely to set high prices and to lead price increases while firms with low brand value are more likely to set low prices and to lead price decreases, as illustrated in [figure 8](#).

The underlying theoretical mechanism has already been pointed out by [Eckert \(2003\)](#) and is confirmed in our model. Eckert, however, refers to firm size rather than brand value, but the inherent argumentation is the same. Indeed, our weighting function \tilde{w} also would also arise from a spatial model in which firm 1 has x times as many shops as firm 2, indicating the firm size and brand value are equivalent from our modeling perspective.

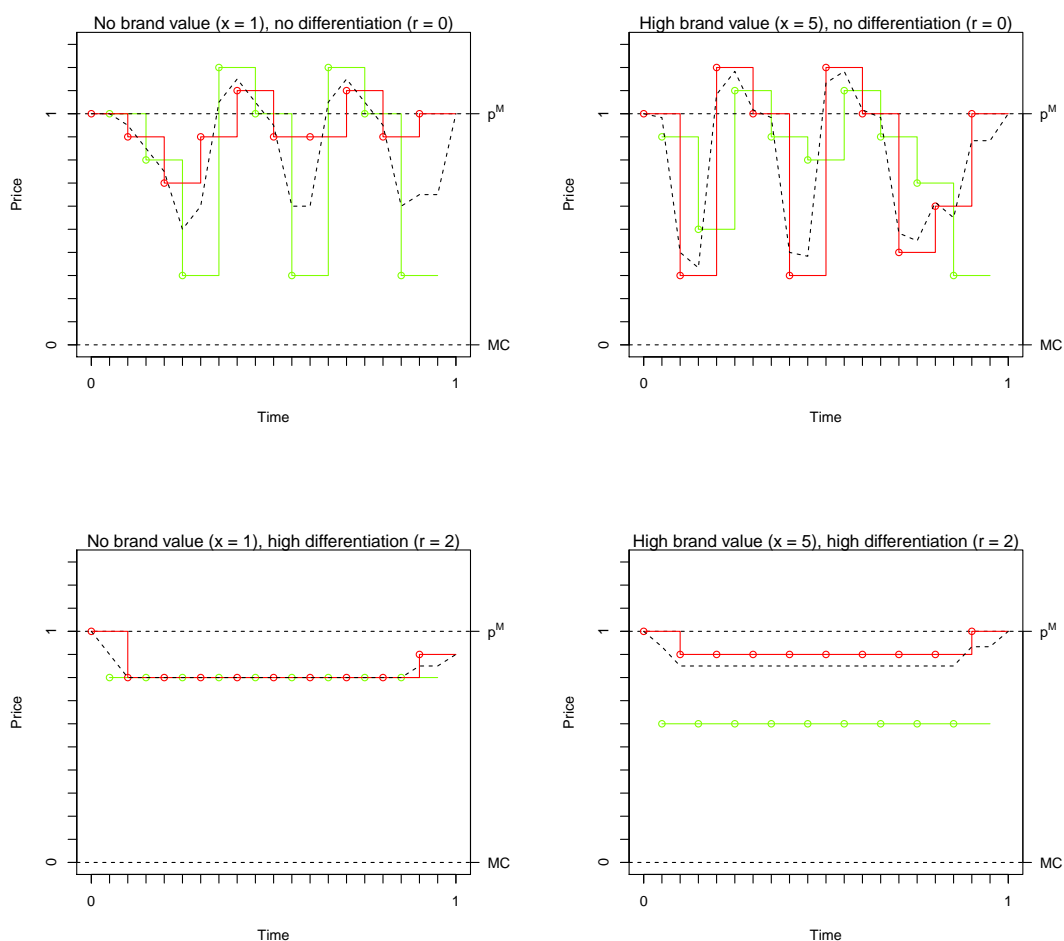
3.4 Summary: Cyclical Changes in Market Structure

In order to study dynamic intraday price competition, we have analyzed a model of repeated business days where every business day constitutes a finite game of sequential price competition. We have characterized the Nash equilibrium of the supergame in which the subgame perfect equilibrium of the stage game is played repeatedly. In equilibrium, prices may be constant or cycling, depending on whether differentiation among firms is high or low, respectively.

In terms of the supergame, we can think of two stage games with different degrees of differentiation that are played alternately. One of the stage games represents intraday price competition with low differentiation and the other stage game represents overnight price competition with high differentiation. Combining the two stage games, the model allows for the following equilibrium price pattern. During the night, when many firms are closed and the remaining firms are spatially very differentiated, the model suggests constant prices at oligopoly levels. During the day, when all firms are open and spatial differentiation is relatively low, the model suggests cycling prices. Intraday price cycles are derived by backward induction because firms anticipate the static oligopoly price of the night. Therefore, price cycles are non-random and have a regular shape every day, contrasting the results of Maskin and Tirole who find price cycles have random lengths.

Figure 8: Brand Value

This figure depicts the equilibrium price paths for two different brand values of firm 1. Firms with high brand value enjoy disproportionately larger benefits from high price levels while firms with low brand value must be significantly cheaper than their competitors to attract demand. In a price cycle equilibrium, the higher the brand value of firm 1, the more likely firm 1 is to initiate price increases and the more likely firm 2 is to initiate undercutting. In an equilibrium with constant prices, the higher the brand value of firm 1, the larger firm 1's price relative to firm 2's price.



3.5 Testable Predictions

We close this section by restating several implications of our model of dynamic intraday price competition that can be tested empirically.

Prediction 1. *Repeating Price Pattern*

With sufficient product differentiation, there exists a unique and non-stochastic subgame perfect equilibrium in the stage game that can be supported as a Nash equilibrium of the supergame. Accordingly, we expect price patterns to repeat every business days.

Prediction 2. *Differentiation Determines Price Pattern*

The equilibrium price pattern depends on the degree of differentiation among firms. We expect price cycles when differentiation is low, less pronounced cycles when differentiation is moderate and constant prices when differentiation is high.

Prediction 3. *Number of Price Cycles*

In any equilibrium with price cycles, the number of price cycles depends on the number of price adjustments per firm. We expect to see more intraday price cycles with increasing price adjustment activity.

Prediction 4. *High Opening and Closing Prices*

In any equilibrium with price cycles, sequential closing times prevent undercutting at the end of the business day. Therefore, due to differing business hours, we expect business days to start and to end with high market prices. Furthermore, we expect that firms which close early keep their prices low before closing. On the contrary, we expect firms with longer business hours to increase their price after most of their competitors have closed.

Prediction 5. *Large Retailer Set Higher Prices and Lead Price Cycles*

Large retail networks affiliated to a brand attract disproportionately high demand at all prices so that the benefits of high price levels are relatively high. Therefore, we expect large retail networks to set higher prices and to initiate price increases. Accordingly, we expect small independent retailers to set lower prices and to initiate undercutting.

4 Empirical Application

In this section, we evaluate our model using an extensive dataset on the retail gasoline market in Germany. First, we present the underlying dataset and explain the market characteristics. Second, we test and verify the model’s main predictions. Finally, we perform a structural estimation of the model to evaluate a number of counterfactual market environments.

4.1 Data Description

The panel consists of the universe of all 14,934 German gasoline stations and all 97,761,311 price adjustments of 95 RON unleaded gasoline from June 8, 2014 to May 31, 2017. The data is reported by the German Market Transparency Unit for Fuels and provided by a service provider called Tankerkönig. The final dataset includes information about prices, time of price change, brand, address, geographic coordinates and business hours.

4.2 Market Characteristics

The market situation on the German gasoline retail market is well documented in multiple market reports of the Federal Institute for Competition ([Bundeskartellamt, 2011, 2014, 2015, 2017](#)). Gasoline stations in Germany sell gasoline exclusively. Most common fuel types are Diesel and unleaded gasoline represented by Super E5 (95 RON unleaded gasoline) and Super E10 (95 RON with up to 10% Ethanol unleaded gasoline). Most consumers may freely choose between Super E5 and Super E10, only older cars are not recommended to use Super E10. However, Super E10 has a limited importance in comparison to Super E5 ([Bundeskartellamt, 2014](#)). Moreover, in terms of their physical characteristics gasoline across stations is very homogeneous ([Bundeskartellamt, 2011](#)).

The ten largest retailers and their network size are listed in [table 6](#) in [appendix B.2](#). Aral is the largest retailer with a relative share of 16% of stations, Shell is the second largest retailer with a 12% share while the market share of remaining retailers is below 10%. Independent retailers own 8% of the stations. The number of gasoline stations decreased by 0.3% per year between 2009 and 2015. Sale

volumes exhibit a downward trend of 1.7% per year during that time.⁶ Overall, we observe a mature market with relatively stable size.

Gasoline pricing in Germany is not subject to pricing regulations. Station operators' menu costs are almost absent and consumers' switching costs are mainly given by the cost of traveling to a different station (Noel, 2007b). Discussions with business insiders suggest that stations monitor competitors that are geographically close and set their own prices in response to competitors' prices. Pricing decisions are usually taken by retailers' pricing departments (Bundeskartellamt, 2011), which set prices for every station individually.

4.2.1 Operating Hours

During the night, 60.3% of the German gasoline retailers close. Typically, these stations open between 4:00 and 8:00 and close between 18:00 and 0:00.⁷ The median opening hour is 6:00 on weekdays, 7:00 on Saturdays and 7:30 on Sundays. Stations' closing times are similar over the entire week with a median closing time of 22:00. Moreover, 4.96% of stations do not operate on Sundays.

4.2.2 Price Transparency Policy

Due to a transparency policy, the Market Transparency Unit for Fuels collects and reports price information for the population of German gasoline retail stations to service providers since December 2013⁸. These, in turn, publish the prices to customers through websites and mobile applications.

Bundeskartellamt (2015) reports that gasoline retailers make extensive use of the real time data on competitors' prices. Examples include tools for independent retailers receive notifications about price changes.⁹ Two large retailer implemented price-matching policies for customers based on this data (Wilhelm, 2016). A

⁶Reported by the association of the German Petroleum Industry (<https://www.mwv.de/statistiken/mineraloelabsatz/>, accessed Jun 02, 2017).

⁷A box plot of operating hours is provided in figure 24 and table 4 summarizes the average operating hours, its standard deviation and the number of operating stations by day of the week (in appendix B).

⁸Gesetz gegen Wettbewerbsbeschränkungen (GWB); §47k Marktbeobachtung im Bereich Kraftstoffe

⁹An existing tool is a price information system developed by CHW Software is available since 2015 (<http://www.chwsoftware.de/produkte/phoenix/>, accessed June 02, 2017).

data provider of an automated programming interface confirmed that some users provide price information to retailers for automated processing.

The market transparency policy impacts both the demand and the supply side of the market. On the demand side, customers' cross-price elasticities increase as customers can easily compare prices across stations. On the supply side, retailers face lower monitoring costs as they can be notified about competitors' price changes in real time. However, the adaption of new technologies is rather a steady process than a single treatment. Market participants needed time to adopt the new technology. After the introduction of the price transparency initiative, only a few data providers were available and none of them provided an automated programming interface necessary to process prices automatically. A retailer confirmed that it took more months than expected to make use of the data due to its complexity. Smaller retailer needed even more time to adapt new software into their pricing systems.

