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Working Paper
Competitive Price Cycles

CESifo Working Paper, No. 11971

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Fischer, Kai; Martin, Simon; Schlag, Karl (2025) : Competitive Price Cycles, CESifo Working Paper, No. 11971, CESifo GmbH, Munich

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Impressum:

CESifo Working Papers

ISSN 2364-1428 (electronic version)

Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH

The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute

Poschingerstr. 5, 81679 Munich, Germany

Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de

Editor: Clemens Fuest

<https://www.ifo.de/en/cesifo/publications/cesifo-working-papers>

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Competitive price cycles[◇]

Kai Fischer* Simon Martin** Karl H. Schlag***

July 2, 2025

Abstract

We develop a tractable model of competitive price cycles where prices are chosen alternately and consumers have heterogeneous information. The model yields sharp empirical predictions about price patterns, impact of captive consumers and pass-through. Using rich station-level price data from the German retail gasoline market, we test these predictions. Consistent with the model, we find price cycles, characterized by frequent small price cuts and infrequent sharp increases. These cycles shorten as costs rise and are more likely to be initiated by firms with more captive consumers. Pass-through of input costs is incomplete, in contrast to alternative theories.

Keywords: price cycles, tacit collusion, coordination, gasoline markets

JEL Codes: D43, D83, L11, L41

[◇]We thank David Byrne, Nicolas de Roos, Joseph E. Harrington, Philipp Schmidt-Dengler, Frank Verboven, Andy Wu, and Christine Zulehner for useful suggestions and comments.

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1 Introduction

Edgeworth cycles have long attracted interest in economic research. These cycles typically feature a phase of gradually decreasing prices (undercutting phase), followed by a sharp and sudden increase (relenting phase). Empirical evidence documents their presence across various industries, particularly in retail gasoline markets, including the United States (Noel, 2007a, Lewis and Noel, 2011), Canada (Noel, 2015), Australia (Byrne and De Roos, 2019, Wang, 2009), and Germany (Holt et al., 2024). More recently, price cycles have also been linked to algorithmic pricing, where firms employ automated pricing strategies to adjust to competitors dynamically (Brown and MacKay, 2023, Musolf, 2022).

This paper provides a simple and parsimonious explanation of price cycles that does not rely on specific conduct assumptions such as (tacit) collusion but instead relies on firms' temporary price commitment and consumer-side heterogeneity in price information. We consider a setting in which firms are myopic oligopolists operating in an alternating-moves framework. The market consists of captive consumers, who are randomly distributed among firms and remain loyal regardless of price changes, and shopping consumers, who seek out the lowest available price (Varian, 1980). De Roos (2012) alludes to the possibility of a similar framework generating price cycles. We formalize this idea and extend it to include several forms of firm asymmetry and input cost variation. In the unique subgame-perfect equilibrium (SPE), firms use undercutting to attract shopping consumers whenever competitor prices are not too low. However, once prices are sufficiently low, firms find it optimal to relent by setting prices at the monopoly level, thereby initiating a new cycle.

We emphasize that our framework yields a rich set of testable empirical predictions regarding price patterns, heterogeneity in firm behaviour and pass-through. We test these predictions in the German retail gasoline market, an environment with a homogeneous product and heterogeneously informed consumers (Montag et al., 2023, Fischer et al., 2024). Our empirical analysis confirms key predictions of the model: price cycles feature frequent small cuts and infrequent large hikes; price spell durations are similar across the

cycle; cycles shorten with higher input costs; and firms with more captive consumers are more likely to initiate the relenting phase. We also find that pass-through of input costs is incomplete - especially among firms with larger captive bases - and show that prices at the bottom of the cycle remain well above marginal cost.

These empirical findings are partly inconsistent with existing theories. A central feature of models in the spirit of Maskin and Tirole (1988) and Noel (2008) is that firms mix at the bottom of the cycle, resulting in extended price durations - contradicting our finding that price spell durations are not longer at the end of the cycle. They predict full pass-through of input costs and price levels near marginal cost at the bottom of the cycle, both of which are at odds with our empirical evidence of incomplete pass-through and prices remaining well above marginal cost. De Roos (2012) explores the potential for cycles arising from heterogeneous consumer information but does not formalize this concept, nor does it provide testable empirical predictions.

Moreover, existing explanations for price cycles also face conceptual limitations. They either rely on folk-theorem-style arguments (e.g., Byrne and De Roos, 2019) that yield limited predictive power, or on complex mixing strategies that are analytically intractable (Maskin and Tirole, 1988, Noel, 2008). Additionally, Maskin and Tirole (1988) is directly applicable to two symmetric firms only. In contrast, our framework offers a tractable and transparent structure that captures the essence of cyclical pricing dynamics and accommodates various forms of firm heterogeneity in oligopoly. Importantly, while algorithmic pricing can generate mechanical price cycles (e.g., Brown and MacKay, 2023, Musolff, 2022), these patterns often arise from hard-coded rules rather than profit-maximizing behavior. In our model firms are always optimizing.

The remainder of this paper is structured as follows. In Section 2, we lay out the theoretical framework and present the main results and empirical predictions. We empirically test these predictions in Section 3, and discuss our results and contrast them to other theories of price cycles in Section 4. Section 5 concludes.

2 Theoretical framework

2.1 Model

Consider a market with N firms, with typical index i , playing an infinitely repeated game. We assume that all firms are myopic, i.e., they have a common discount factor $\delta = 0$, and hence optimize contemporaneous profits whenever active. Firms move alternately in the order of their indices, from smallest to largest and back to smallest. We denote the marginal costs of production of firm i by $c_i \geq 0$. Fixed costs are assumed to be 0. When a firm moves and sets a price, any previous price of this firm is no longer valid. Let p_i be the most recent price posted by firm i . Denote the lowest price in the market by $\hat{p} = \min\{p_i\}_{i=1}^N$. For notational clarity, we do not include a period- t subscript.

On the demand side, there are two types of consumers, captive and shoppers (Varian, 1980, Narasimhan, 1988). Consumers are short-lived, i.e., active in a single period only. *Captive consumers* are loyal to a certain firm and purchase from this firm whenever the price p_i is below their willingness to pay. Denote the measure of firm i 's captive consumers by γ_i , $\gamma_i > 0$. *Shoppers* are consumers who observe all prices and purchase from the firm that offers the lowest price (and purchase equally likely in case of ties), as long as \hat{p} is weakly below their willingness to pay. The total measure of shoppers is $\lambda > 0$. We normalize the total mass of consumers per period so that $\sum_{i=1}^N \gamma_i + \lambda = 1$. All consumers have a willingness to pay $v > 0$ and unit demand. Our framework could also accommodate heterogeneity in valuations easily, but this only hampers parsimony.

We assume that prices are chosen from a grid with step size k , $0 < k < \bar{k}$ where $\bar{k} = \max_i\{\lambda(v - c_i)\gamma_i\}/(2(\lambda + \gamma_i)^2)$. The upper bound \bar{k} ensures that undercutting and attracting shoppers is appealing when prices are high.

Whenever a firm moves, it chooses a price maximizing its contemporaneous profits, given the currently lowest price \hat{p} :

$$\pi_i(p_i, \hat{p}) = (p_i - c_i)D_i(p_i, \hat{p})$$

where

$$D_i(p_i, \hat{p}) = \begin{cases} \gamma_i + \lambda & \text{if } p_i < \hat{p} \text{ and } p_i \leq v \\ \gamma_i + \lambda_i/2 & \text{if } p_i = \hat{p} \text{ and } p_i \leq v \\ \gamma_i & \text{if } p_i > \hat{p} \text{ and } p_i \leq v \\ 0 & \text{otherwise.} \end{cases}$$

For each firm i there is a lower bound under which undercutting is no longer attractive. This bound will play an important role in our analysis and is given by:

$$\underline{p}_i = k + c_i + \frac{(v - c_i)\gamma_i}{\gamma_i + \lambda}. \quad (1)$$

Throughout, we investigate subgame-perfect equilibria (SPE).

2.2 Analysis

In this subsection, we present our model's main theoretical results. In the following, we will identify equilibria characterized by a price cycle - a recurring pattern in which firms successively undercut each other's prices, then abruptly raise prices, only to resume undercutting once again.