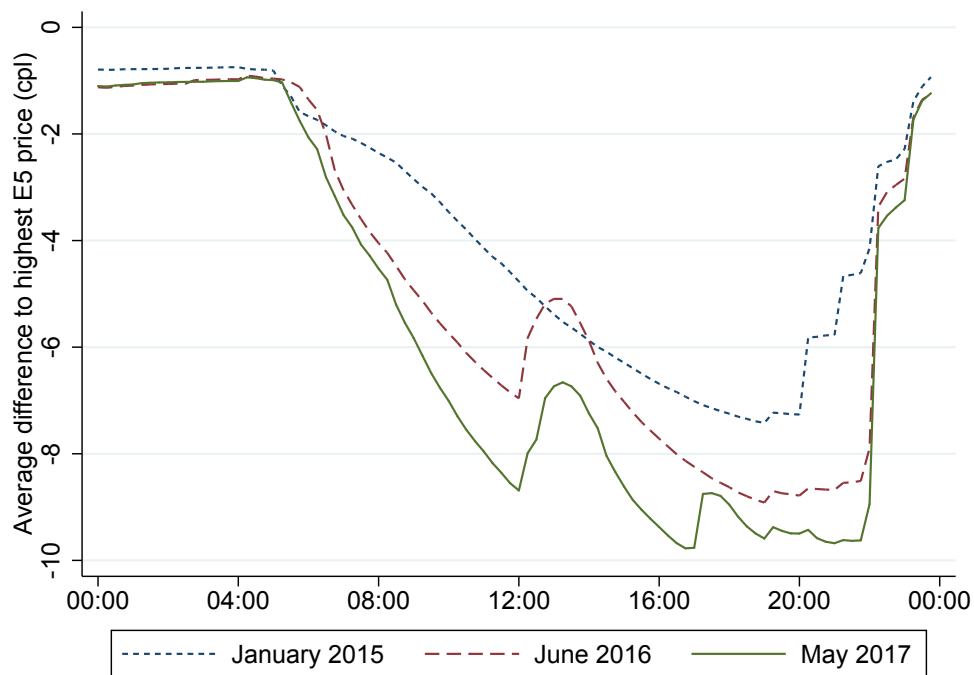
4.3 Model Verification

4.3.1 Prediction 1: Repeating Price Pattern

For fixed parameters, our model predicts deterministic price cycles reoccurring every day. That prediction is confirmed by our price data. Over the entire time horizon of three years, we observe three different manifestations of daily price patterns. First, between 2014 and June 2015, there is a purely undercutting price pattern with high price over night and decreasing prices during the day. Second, between July 2015 and March 2017, prices continue to be stable over night and decreasing during the day, but feature an intraday price increase at noon. Third, since April 2017, we observe an additional price increase around 17:00. [Figure 9](#) illustrates the three phases. Within each of these phases, the corresponding pattern is stable and repeats every day. As anecdotal evidence, [figure 25](#), [figure 26](#) and [figure 27](#) in [appendix B.2](#) show the repeating price pattern for every day during June 2015, June 2016 and May 2017, respectively.

Figure 9: Daily Price Patterns over Time

Notes: This figure shows the three daily patterns of the average price reductions in euro cents per liter (cpl) over daytime of 24/7 operating gasoline stations. Over time, we observe faster reactions to competitors' price changes, which is represented by a steeper slope of the price curves. Once prices drop below a certain threshold, firms initiate an additional price increase. We observe up to two intraday price increases and one large evening price increase when 60% of stations close.



4.3.2 Prediction 2: Differentiation Determines Price Patterns

Spatial differentiation is a major determinant of heterogeneity in brick-and-mortar retailing. Customers face heterogeneous transportation costs in buying gasoline at different stations (Bundeskartellamt, 2011). We expect market participants to undercut each other more intensely in markets with low spatial differentiation. Conversely, we expect cycles to become smaller and eventually converge to stable prices when spatial differentiation increases. Empirically, spatial differentiation can be proxied by the density of operating stations. We conduct two different analyses to test the influence of differentiation on pricing. First, we exploit heterogeneity in the number of operating stations over time. Second, we exploit regional differences in the density of stations. Both tests confirm that price cycles are amplified when spatial differentiation is low.

First, table 1 lists the different competition intensities in terms of operating stations in the entire market for different time periods. Furthermore, it shows two proxies for the size of price cycles: First, the price spread between minimum and maximum daily prices for individual stations and, second, the average number of hourly price adjustments per station. According to both measures, price cycles are smaller on weekends when fewer stations operate and vanish during the night when more than 60% of stations are closed.¹⁰ The relationship between the number of operating stations and prices is also shown in figure 22 in appendix B.1, which plots the evolution of prices over time alongside the number of operating stations. One can see that price cycles end in the evening at the time when competing stations close for the night and restart when stations open in the morning.

Second, we test whether regional differences station density explain the size of price cycles. To derive a station-specific measure for station density, we employ a kernel density estimation of geographical locations.¹¹ The estimated distribution of stations is visualized in figure 23 in appendix B.1. Again, we proxy the amplitude of price cycles by the average intraday price spread of each station and the average number of daily price reductions per station. Finally, we regress our proxies for cycle size on station density in table 2. All coefficients are highly sig-

¹⁰The night phase is defined as the time from 0:00 (mean station closes plus one standard deviation) to 5:00 (mean station opens minus one standard deviation).

¹¹Specifically, we use a non-parametric approximation of the station distribution with bivariate and multimodal Gaussian kernels. Bandwidth selection is performed by pseudo-likelihood cross-validation (Cao et al., 1994) leading to a bandwidth of 0.000486 radians in longitude and latitude.

Table 1: Competition and Pricing Heterogeneity on Time

Notes: Data between June 2014 and May 2017. Restricted to 24/7 operating stations. Daytime is defined as time between 5:00 and 0:00 while nighttime is defined as 0:00–5:00. Working days include Monday till Friday.

Period	Relative competition intensity	Observed pattern	Price spread	Price changes per hour
Working day daytime	100%	<i>Largest</i> Edgeworth cycles	9.799	.322
Saturday daytime	99.4%	<i>Largest</i> Edgeworth cycles	9.336	.297
Sunday daytime	95.0%	<i>Smaller</i> Edgeworth cycles	8.895	.269
Nighttime	39.7%	Stable price at high level	0.617	.025

nificant. A 1% increase in station density yields a 0.2% increase in the spread and a 0.13% increase in the frequency of price reductions. With brand fixed effects, a 1% increase in station density leads to a 0.055% increase in daily price spread, verifying the hypothesis that undercutting is more severe in regions with high station density.

4.3.3 Prediction 3: Number of Price Cycles

In the model, the number of price cycles depends on the number of price adjustments, i.e. on the frequency at which stations interact with each other in the course of a day. Once the number of price adjustments exceeds a certain threshold, the model predicts the emergence of an additional cycle.

During the time frame covered by our dataset, we find that retailers’ reaction times to competitor price changes decrease and, therefore, retailers undercut each faster and faster.¹² Figure 10 plots the average number of price changes and the number of price decreases per station and day from June 2014 to May 2017. The figure confirms that the number of price reductions has steadily been rising. Furthermore, it indicates two jumps, one in June 2015 and another one in April 2017, each marking the emergence of an additional intraday price increase. When the average number of price adjustments reaches five in June 2015 and eight in

¹²Most likely, this is driven by more efficient use of the data provided by the market transparency unit over time as more retailers integrate software notifying them of competitor price changes in real time, see section 4.2.2.

Table 2: Regional Heterogeneity

Notes: Logs of stations' average price spreads and frequency of stations' price reductions are regressed on the log of station density. Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

VARIABLES	(1) $\ln(\text{price spread})$	(2) $\ln(\text{price spread})$	(3) $\ln(\text{red. freq.})$	(4) $\ln(\text{red. freq.})$
$\ln(\text{comp. density})$	0.205*** (0.00848)	0.0546*** (0.0119)	0.131*** (0.00425)	0.0587*** (0.00819)
Constant	3.207*** (0.0521)	4.058*** (0.0675)	0.869*** (0.0258)	1.279*** (0.0463)
Observations	14,544	14,544	14,544	14,544
Adj. R^2	0.044	0.012	0.064	0.027
Brand FE		2,116		2,116

April 2017, a new pattern with an additional price increase emerged, confirming the model's prediction.

To illustrate that the number of price adjustments is directly related to the competition among stations, [figure 11](#) illustrates the price undercutting intensities for the last six month before a new intraday price increase occurred. Additionally, the figure includes the average daily markdown defined as the difference between the daily maximum price and the time-weighted average price¹³ in the month prior to a new price spike. A high value indicates fast undercutting and relatively low average prices. In the run-up to a new intraday price increase, average daily prices are up to 5.4 cents per liter lower than the maximum price. Immediately after a new intraday price increase, average daily markdowns decrease up to 4 cents per liter. Afterwards, the trend of intensified undercutting continues as average daily markdowns increase again.

4.3.4 Prediction 4: High Opening and Closing Prices

The model predicts retailers operating 24/7 to behave differently compared to retailers *not* operating 24/7. Retailers operating 24/7 are expected to increase

¹³Formally, we define the average daily markdown as $\frac{1}{NT} \sum_i \sum_t \int_{\underline{\tau}_{i,t}}^{\bar{\tau}_{i,t}} \frac{p_{i,t}^{\max} - p_{i,\tau}}{\bar{p}_{i,t} - \underline{p}_{i,t}} d\tau$, where i iterates through all firms and t iterated through all days of a given month. Furthermore, $\underline{\tau}_{i,t}$ and $\bar{\tau}_{i,t}$ represent the opening and closing times of firm i on day t , respectively.

Figure 10: Number of Prices per Day over Time

Notes: This figure depicts the average number of daily price adjustments and price reductions per station and month. The last month before the emergence of an additional cycle is marked by a vertical red line. Noon price increases started in June 2015 and additional afternoon increases in April 2017. The exact shapes of intraday cycles are shown in [figure 9](#) in [section 4.3.1](#).

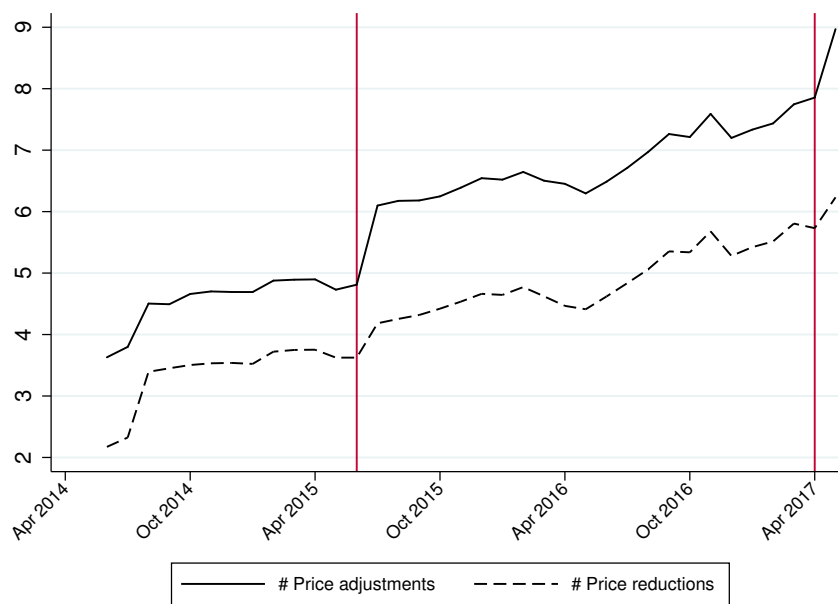


Figure 11: Competition Intensity

Note: This graph illustrates price undercutting intensities for the last six month before a new intraday price increase occurred. The upper left graph plots the daily price pattern by month between December 2014 and May 2015 and the upper right graph between October 2016 and March 2017. Below each graph, one finds the competition markdown defined as the difference between daily maximum and mean price.