Proposition 1. *In the unique SPE of the game, each firm marginally undercuts the currently lowest price \hat{p} (i.e., sets a price $p_i = \hat{p} - k$) whenever $\hat{p} \geq \underline{p}_i$, and returns to monopoly pricing (i.e., sets a price $p_i = v$) otherwise. Thus, the equilibrium path exhibits price cycles.*

Proof. The firm effectively has three choices: Charging a price above, at, or below \hat{p} . A price above attracts captive consumers only, so the most profitable price above is at the monopoly level v . Similarly, a price below attracts both captive and shopping consumers with certainty, so the most profitable price is right below \hat{p} .

Consider first the case where $\hat{p} \geq \underline{p}_i$. We need to show that the firm prefers undercutting (i.e., setting a price $p_i = \hat{p} - k$) to relenting (i.e., setting a price $p_i = v$), which

requires that

$$(\gamma_i + \lambda)(\hat{p} - k - c_i) \geq (v - c_i)\gamma_i \quad (2)$$

which holds since

$$\begin{aligned} (\gamma_i + \lambda)(\hat{p} - k - c_i) &\geq (\gamma_i + \lambda)(\underline{p}_i - k - c_i) \\ &= (\gamma_i + \lambda) \left(k + c_i + \frac{(v - c_i)\gamma_i}{\gamma_i + \lambda} - k - c_i \right) \\ &= (\gamma_i + \lambda) \frac{(v - c_i)\gamma_i}{\gamma_i + \lambda} \\ &= (v - c_i)\gamma_i. \end{aligned} \quad (3)$$

Additionally, we need to show that the firm prefers undercutting to matching the price \hat{p} , which requires that

$$(\gamma_i + \lambda)(\hat{p} - k - c_i) \geq (\gamma_i + \lambda/2)(\hat{p} - c_i)$$

or equivalently

$$k \leq (\hat{p} - c_i) \frac{\gamma_i + \lambda/2}{\gamma_i + \lambda}$$

which is satisfied for all $\hat{p} \geq \underline{p}_i$ and whenever k is sufficiently small, which is ensured through the upper bound on k through \bar{k} .

Next, consider the case where $\hat{p} < \underline{p}_i$, where we need to show that relenting is preferred to undercutting, i.e., that

$$(v - c_i)\gamma_i \geq (\gamma_i + \lambda)(\hat{p} - k - c_i) \quad (4)$$

which is precisely the mirror image of the undercutting condition (2). Using the fact that now $\hat{p} < \underline{p}_i$, the result follows immediately through a chain of inequalities as in (3).

Uniqueness of the equilibrium follows readily since firms always play strictly preferred actions, not taking into account possible reactions by their competitors due to their my-

opia. □

Proposition 1 provides an explanation for the occurrence of price cycles. Whenever a firm moves, it is appealing to undercut the currently lowest price as long as this price is sufficiently high. Once a certain, firm-specific lower bound is reached, undercutting is no longer attractive. The firm rather gives up on shopping consumers entirely by setting the monopoly price and selling only to their captive consumers. This reinitiates the cycle.

In the following, we will discuss the cycle length, which is determined by the number of price decreases and by the duration between price increases.

Proposition 2. *Cycles are shorter when input costs are high, or in markets in which the fraction of shoppers is low. Incentives to set the monopoly price instead of undercutting the lowest market price are higher for firms with high marginal costs or a larger captive consumer base.*

Proof. These statements are based on comparative statics on the lower bound of prices for the undercutting phase in (1). This expressions increases in c_i , so undercutting arises in equilibrium only for a smaller range of prices, and hence the cycle will be shorter. Similarly, \underline{p}_i decreases in λ , leading to shorter cycles when there are few shoppers.

The second part of the proposition originates from comparative statics of (1) across firms. Since \underline{p}_i increases in c_i , the bound will be more binding for firms with high marginal costs, rendering them more likely to stop undercutting and initiate a new relenting phase. Similarly, \underline{p}_i increases in γ_i , making a firm with a larger captive consumer base γ_i more likely to initiate a new relenting phase. □

Proposition 2 provides comparative statics regarding cycle length and initiators of new cycles across markets. It is based on the trade-off to keep undercutting (increasing demand at the expense of a lower margin per consumer) or relenting (drastically increasing the margin per consumer, but appealing to captive consumers only). When marginal costs are high, or there are only few shopping consumers, undercutting is relatively unprofitable, and re-initiating the cycle faster relatively more appealing. Comparing the trade-off between firms, a similar argument holds. Those firms which have high marginal costs are operating under tighter margins to start with, so demand expansion is less important to

them. Similarly, those firms that can rely on a larger captive consumer base need not rely on attracting shoppers, so again, they are more likely to focus on their captive consumers by relenting (charging the monopoly price).

Finally, we also consider pass-through of marginal cost to the lower bound as defined by $\frac{\partial p_i}{\partial c_i}$.

Corollary 1. *The pass-through of firm i of marginal costs to their lower bound \underline{p}_i (i) is strictly below 100% and (ii) decreases in the share of captive consumers γ_i .*

Proof. The results follow immediately from the respective definitions:

$$\begin{aligned}\frac{\partial \underline{p}_i}{\partial c_i} &= 1 - \frac{\gamma_i}{\gamma_i + \lambda} < 1 \\ \frac{\partial^2 \underline{p}_i}{\partial c_i \partial \gamma_i} &= -\frac{\lambda}{(\gamma_i + \lambda)^2} < 0\end{aligned}$$

□

2.3 Empirical Predictions

In this subsection, we present testable predictions generated by our model, and contrast them with predictions by other theories. We collect these predictions into three categories, pricing patterns, comparative statics, and pass-through.

Prediction 1 (Pricing patterns). *(i) The observed price patterns are characterized by many gradual price decreases, and rare and substantial price increases. (ii) Prices stay above marginal costs. (iii) The time to the next price adjustment is independent of the level of the last price.*

This prediction follows from Proposition 1. Parts (i) and (ii) describe *how* pricing evolves during the cycle. Part (i) closely resembles the pattern of Edgeworth cycles described by Maskin and Tirole (1988) and De Roos (2012).

Part (ii) highlights a fundamental distinction from Maskin and Tirole (1988), where cycles are re-initiated only once prices approach marginal costs. In contrast, our model predicts that firms revert to monopoly pricing well before reaching marginal cost levels, especially when they have a sizable base of captive consumers who are less price-sensitive.

Part (iii) addresses *when* price changes occur. In empirical work, this is frequently reflected in the duration of a *price spell*, defined as the time between price adjustments. Unlike Maskin and Tirole (1988), which predicts mixed strategies and extended price durations at the bottom of the cycle, our model implies that price spells at the bottom of the cycle are not longer than at other phases of the cycle.

Prediction 2 (Comparative statics). *(i) Cycles are shorter when input costs are high. (ii) Firms with a larger captive consumer base are more likely to be the first to revert to monopoly prices.*

This prediction follows from Proposition 2 and provides comparative statics with respect to input cost variation and the size of a firm's captive consumer base. In contrast, Edgeworth cycle models such as Maskin and Tirole (1988) and Noel (2008) become analytically intractable when more than three firms are present or when firms differ in key dimensions, preventing them from generating comparable comparative statics. Similarly, explanations based on tacit collusion rely on Folk Theorem arguments, which make it conceptually difficult to derive comparative statics.

Prediction 3 (Pass-through). *The pass-through of firm i of marginal costs to their lower bound of prices (i) is less than 100% and (ii) is smaller when there is a larger captive consumer base.*

This prediction follows from Corollary 1 and relates the pass-through of marginal cost changes to the lower bound of price cycles, potentially varying across firms. We focus on the lower bound rather than average prices, as it aligns more directly with our theoretical model. In Maskin and Tirole (1988), in contrast, the pass-through of marginal cost to the lower bound of price cycles is 100%. Neither Maskin and Tirole (1988) nor collusion-based theories such as Byrne and De Roos (2019) offer predictions regarding heterogeneous pass-through across firms.

3 Empirical Evidence

In this section, we test the model’s empirical predictions in the German gasoline market, where price cycles have been prevalent and persistent (Holt et al., 2024, Eibelshäuser and Wilhelm, 2017, Siekmann, 2017). In line with our model, survey evidence reveals that there is sufficient heterogeneity in search effort and price information across consumers. 40% of consumers always fuel at the same station in Germany (Dewenter et al., 2012), and 25% of consumers actively use price comparison apps (Bundesministerium für Wirtschaft und Energie, 2018)¹. Note that in the German market, the frequency and type of price adjustments are not regulated, in contrast to e.g., Austria, Belgium, and Western Australia.