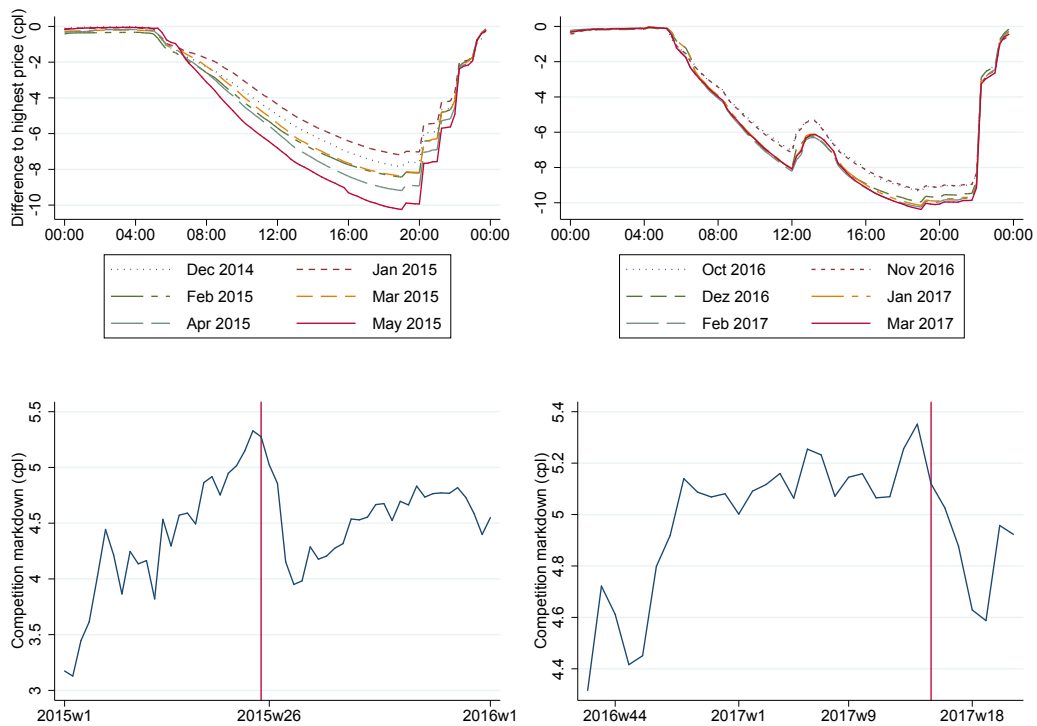
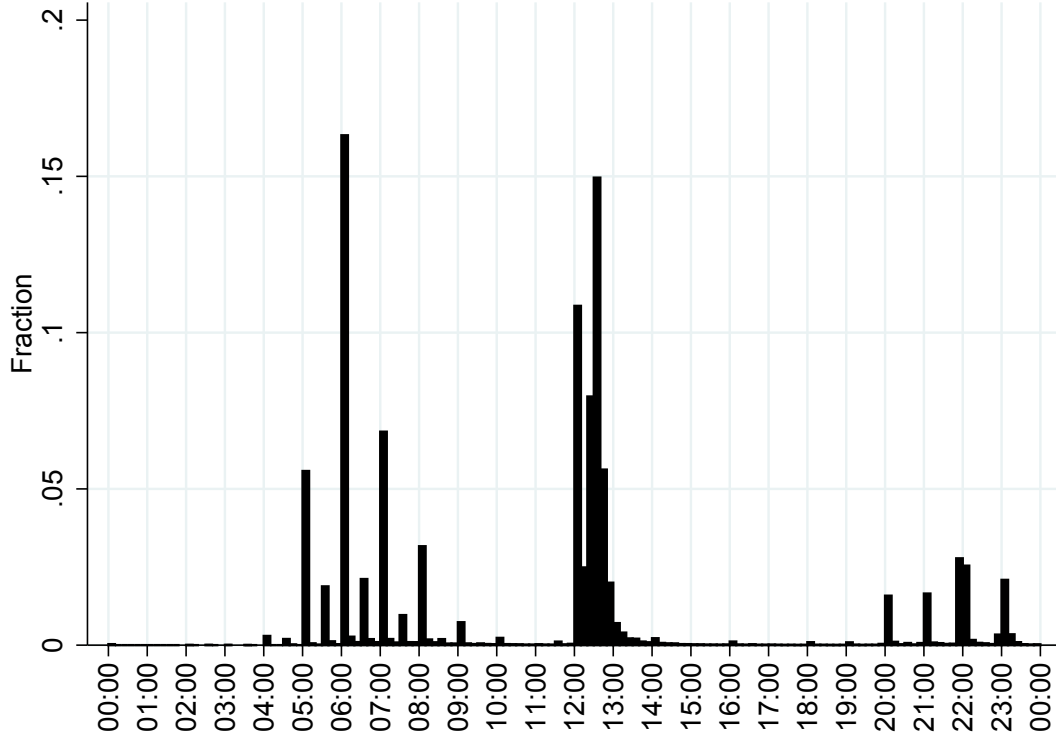


Figure 12: Time of Price Increases over Daytime

Notes: The histogram plots the frequencies of price increases over daytime in between July 2015 and March 2017 for stations not operating 24/7. Retailers rarely increase their prices in the evening. Instead, they mainly increase prices at noon or around opening times.



their prices when their competitors close for the night. Conversely, retailers not operating 24/7 do not have an incentive to increase their prices shortly before closing and are expected to keep their prices low towards the end of their operating times.

To verify the prediction, [figure 12](#) plots a histogram of price increases over daytime between July 2015 and March 2017 which features the period with price increases at noon and in the evening. Retailers not operating 24/7 rarely increase their prices in the evening. Instead, they mostly increase their prices at noon or around opening times, visible by the peaks in the morning at round times.¹⁴

Even though most stations not operating 24/7 do not increase their prices in the

¹⁴Consult [figure 28](#) for a histogram of price increases including the afternoon increase at 17:00 in May 2017.

evenings, some of them still do. Our model predicts that price increases in the evenings are only profitable when many stations have already closed. Therefore, we have a closer look at the stations that perform price increases before closing. It turns out that these stations are indeed the ones with particularly long opening hours so that, at the time of the price increases, most competitors have already closed for the night. A t-test confirms that stations with evening price increases close on average 105 minutes after stations without evening price increases (p-value < 0.0001 with standard errors clustered on station level). A boxplot comparing non-24/7 stations with and without evening price increase is provided in [figure 29](#) in [appendix B.2](#).

4.3.5 Prediction 5: Large Retailer Set Higher Prices and Lead Price Cycles

The model extension for heterogeneous brand values predicts that retailers of larger brands are more likely to initiate price increases relative to retailers of smaller brands. To test this prediction, we analyze the relationship between brand size and the timing of price increases. It turns out that large retail brands perform intraday price increases significantly earlier than small brands.

Specifically, we regress timings of intraday price increases on the number of stations in the retail network. For the noon spike, we use data from July 2015 to March 2017 on price increases between 11:00 and 17:00 and, for the afternoon spike, we use data from May 2017 on price increases between 17:00 and 19:00. The regression results are reported in [table 3](#). At noon, one additional station in the retailer network leads to price increases initiated around 1.1 seconds earlier. For network rankings, a lower marginal ranking¹⁵ leads to price increases initiated around 7.8 seconds earlier. As the retailer size varies between 1 and 2330 and the retailer rank between 1 and 232, an individual station reacts on average 73 minutes after the largest retailer ARAL increases its price at around 12:00 and 33 minutes after ARAL increases its price at around 17:00. Overall, stations belonging to larger retail networks perform intraday price increases significantly earlier than stations of smaller retail networks, confirming the model’s prediction.¹⁶

¹⁵The largest retail network is ranked first and the smallest retail network is ranked last, i.e. a lower marginal ranking corresponds to belonging to the next largest retail network.

¹⁶Further anecdotal evidence is provided in [table 6](#) and [table 7](#) in [appendix B.2](#) where we list the size of the ten largest retail brands together with the average time of price increase around 12:00 and 17:00.

Table 3: Price Increase Timing on Retailer Size

Notes: Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The table states the regression coefficients of the average time price increase on stations size between 11:00 and 17:00 in for June 2015 to March 2017 in column (1) and between 16:00 and 19:00 for May 2017 in column (2). Retailer station size represents the number of stations operating in the same network. Retailer station rank represents how many competitors have more stations in their network. Unit of measure are seconds after 0:00. Due to different time spans, the number of observations in columns 1 and 2 differs. Column 2 covers only one month and a number of particularly small retailers have not adopted afternoon price increases.

VARIABLES	(1) 12:00 price increase time	(2) 17:00 price increase time
Retailer station size	-1.149*** (162.8)	-0.367*** (116.6)
Retailer station rank	7.793*** (811.7)	4.804*** (593.0)
Constant	45,950*** (172.2)	62,113*** (122.4)
Observations	2,085	1,337
R-squared	0.025	0.030

4.4 Calibration

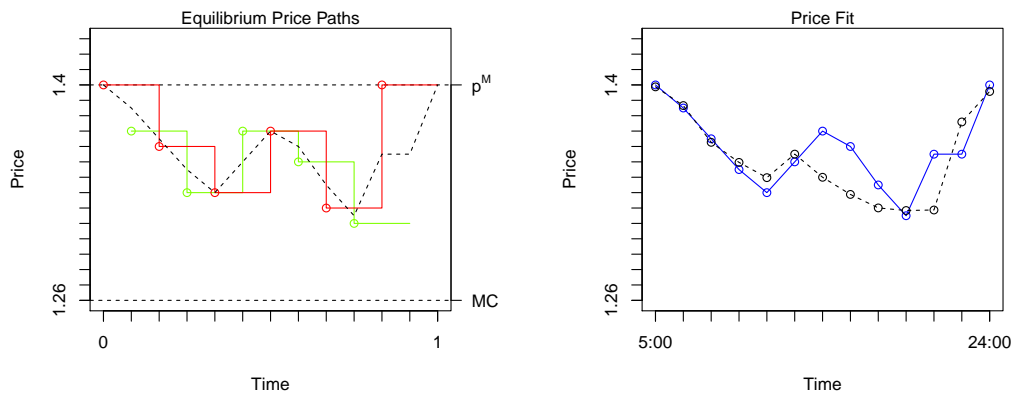
The extended price competition model with differing operating hours and product differentiation is able to capture many important features of retail gasoline markets. For reasonable parameters, the model yields price patterns similar to those observed in Germany. To be more specific, we perform a structural estimation of the model to fit average prices for Germany in June 2016. We fix the model to $N = 2$ players and determine the price grid \mathcal{P} , number of moves M , and the degree of differentiation r to minimize the squared deviation from the given price path.

We obtain the following estimates for the model with $N = 2$ firms: Prices are chosen from the grid $\{1.26, 1.27, \dots, 1.54\}$, each firm has $M = 6$ moves and products are slightly differentiated with travel cost parameter $r = 0.031$. [Figure 13](#) shows the unique subgame perfect equilibrium of that model specification and compares it to observed gasoline prices in Germany in June 2016.

A number of model ingredients are crucial to replicate the price pattern in the Ger-

Figure 13: Calibrated Model

This figure depicts the equilibrium prices of the calibrated model specification in comparison to the average prices in the German retail gasoline market. On the left, the theoretical equilibrium prices of both firms (red and green) as well as the average price (black, dashed) are shown. On the left, the theoretical average price (black, dashed) is plotted against the true average price (blue) in the German market in June 2016 (based on 15-minute intervals). The fitted model is able to match both the shape as well the magnitude of intraday price cycles.



man retail gasoline market. First, a sufficiently high number of price adjustments per firm is necessary to generate a second price cycle during the day. Second, the finite business day with differing operating hours is needed to create an endgame effect, which leads to further underbidding towards the end of the day. The reason is that a new price cycle, which only pays off in the future after repeated undercutting, is not worthwhile shortly before the end of the business day. Instead of raising their price shortly before the business day ends, firms prefer to undercut each other even a bit further in the evening. Last, mild product differentiation is responsible for small price increases at the start of a new price cycle. With product differentiation, firms can retain parts of the demand if they do not raise their price too far above the competitor's price. As a result, it becomes optimal to set the relenting price below the monopoly level, creating a small price spike in the middle of the day.

5 Welfare Analysis

Now that we have found strong support for the price competition model in the German retail gasoline market, we calibrate the model to the data and use it to perform a welfare analysis and to evaluate several policy measures that have been proposed recently.

5.1 Welfare Measure

Before conducting a structural welfare analysis, we define a welfare measure, namely *welfare efficiency*, of the model. Welfare efficiency is a relative welfare measure that allows to study market efficiency and the distribution of welfare across different model specifications.

First, we define *static welfare* $w(p)$ at market price p in the standard way: consumer surplus is given as the integral under the demand function and producer surplus is equal to profits.

$$w(p) = \underbrace{\int_p^{\infty} d(s) ds}_{\text{consumer surplus}} + \underbrace{\sum_{i=1}^N \pi_i(p_1, \dots, p_N)}_{\text{producer surplus}}$$

With constant marginal costs and linearly decreasing demand, static welfare is maximized at prices equal to marginal costs, i.e. at $p = 0$. For future reference, denote the *maximum welfare* by $W^* = w(0)$, which will serve as a benchmark later on.

In the present model, market prices may change throughout the business day. Therefore, we define *dynamic welfare* W to be the average static welfare over the day. Let $(p_1, p_2, \dots, p_{NM})$ be the vector of market prices at the NM price setting times. Then welfare is given by

$$W = \frac{1}{NM} \sum_{k=1}^{NM} w(p_k).$$

When products are differentiated, consumer surplus is computed as the weighted average of individual consumer surpluses (because consumers may buy at different prices). Furthermore, travel costs have to be deducted from consumer surplus.