3.1 Data

We use gasoline station and year-2019 Diesel price data for the universe of German, non-highway stations. For each station, we observe all price changes with an exact time stamp as well as their branding and geolocation.

The data is collected by the German Federal Cartel Authority, to which all stations mandatorily report their prices in real time. The data is made available to researchers through *TankerKönig*.² Our sample includes data on almost 14,000 stations and more than 66 million price changes throughout 2019.

We complement this data with daily input cost data by region purchased from *Argus Media*, commonly used in the literature (Assad et al., 2024, Fischer et al., 2023, 2024). We match input cost data based on refinery-station distance.

Defining Markets. We define markets as a 2km radius circle around each station, similar to Fischer et al. (2023). Our model predicts cycling behavior in markets with at least two stations. Monopoly stations would set the price to v , not causing any cycles. We therefore restrict our focus to non-monopoly markets. This leaves us with approximately 77% of stations classified as non-monopolists.

¹Similar numbers are, for example, available for Australia, where 44% use price comparison tools (Australian Competition and Consumer Commission, 2024).

²<http://https://www.tankerkoenig.de/>

Identifying \underline{p}_i . While a station’s lowest price is a suitable proxy for \underline{p}_i , we only observe it (up to the precision of the price grid) for the station with the highest \underline{p}_i in a market. Prices will not fall below $\max_i\{\underline{p}_i\}$ and hence \underline{p}_i for the other firms will not be observed. When studying \underline{p}_i , we only use stations which have the highest minimum price on a day within their market.

Proxying γ_i . We proxy the share of captive consumers γ_i in two ways. Our first method is by capturing brand-level loyalty card programs that have been found to be important in the German gasoline market (Bundeskartellamt, 2011). We manually collected information on the existence of loyalty programs among the largest 53 gasoline brands in 2024, making up 83% of all stations. 51% of the largest gasoline brands, and hence 68% of gasoline stations, have a loyalty program. Loyalty programs include loyalty cards, premiums, and price advantages. They incentivize consumers to stay with a certain station and to not switch away. We do not include fleet cards for commercial companies as loyalty programs.

Our second method is to proxy the share of captive consumers γ_i by brand network size. Stations with larger networks are more likely to appeal to consumers due to their desirable locations, stronger brand recognition, or perceived quality. We categorize the big 5 brands (ARAL, Shell, Total, JET, ESSO), holding 40% of all stations, as stations with a high share of captive consumers. This classification is adopted from Bundeskartellamt (2011) and also used in Fischer et al. (2024) and Martin (2024).

Classifying Cycles. A price cycle is defined to start with a sizeable price increase of at least 3 Eurocent/l (ct/l), similar to the definition of a cycle start in Byrne and De Roos (2019). The firm that made that price increase is said to *initiate* the price cycle. A subsequent increase larger than this threshold then identifies the end of the cycle and the beginning of the next cycle. We define the *duration of a cycle* (also referred to as the cycle length) as the time elapsed between these two events.

3.2 Evidence of price cycles

We start by showing the price cycles in our data.

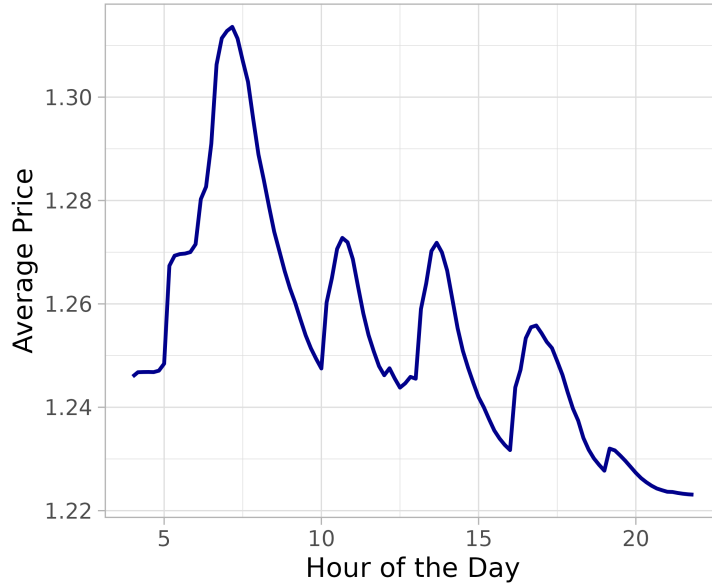


Figure 1: Average Price by Time of the Day

Note: This figure presents the average price in the German gasoline market in 10 minute steps between 4am and 10pm (data: Jan 01, 2019 to Dec 31, 2019).