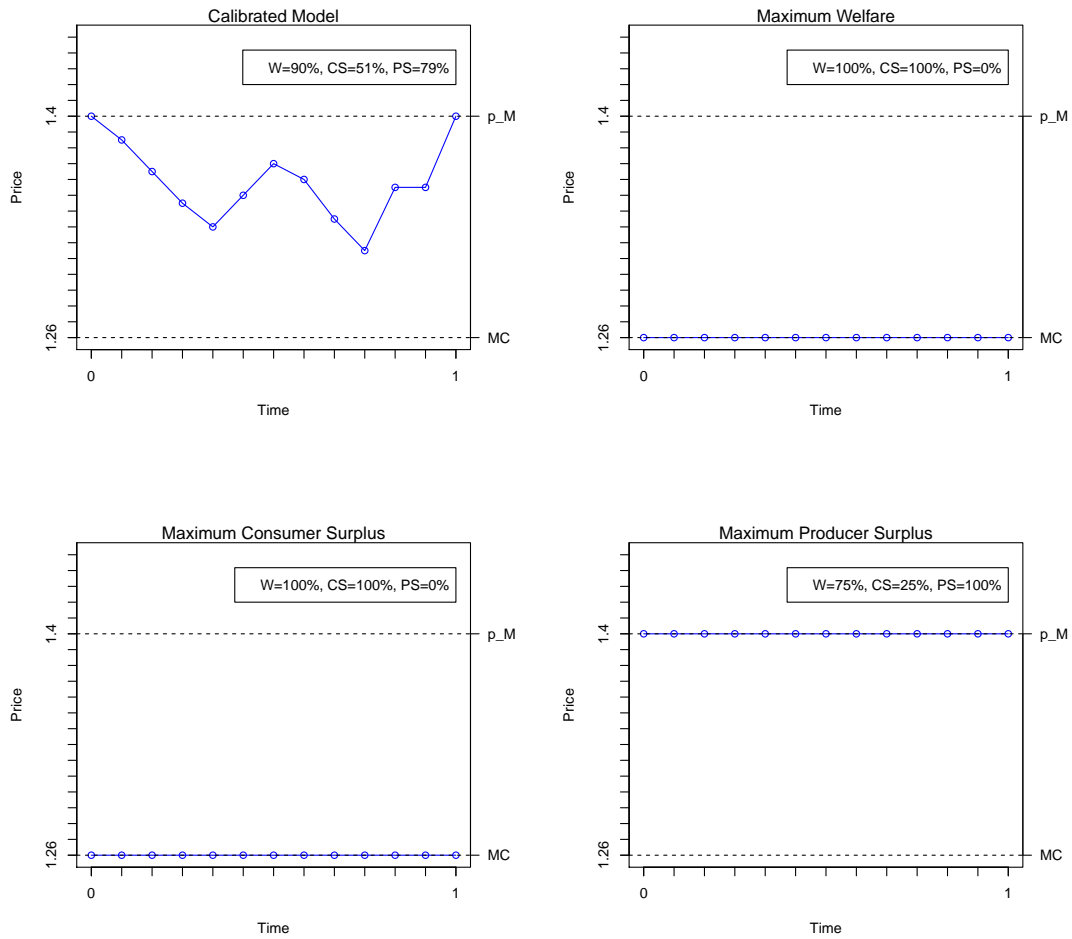
Finally, in order to provide a welfare measure that does not depend on units, we define *welfare efficiency* $\frac{W}{W^*}$ to be the share of maximum welfare that has been realized. Likewise, we define *consumer surplus efficiency* and *producer surplus efficiency* as the percentage of surplus relative to their maximum possible values for the given model specification. The advantage of that measure is that it allows comparisons across different model specifications when maximum attainable welfare differs, for example due to different travel costs. For any given specification of the model, welfare efficiency indicates how far the equilibrium outcome is away from its socially desirable path. [Figure 14](#) illustrates the welfare efficiency realized in the calibrated model in comparison to the price paths generating the maximum welfare efficiency. As in standard microeconomic textbooks, consumer surplus and welfare are maximized at the lowest price where demand is highest. Producer surplus, on the other hand, is maximized at the monopoly price.

5.2 Counterfactuals

Equipped with a theoretical welfare measure, we can use the model to evaluate changes in market characteristics and policy interventions. We focus on three counterfactuals: transparency, product differentiation and direct restrictions on price setting.

Figure 14: Welfare Illustration

This figure depicts welfare efficiency (W) as well as consumer surplus (CS) and producer surplus (PS) for given price paths relative to their maximum possible values. Welfare and consumer surplus are maximized at marginal costs, whereas producer surplus is maximized at the monopoly price. The calibrated model achieves a pretty high welfare efficiency and producer surplus, but only moderate consumer surplus.



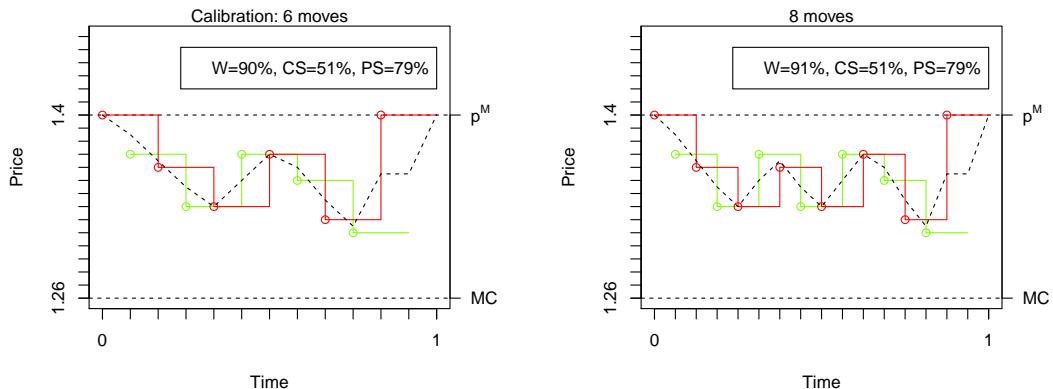
5.2.1 Transparency

First, we believe that transparency in the German retail gasoline market will increase further in the near future. Several conversations with industry participants confirmed that an increasing number of gasoline retailers are going to implement automatic monitoring and pricing systems. As a result, reaction times are likely to decrease in the years to come, leading to more price adjustments during business day. But how much transparency is optimal? Will prices get stable at some point or will they become even more volatile?

The model can offer some insight into these and related questions. [Figure 15](#) shows the equilibrium price pattern of the extended model with increased price adjustment activity during the day. Indeed, welfare turns out to remain fairly stable, but prices are more volatile. When the number of daily price adjustments reaches a threshold level, we expect to see a second price peak during the day.

Figure 15: Transparency and Price Cycles

This figure depicts the equilibrium prices of the calibrated specification of the model for two different levels of price adjustment activity during the day. While welfare efficiency remains stable, prices become more volatile with increased activity. When price adjustment activity is sufficiently high, we expect to see a second price increase during business days.

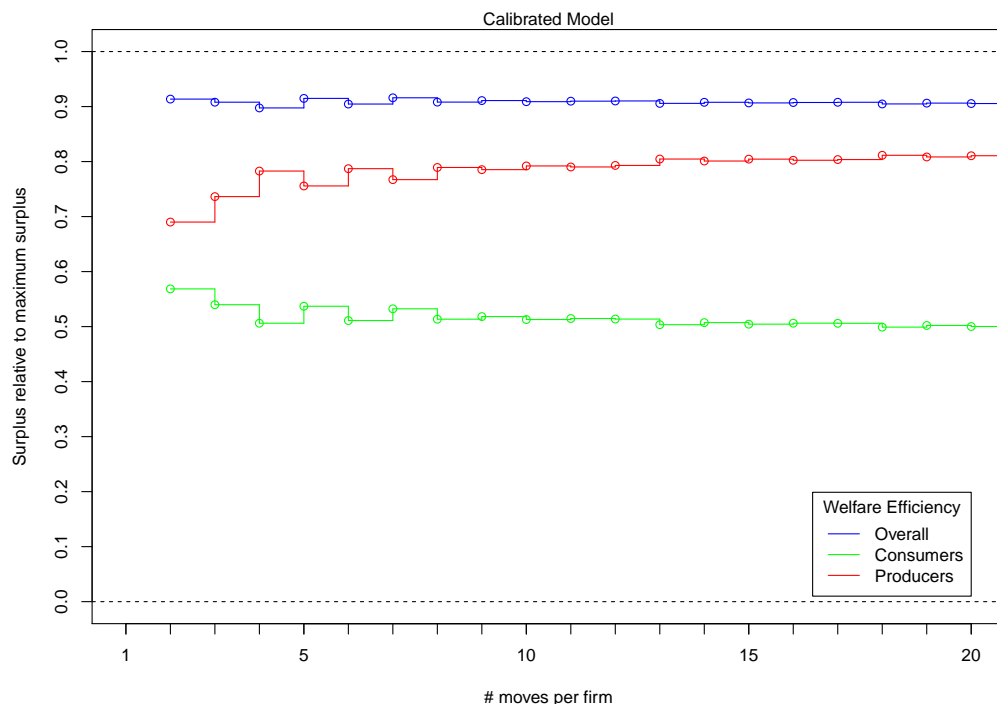


Transparency (represented by the number of moves in our model) has a subtle impact on welfare. Depending on the shape of price cycles, more moves (leading

to more price cycles) can have a positive or negative effect on welfare. In any case, welfare efficiency stabilizes as the number of moves gets large and cycles repeat quickly. Figure 16 shows the relationship between the number of moves and welfare efficiency in the calibrated model. Interestingly, more transparency leads to lower overall welfare in that specification. Consumer surplus tends to decrease with transparency, while producer surplus tends to increase. Our results are in line with Dewenter et al. (2016), who also find that the transparency initiative in the German retail gasoline market has increased prices and, thus, decreased consumers surplus.

Figure 16: Transparency and Welfare

This figure depicts welfare measures for different levels of market transparency, where market transparency is translated into number of price setting times in our model. Interestingly, the relationship between transparency and welfare is negative the calibrated versions of the model, indicating that market transparency does not necessarily need to be beneficial for customers. Instead, firms can also benefit from increased transparency, for example through effective reactions to their competitors' pricing strategies.



5.2.2 Product Differentiation

What are the effects on prices and welfare when gasoline retailers manage to differentiate their products more? To shed some light on this question, [figure 17](#) shows the equilibrium price paths of the calibrated model version for different levels of product differentiation. Interestingly, higher levels of product differentiation can lead to smaller price cycles or even to stable prices. However, if differentiation becomes too large, firms can act as local monopolies and charge high prices close to the monopoly price, leading to increased producer surplus, but decreased welfare.

5.2.3 Direct Restrictions on Price Setting

Unstable prices are widely considered to be a legitimate reason to intervene in competitive markets. In Austria and Australia, for example, price adjustments and especially price increases are largely restricted. In the Austrian retail gasoline market, for example, price increases are only allowed once per day at exactly 12 pm, while price decreases are allowed anytime. However, it is unclear whether such interventions lead to more stable prices and whether they increase welfare in the first place.

In [figure 18](#), we evaluate this issue by solving the calibrated model under the additional restriction that price increases are not allowed during the day and that firms simultaneously close at the end of the day.¹⁷ It turns out that restricting price increases can in fact amplify price volatility and decrease welfare. Rational firms take into account that they will be unable to raise prices later on. Anticipating mutual undercutting throughout the day, firms will start the day with much higher prices compared to free price setting. Overall, welfare can actually decrease when price increases are restricted.

Overall, our model suggests that restrictions on price setting might not be desirable from a social planner's point of view. Maybe economists and policy makers alike just need to get used to the idea that cycling prices are a natural phenomenon in dynamic competitive markets. Unstable prices neither have to be a sign of collusion nor of malfunctioning markets. Conversely, unstable prices can likely be

¹⁷This setting is inspired by the Austrian market: 12:00 in Austria corresponds to the beginning of the business day at time $t = 0$ in the model, while the business day ends after 24 hours denoted by time $t = 1$.

Figure 17: Product Differentiation

This figure depicts the effect of product differentiation on prices. Differentiation is still quite low in the model calibrations. If differentiation increases, price cycles get smaller and eventually vanish. If differentiation increases further, however, firms can charge monopolistic prices and welfare would be decreased.

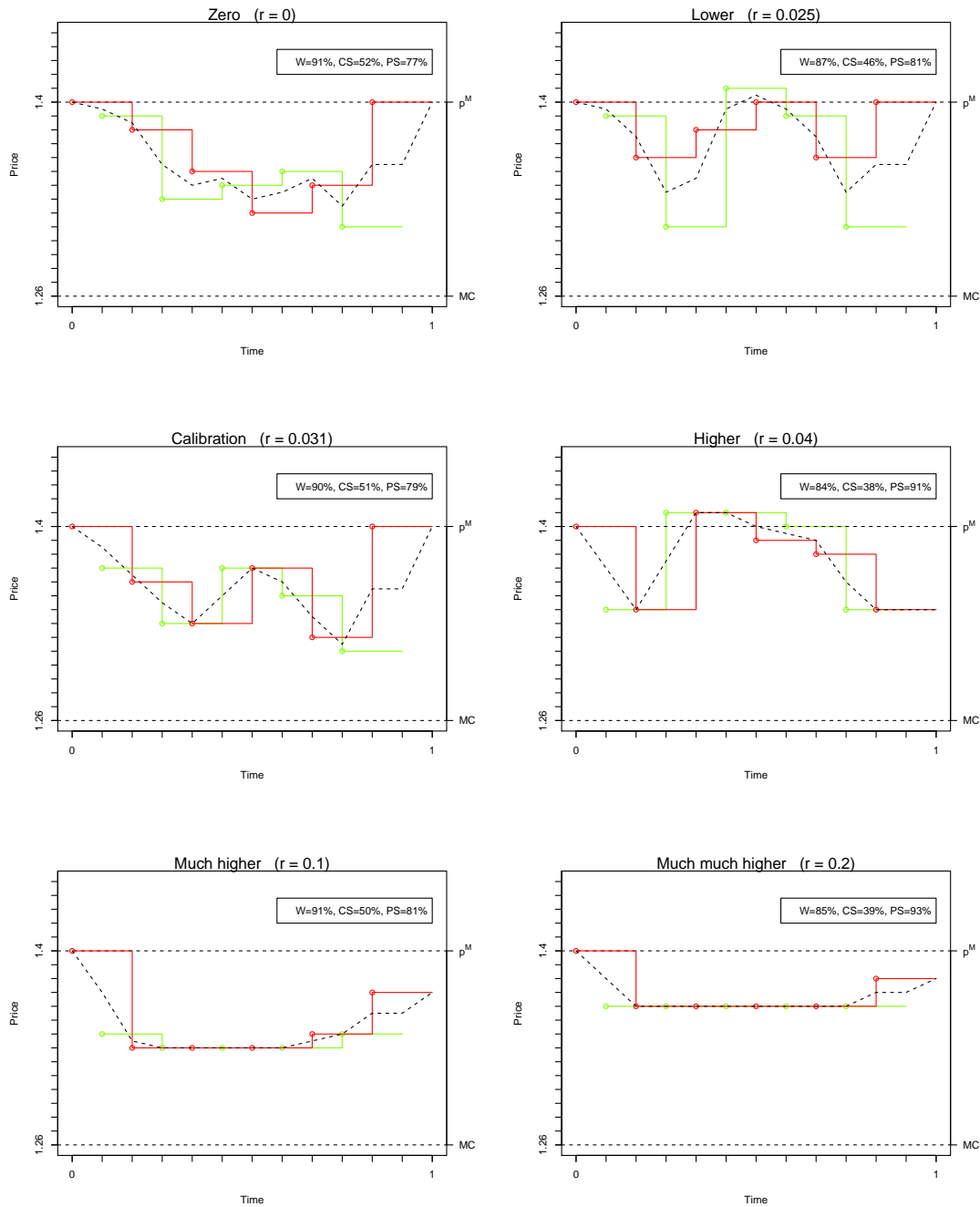
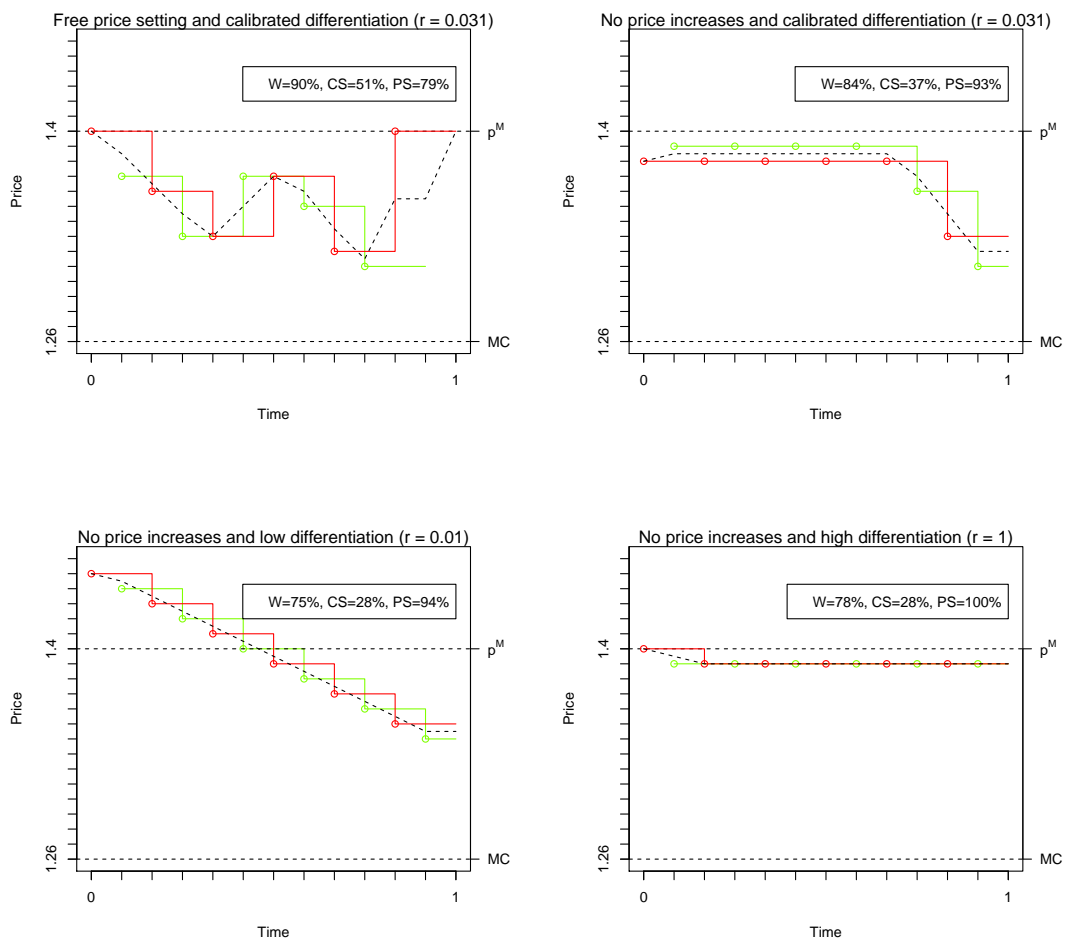


Figure 18: Direct Restrictions on Price Setting

This figure shows the equilibrium price path of the calibrated model specification, in which price increases throughout the day are not allowed. Anticipating their inability to increase prices, rational firms would start out at much higher price levels. As a result, welfare can actually be decreased compared to the benchmark with free price setting.



a sign of viable markets with strong competition.

6 Discussion

The model described in this paper is arguably one of the simplest possible models to analyze dynamic intraday price competition. However, all our results are robust to alternative specifications. In [appendix A](#), we present further variations such as time-varying demand, more than two firms and intraday discounting.

Some other inherent simplifications of the models might call for clarification. Firstly, assuming an exogenously fixed number of moves for each player might look like an oversimplification of the market setting. In reality, firms *choose* how closely to track the market and how often to adjust their prices. Their optimal number of price adjustments is constraint by some costs for monitoring the market. Our model can be regarded as a reduced form of a model in which firms choose their number of moves optimally, balancing costs from monitoring the market and benefits from reacting to price changes quickly. Any exogenous number of moves can easily be endogenized through appropriate monitoring costs.

Secondly, time-invariant demand throughout the business day is certainly an unrealistic assumption. Nevertheless, this simplification helps to isolate the price competition mechanism from potential demand shock effects. Therefore, we have chosen to stick to the time-invariant demand specification here. Note that the linear specification of the demand function already incorporates consumer reactions to different prices over the day. Additionally, in [appendix A.1](#), we demonstrate that our results are robust to time-varying demand.

Lastly, even though every business day is finite, business days themselves repeat indefinitely. The supergame of repeated business days may have an abundance of equilibria, but the stage game equilibrium can naturally be supported as a salient Nash equilibrium of the supergame.

On the empirical side, an alternative explanation for cycling prices are demand driven effects. These are described in [appendix B.3](#). If the market is not competitive, firms are able to exploit different consumer behavior at different times of the day. This hypothesis is not in line with two empirical observations: First, cycling pattern are similar on working and weekdays while traffic intensity is dif-

ferent. Second, we cannot find any significant change in traffic intensity, which could explain the emergence of additional intraday price cycles over time.

7 Conclusion

In this paper, we try to account for recent technological developments that have sped up the pricing game among retailers. In order to study high-frequency intraday price competition, we integrate operating hours into the [Maskin and Tirole \(1988\)](#) model of dynamic pricing. Operating hours generate breaks in the competitive market structure, inducing time-dependent pricing strategies.

Based on the model, we derive and verify a number of predictions from the model using an extensive dataset on the German retail gasoline market. The model explains the transition from a simple undercutting equilibrium before June 2015 to an equilibrium which features an intraday price cycle. We claim that retailers have reduced their reaction times and increased the frequency of price adjustments over time. At some point, the equilibrium price pattern transitioned from one daily cycle to two daily cycles, as predicted by our model.

Furthermore, we structurally estimate the model and evaluate a number of counterfactuals. At the estimates, increased transparency leads to higher average retail prices. Furthermore, regulatory interventions on price setting harm both consumer and producer welfare. Therefore, interventions on markets with price cycles should be taken with caution.

Finally, we propose two strategies to test our model: First, we predict more price cycles if the number of price adjustments continues to increase. Similarly, we predict fewer intraday price cycles if the number of price adjustments decreases. Due to the ongoing progress of digitization, it seems reasonable to expect more price adjustments and thus more price cycles in Germany in the near future. Second, one can test the predictions of the model's counterfactuals on the Austrian retail gasoline market. The Austrian market is regulated by price increases being limited to one per day at exactly 12pm, whereas price decreases are allowed at all times. Our model predicts average prices to be higher and consumer welfare to be lower in that case.

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A Details on Model

A.1 Time-Varying Demand

All our results are robust to variations in demand.

First, we have experimented with alternative demand functions $d(p)$. It turns out that constant demand, linear demand and other functional forms of the demand function all produce very similar equilibrium price paths.

Second, we have experimented with time-varying demand as well and obtain the exact same equilibrium price paths as with time-independent demand. As a benchmark, we have used the time-variation of traffic intensities in Germany over the day.¹⁸ Figure 19 shows the time-variation in traffic intensity relative to the highest traffic intensity observed over the day. We have used this ratio to scale demand over the business day in our model. It turns out that the time-variation in demand over the day does not influence the equilibrium price paths.

A.2 Further Extensions

A.2.1 More Than Two Firms

The model can easily be extended to feature more than two firms. All results in this paper hold for $N \in \mathbb{N}$ firms as well. In a model specification N firms, firms enter the market sequentially one after another. This way, the game remains extensive and simple to solve through backward induction. Exiting times, on the other hand, have no impact on the solvability of the model. At the end of the day, firms can exit the market sequentially or simultaneously. Both specifications produce very similar price paths in equilibrium. Figure 20 illustrates the baseline specification of the model with more than two firms. The resulting equilibrium price cycles are structurally very similar to the ones for two firms.

¹⁸Traffic intensities are widely used as a reliable proxy variable for gasoline demand. We use travel times predicted by the Google Maps traffic model between November 7 and November 13, 2016, between Wittelsbacherallee 153, 60385 Frankfurt am Main, and Borsigallee 37, 60388 Frankfurt am Main.