Figure 1 shows the average price across German stations by time of the day. Average prices clearly follow a cyclical pattern. Average prices are low in the early morning. When morning commute starts at around 7:30am, average prices are highest. Afterwards, average prices slowly decrease until around 10am, where prices are around 7 ct/l lower than at the peak of the cycle. There are two subsequent, shorter cycles in average prices from 10am to 1pm and 1pm to 4pm. A last cycle can be observed in the late afternoon to evening. These findings are consistent with earlier results on the German gasoline market (Assad et al., 2024, Siekmann, 2017).

Figure 1 focuses on average prices over the year and across stations. In Figure A.1 (a) in the Online Appendix, we additionally show that price cycles are also clearly visible at the beginning, middle and end of our sample. In Figure A.1 (b) we show the distribution of the number of price jumps per day and per station. A price jump is therein defined either as being greater than 3ct/l or than 4ct/l. 96.1% (95.1%) of station-day time series have at least one jump, and the mean number of jumps is 3.74 (3.08) when jumps are at least 3ct/l (4ct/l).

Finally, for each day, we categorize stations into *cycling* and *non-cycling* based on several simple criteria commonly used to systematically identify cycling behavior (see Holt

et al., 2024, for an overview). These criteria build on typical characteristics of price cycles, especially the asymmetry of few large price hikes and many small price decreases (e.g., negative median price change). Across specifications, described in Online Appendix B, we robustly find that at least 85% of all station-date price series exhibit cycling behavior.

3.3 Testing empirical predictions

Having documented the existence of cycles in our data, we turn to testing the empirical predictions identified in Section 2.3.

Prediction 1 concerns pricing patterns, and part (i) speaks to the relative prevalence and intensity of price decreases and price increases. In the left panel of Figure 2, we depict the number of price increases and decreases per station and day. Observe that price decreases are much more common than price increases. On average, the number of price decreases per day is 8.9, in contrast to 4.2 price increases per day. A t-test reports that the mean number of price decreases is significantly higher than the mean number of price increases ($p < 0.001$, SE clustered at municipality level).



Figure 2: Price Increases and Decreases

Note: The left panel shows the distribution of the number of price increases and decreases per station and day. The right panel shows the distribution over the size of price increases and decreases. The distributions are winsorized at the 99th percentile to account for outliers and include data for all stations and days of the year 2019. Only non-monopoly stations included.

In the right panel of Figure 2, we show the distribution of the size of price changes, separately for price increases and price decreases. The average increase is 5.3 ct/l while

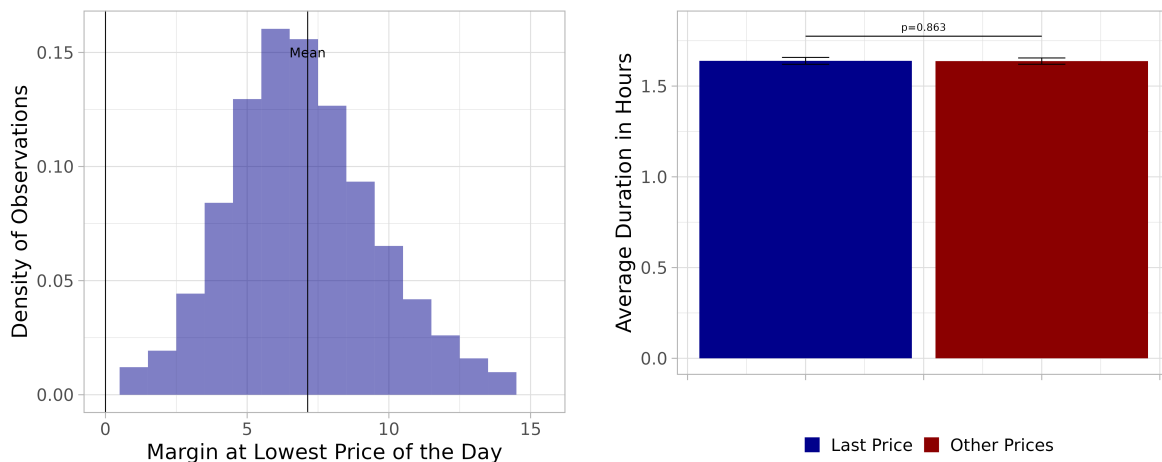
the average decrease is 2.5ct/l. The difference between these two is statistically significant ($p < 0.001$, t-test, SE clustered at municipality level).