Figure 19: Time-Varying Demand: Weighting Function

This figure depicts the weighting function used to evaluate whether the results of the theoretical model are robust to time-varying demand. The weighting function plots the relative travel intensity throughout the day on a popular route through Frankfurt, averaged over one week in November 2016. Travel intensities are highly correlated with other measures of demand and are widely used as a reliable proxy variable for gasoline demand. It turns out that the time-variation in demand does not influence the equilibrium price paths of the model.

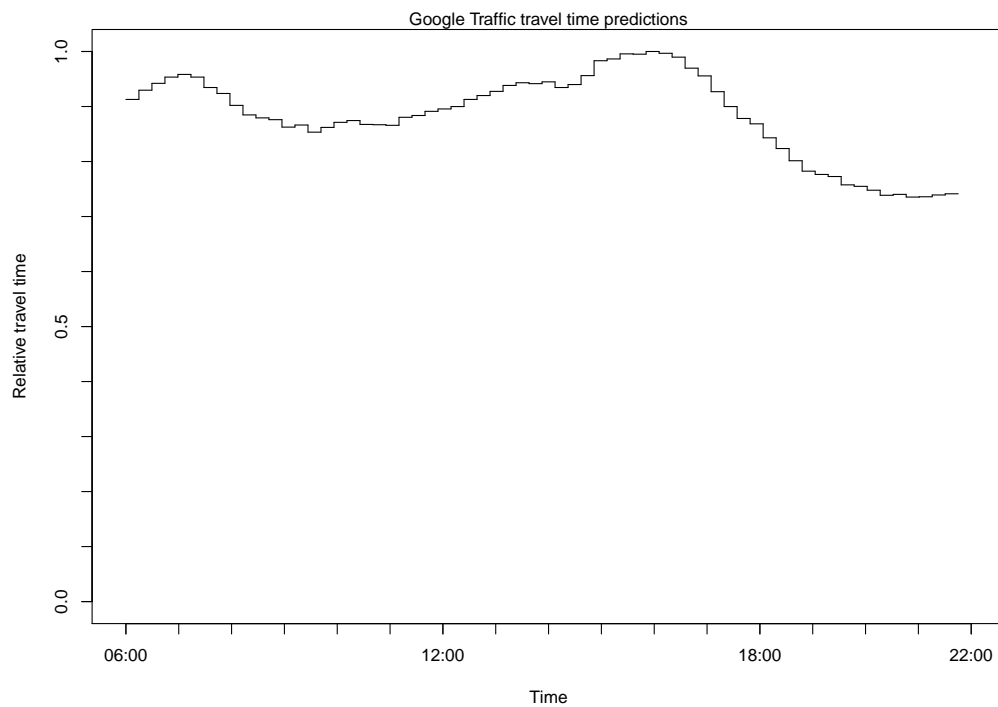
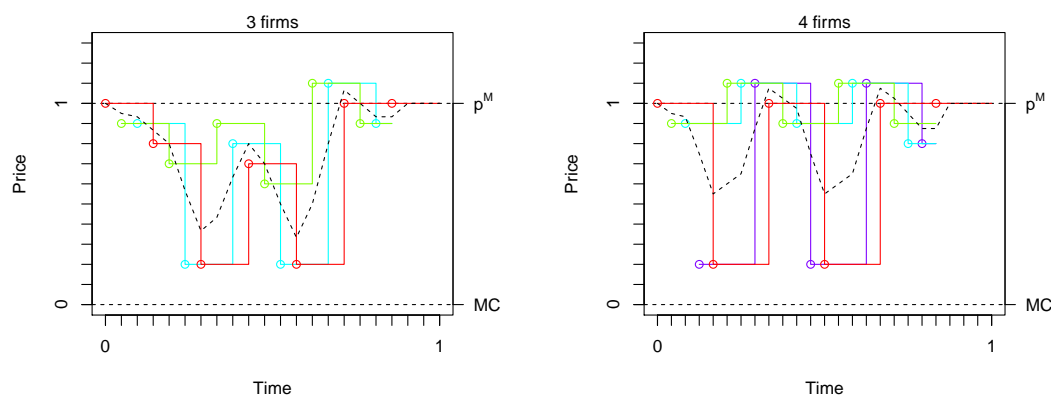


Figure 20: More Than Two Firms

This figure depicts the baseline specification of the model for $N = 3$ and $N = 4$ firms. The resulting equilibrium price cycles have the same shape as the ones for the duopoly case.



A.2.2 Discounting

Since the baseline model by [Maskin and Tirole \(1988\)](#) is a repeated game which includes discounting in order to be well-defined, we investigate the effects of discounting in our finite-horizon version of the model as well. Like in [Maskin and Tirole \(1988\)](#), price cycles remain stable as long as the discount factor is sufficiently close to one. Interestingly, when discounting increases to intermediate levels, price cycles become larger. That is because benefits from future cycles are discounted and undercutting becomes more attractive, leading to further undercutting and less frequent price increases. Finally, we confirm [Wallner \(2001\)](#) and show that high levels of discounting prevent cycles. When discounting is high enough (the discount factor is small), price cycles vanish because firms are not patient enough to value the future benefits of price increases.

Discounting can be interpreted as a form of myopia. When firms put more weight on current profits, maybe because they are risk-averse and the future is uncertain, myopia encourages undercutting and increases both the length and amplitude of price cycles.

Figure 21: Discounting

This figure depicts the equilibrium price paths for four different levels of discounting. Cycles are most pronounced for intermediate levels of discounting, but they vanish as discounting gets too extreme.

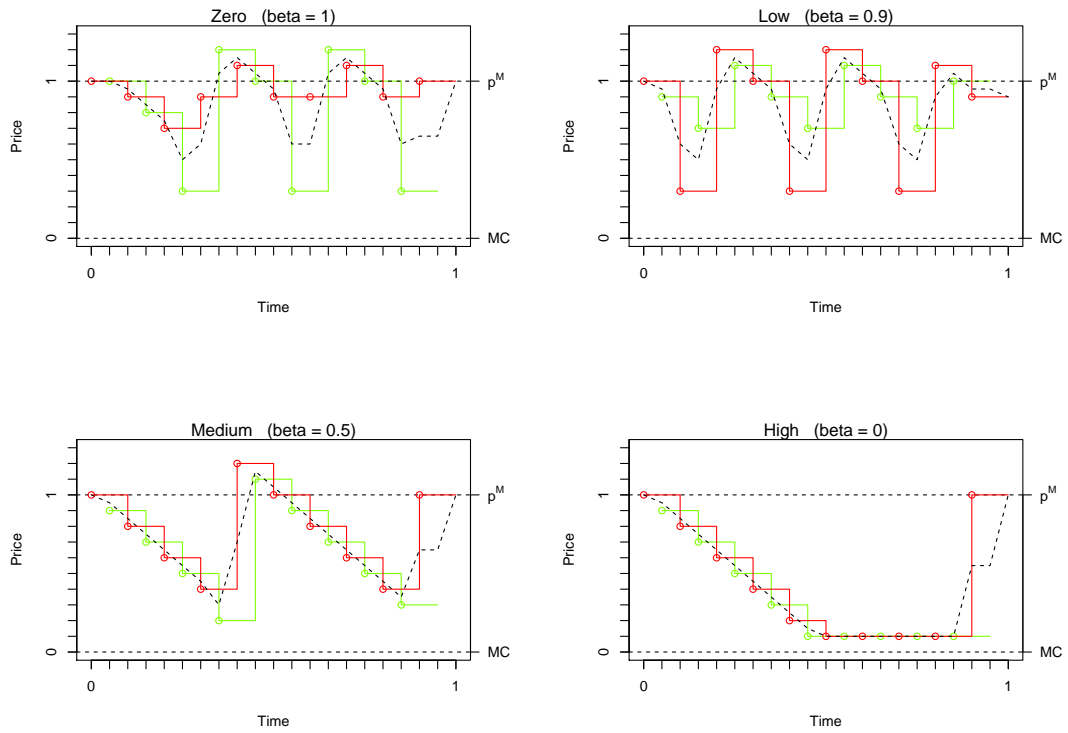
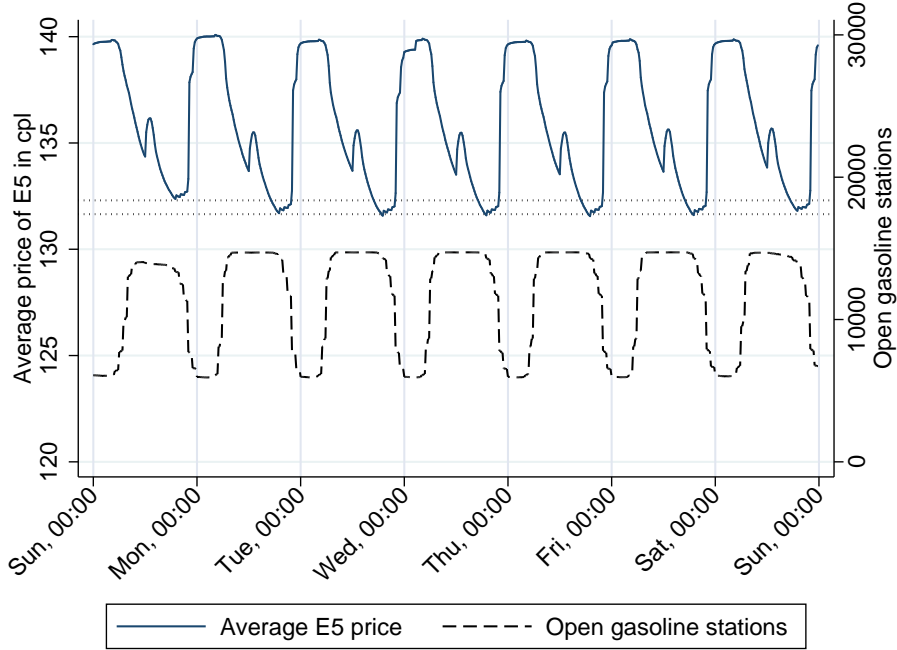


Figure 22: Weekly Price Pattern in June 2016

Notes: The sample was restricted to gasoline stations which open 24/7. The two dotted reference lines represent the lowest price on Sunday and non-Sundays.



B Details on Empirical Analysis

B.1 Descriptive Statistics

B.2 Hypothesis Testing

B.2.1 Timing of price increases

To present an anecdotal evidence price of the relationship between timing of price increases and retailer size, [table 6](#) and [table 7](#) summarize retailers' first price increase between 11:00 and 17:00 and increases between 17:00 and 19:00, respectively. The similarity 5% and 95% percentile between retailers indicates that price increases are coordinated within retailers. Three retailer, AGIP, AVIA and RAIF-FEISEN, do not increase prices for their entire network simultaneously but rather increase them by region. This is in line with the model. If retailer operate in independent sub-markets, it is efficient to coordinate price increases only within

Figure 23: Station Location and Competition Intensity

Notes: Black dots represent stations while the background color represents the relative estimated competition density. Axes represent latitude and longitude coordinates in radians.

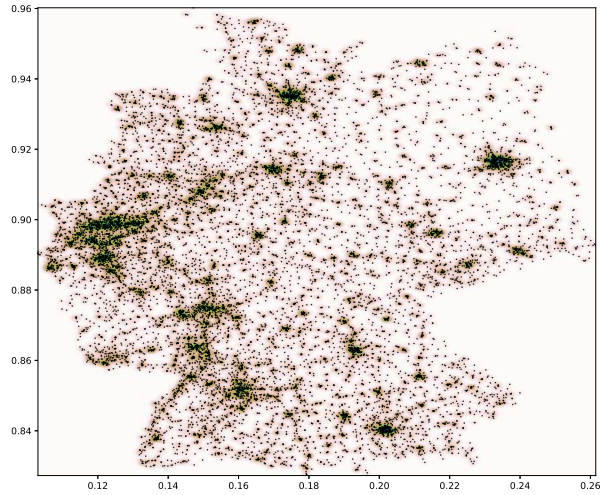


Figure 24: Operating Hours Box Plots by Weekday

Notes: Medians are marked by x . Outside values are excluded.

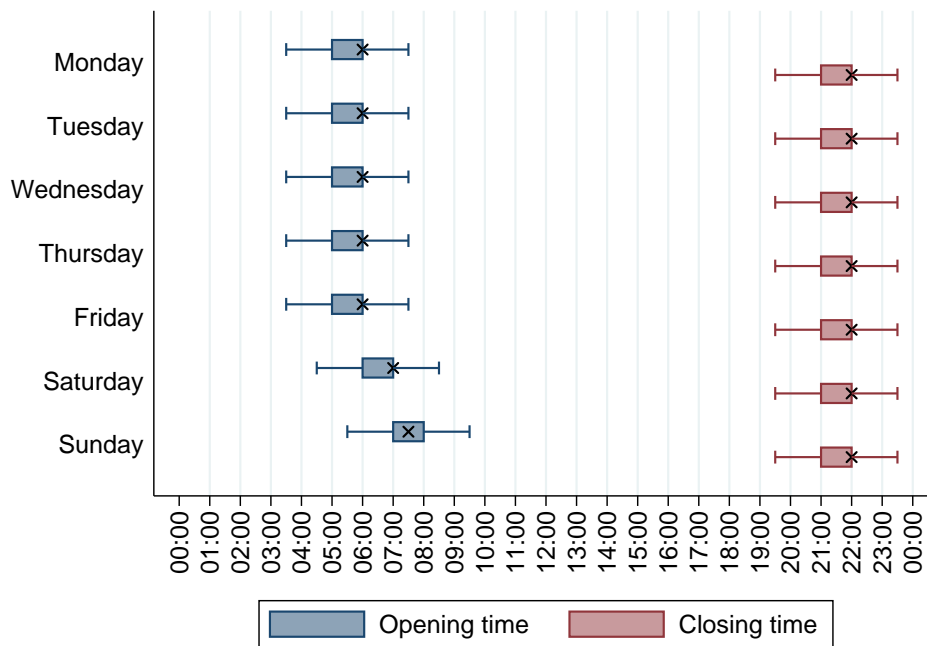


Table 4: Summary of Operating Hours

Weekday	Opening		Closing		Freq.
	Mean	Std. Dev.	Mean	Std. Dev.	
Monday	05:50:16	01:00:33	21:30:04	02:18:59	8,925
Tuesday	05:50:29	00:59:58	21:30:27	02:17:21	8,923
Wednesday	05:50:29	00:59:58	21:30:19	02:17:59	8,924
Thursday	05:50:28	01:00:06	21:30:27	02:17:58	8,923
Friday	05:50:35	00:59:53	21:31:03	02:22:31	8,915
Saturday	06:31:21	01:06:44	21:14:47	02:48:15	8,841
Sunday	07:14:18	01:30:13	21:14:43	02:52:05	8,192
Total	06:07:28	01:12:14	21:26:08	02:28:24	61,643

Figure 25: Intraday Price Pattern by Day in June 2015

Notes: The number in the title of every sub-graph denotes its representing calendar date. The sample is restricted to gasoline stations which open 24/7 (does not lead to qualitative changes in the pattern) and to dates between June 1 and June 22, 2015 as [Bundeskartellamt \(2015\)](#) reports intraday price cycles starting on June 23rd, 2015.

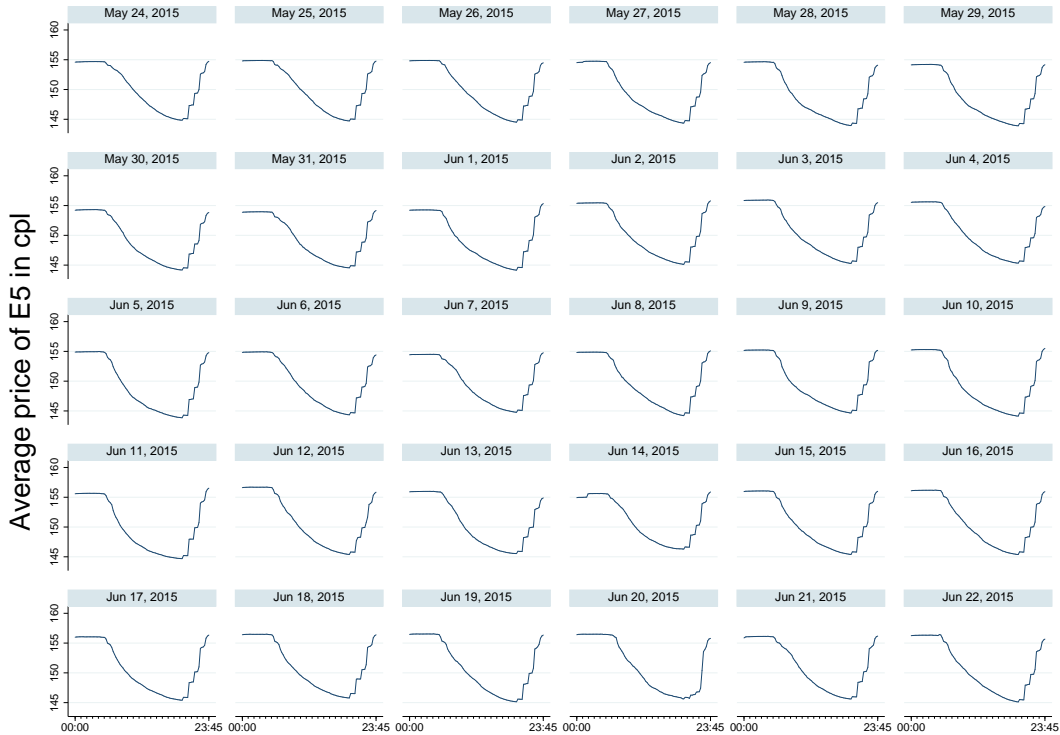


Figure 26: Intraday Price Pattern by Day in June 2016

Notes: Price pattern in the German retail gasoline market in June 2016. The number in the title of every sub-graph denotes its representing calendar date in June 2016. The sample is restricted to gasoline stations which open 24/7.

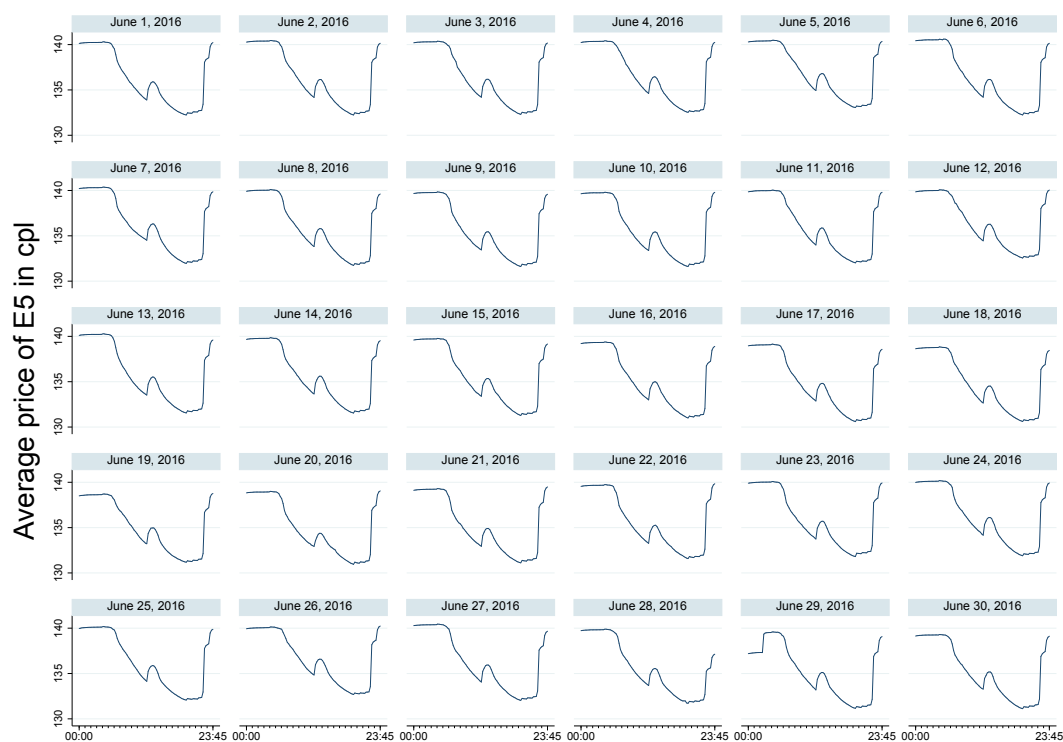


Table 5: Price adjustments between July 2015 and July 2016

Notes: The table summarizes price changes per day between July 2015 and July 2016.

Day of week	Mean	Std. Dev.
Sunday	7.0349372	0.28136347
Monday	8.351608	0.37302022
Tuesday	8.4288403	0.26132525
Wednesday	8.436316	0.38394452
Thursday	8.3400139	0.3923351
Friday	8.2945569	0.4153764
Saturday	7.8095284	0.273158

Figure 27: Intraday Price Pattern by Day in May 2017

Notes: Price pattern in the German retail gasoline market in May 2017. The number in the title of every sub-graph denotes its representing calendar date in May 2017. The sample is restricted to gasoline stations which open 24/7.

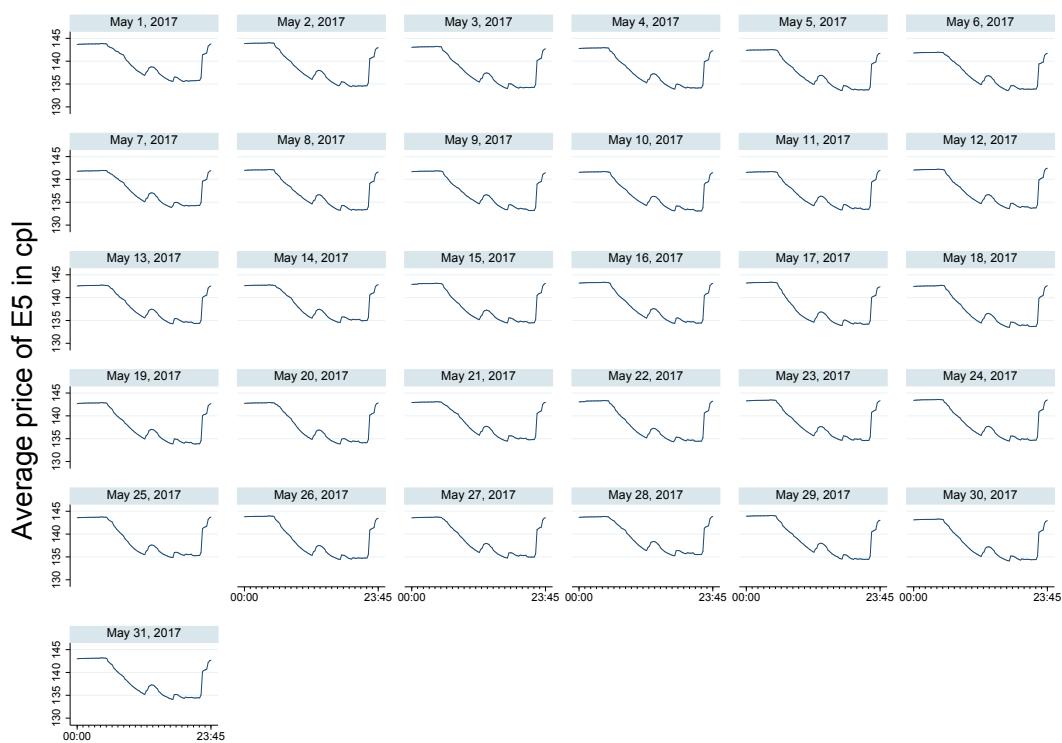


Figure 28: Time of Price Increases over Daytime in May 2017

Notes: The histogram plots the frequencies of price increases over daytime in between May 2017 for stations not operating 24/7. Retailers rarely increase their prices in the evening. Instead, they mainly increase prices at noon, at 17:00 or around opening times.

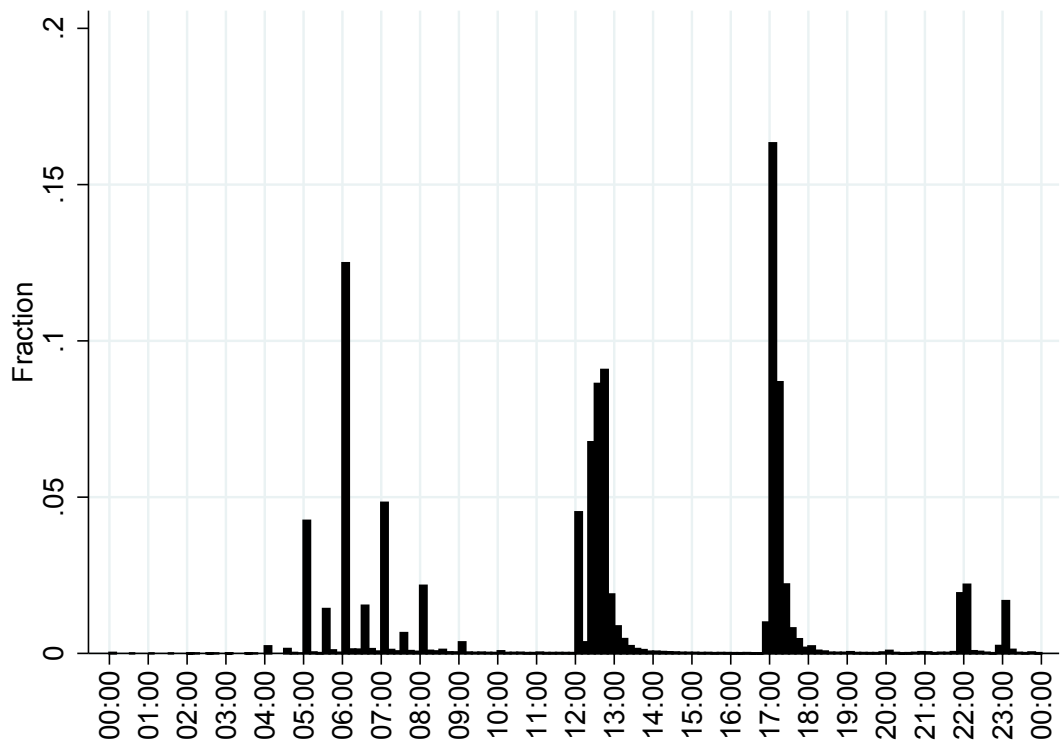
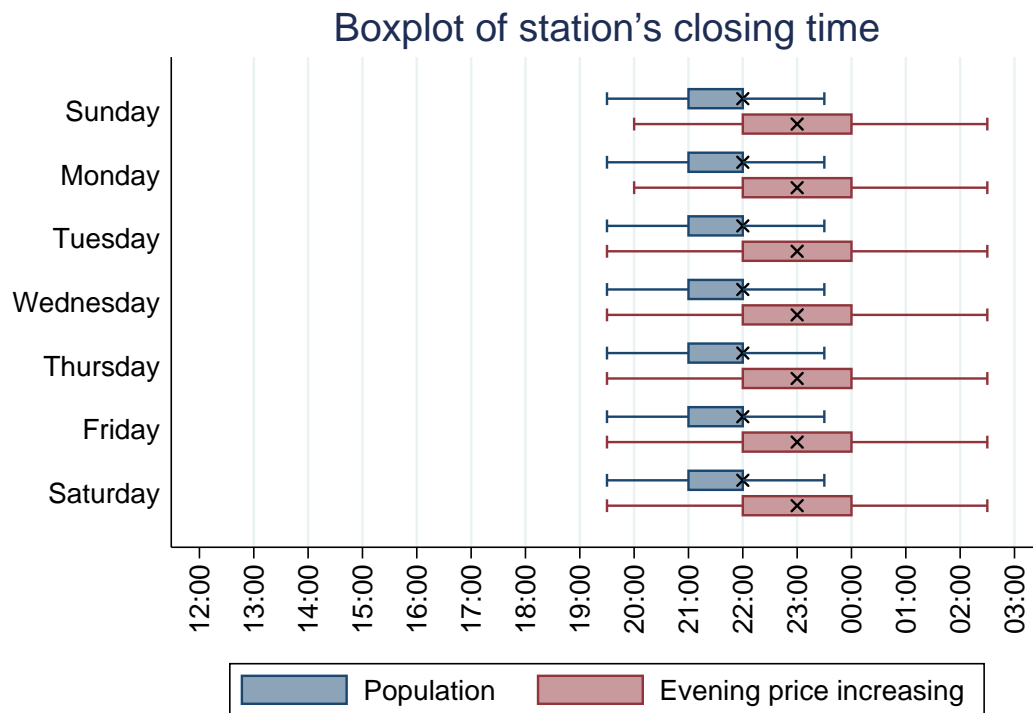


Figure 29: Properties of Stations which Increase Prices before End of Operating Hours

Notes: The plot contains the boxplots of closing times for stations which increased their prices in June 2016 after 18:00 in comparison to the population of gasoline stations. The median is represented by x and outside values are excluded.



these.

Table 6: Timing of first price increase by the largest retailers at 12:00

Notes: The table summarizes the time of the first price increases of the ten (by network size) largest gasoline retailers between 11:00 and 17:00 from June 2015 and March 2017. Price increases are almost simultaneously performed.

Retailer	Mean Time Price Increase	Size Ranking	Size	5% Percentile Price Increase	95% Percentile Price Increase
ARAL	12:02:33	1	2340	12:02:01	12:02:01
SHELL	12:02:35	2	1783	12:01:01	12:03:01
ESSO	12:17:26	3	1047	12:14:01	12:24:01
TOTAL	12:28:05	4	867	12:28:01	12:28:02
AGIP	12:30:06	8	422	12:20:02	13:06:01
JET	12:33:09	6	631	12:32:01	12:34:02
STAR	12:37:10	7	551	12:34:01	12:44:01
AVIA	12:39:49	5	735	12:10:02	13:24:01
HEM	12:41:01	10	363	12:34:01	12:46:01
RAIFFEISEN	12:55:26	9	391	12:17:01	13:42:01

B.3 Robustness checks

Our model shows that price cycles may be the competitive outcome in markets. [Noel \(2007b\)](#) considers several alternative reasons for price cycles: Station level inventory explanations, unobserved cycles in discounts at the wholesale level, cycles in consumer demand and collusion. In this section, we will discuss whether these explanations are reasonable to explain retailers' behavior.

In contrast to literature on the gasoline retail market, price cycles occur within a single day in Germany. Station level inventory constraints should not hit the entire market every day for over three years. Oil, rack prices and inventory discounts do not follow a regular pattern over day. On weekends, they are constant while retail prices continue cycling.

Cycles in consumer demand and collusion will be analyzed in detail in the next sub-chapters.

Table 7: Timing of first price increase by the largest retailers at 17:00

Notes: The table summarizes the time of the first price increases of the ten (by network size) largest gasoline retailers between 16:00 and 19:00 in May 2017. Price increases are almost simultaneously performed.

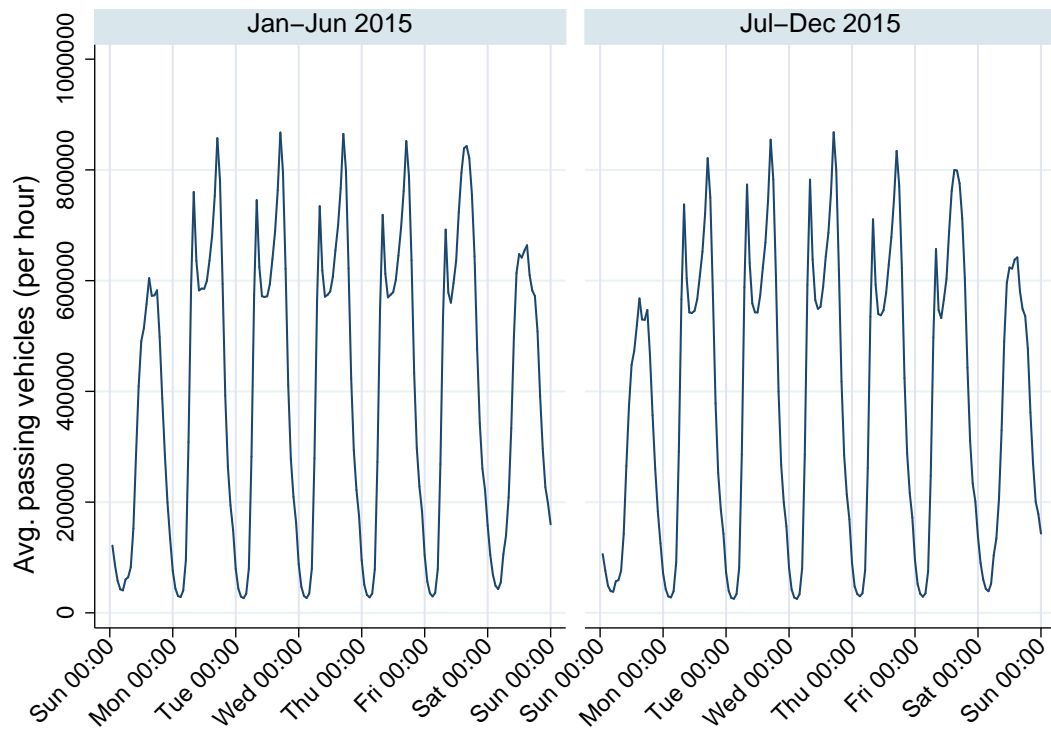
Retailer	Mean Time Price Increase	Size Ranking	Size	5% Percentile Price Increase	95% Percentile Price Increase
ARAL	17:00:37	1	2330	16:59:27	17:01:36
SHELL	17:01:26	2	1775	17:00:35	17:02:27
HEM	17:03:03	10	371	17:02:22	17:04:37
ESSO	17:07:05	3	1035	17:00:03	17:10:56
TOTAL	17:10:16	4	877	17:07:30	17:12:32
JET	17:11:30	6	648	17:10:04	17:13:05
STAR	17:13:28	7	562	17:12:56	17:14:12
AVIA	17:23:00	5	742	17:15:30	17:33:44
RAIFFEISEN	17:26:28	9	392	17:18:05	17:36:21
AGIP	17:32:34	8	421	17:17:52	17:58:03

B.3.1 Cycles in Demand and Price Discrimination

An alternative explanation is shifting demand (Noel, 2007b). The daily shape of prices would be the result of a repeating time variation in demand. Boehnke (2014) argues that German gasoline retailers temporally price discriminate. His results are based on a dataset which was self collected between April 2012 and January 2013. Due to the considered time period, he only observes a daily price pattern without sub-cycles. Like in the case of variation in demand, the emergence of an additional price increase in June 2015 and April 2017 would be determined by a change in day time demand.

We test this hypothesis by comparing demand between January to June 2015 to July to December 2015. We proxy demand by the number of cars tracked on streets by the German Federal Institute for Roadways. They provide us with a dataset consisting of hourly numbers of passing cars on federal streets in 2015 from 638 trackers. figure 30 plots the average number of cars before and after the emergence of intraday price cycles in June 2015. By executing a two sided t-test, it turns out that relative daytime demand proxied by logged first differences did not change significantly ($p = 0.9646$). Furthermore, the shift in demand cannot explain price cycles as price cycles are similar across all days, whereas daytime demand has a different shape on weekends.

Figure 30: Traffic intensity before and after intraday cycles emerged



B.3.2 Collusive Behavior

A number of studies have investigated whether price cycles and the corresponding price increases at the beginning of a cycle are a sign of fierce competition or rather a sign of collusion. The empirical evidence is mixed.

On the one hand, explicit collusion of gasoline retailers has been examined in Québec (Canada) (Clark and Houde, 2013, 2014) and Perth (Australia) in (Wang, 2008, 2009). Furthermore, Atkinson (2009) finds that price increases in Guelph are signaled by a temporary price increase shortly before the permanent increase, which hints to some form of collusion. Lewis (2012) finds that price increases are highly coordinated across cities with one big firm controlling many stations acting as a price leader. Finally, Borenstein and Shepard (1996) and Eckert and West (2005) report evidence in line with supermodels of collusion and against competitive pricing models.

On the other hand, price cycles are connected with lower market concentration and many small firms that initiate the undercutting phase (Eckert, 2003; Noel, 2007a; Atkinson, 2009; Doyle et al., 2010). Moreover, retail gasoline markets with price cycles are found to pass on cost changes two to three times faster than non-cycling markets (Lewis and Noel, 2011), indicating that cycling markets show less price stickiness and seem to be more competitive. Finally, retail gasoline markets with price cycles are shown to have lower prices and lower margins compared to non-cycling markets (Zimmerman et al., 2010; Noel, 2015).

We find evidence that explicit collusion is not necessary to create daily sub-cycles in prices. In case of collusion, retailers would have the opportunity to implement a more efficient price level which is stable.