These investigations yield our first result, supporting part (i) of Prediction 1:

Result 1. (i) *Price decreases are significantly more common than price increases. Price decreases tend to be smaller (in absolute terms) than price increases.*

Relatedly, we next turn to part (ii) of Prediction 1, according to which prices stay well above marginal costs throughout the cycle. We show in panel (a) of Figure 3 the distribution over the margin at the lowest price of the cycle, defined as the difference between station-level daily minimum prices and marginal costs. The mean of this margin is 7.15 ct/l (SE: 0.06 ct/l), which is statistically significantly different from 0 ($p < 0.001$, t-test, SE clustered at municipality level).

Result 1. (ii) *The bottom of the price cycles are significantly above marginal costs.*



(a) Distribution of Margins at Lowest Price (b) Price Duration by Stage in Price Cycle

Figure 3: Margins and Price Duration

Note: Panel (a) presents how station-day level margins at the daily lowest price are distributed. Only non-monopolists included. Distribution winsorized at the 1st and 99th percentile. Panel (b) presents the average duration of prices depending on whether this price is the last in a cycle (i.e., at the bottom of the cycle) or not. Duration winsorized at the 99th percentile to account for far outliers. Standard errors clustered at the municipality level and 95% confidence bands reported.

Part (iii) of Prediction 1 addresses the timing of price adjustments once the bottom of a cycle is reached. In panel (b) of Figure 3, we compare the average duration of cycles' very last price (i.e., before a large price increase as the start of a new cycle) with

the average duration of all prices at other positions in cycles. The average duration of the last prices and other prices is not statistically different, with narrow 95% confidence intervals around the mean durations. Specifically, the mean duration is 1.639 ± 0.019 hours for the last prices and 1.638 ± 0.018 hours for the other prices, where the \pm values represent the 95% confidence intervals. This finding supports part (iii) of Prediction 1:

Result 1. (iii) *The duration of a price spell at the bottom of a price cycle is not significantly different than it is at other phases of the price cycle.*

We now turn to comparative statics, summarized in Prediction 2. Part (i) predicts a negative relationship between cycle length and input costs. In the gasoline market, input costs are highly volatile due to frequent oil price changes. Cycle length (or cycle duration) is measured by the time elapsed between the first price jump of a given cycle and the first price jump of the subsequent cycle. According to this definition, the mean (median) cycle length in our sample is 4.50 (3.82) hours.

Figure 4 presents the relationship between cycle length and input costs as a binscatter plot with mean cycle length by 0.5ct/l input cost bins. The figure reveals a clear negative relationship between cycle length and input costs. The fitted line of the corresponding linear regression is shown in blue in Figure 4. The estimated slope is -0.057 (SE = 0.006, so $p < 0.001$). These estimates are sizable: They imply that a ten ct/l increase in input costs reduces the cycle length by 34 minutes or 13%.

Similarly, we investigate the average number of cycles per day, corresponding to shorter cycles on average. The results are shown in Figure A.2 in the Online Appendix. We find that there are more cycles per day when input costs are higher. The estimated slope is 0.055 (SE = 0.008, so $p < 0.001$).

These results clearly support part (i) of Prediction 2, leading to the following result:

Result 2. (i) *There is a statistically significant negative relationship between cycle length and input costs.*

According to part (ii) of Prediction 2, firms with a large base of captive consumers are more likely to initiate a cycle. We proxy the share of captive consumers by distinguishing

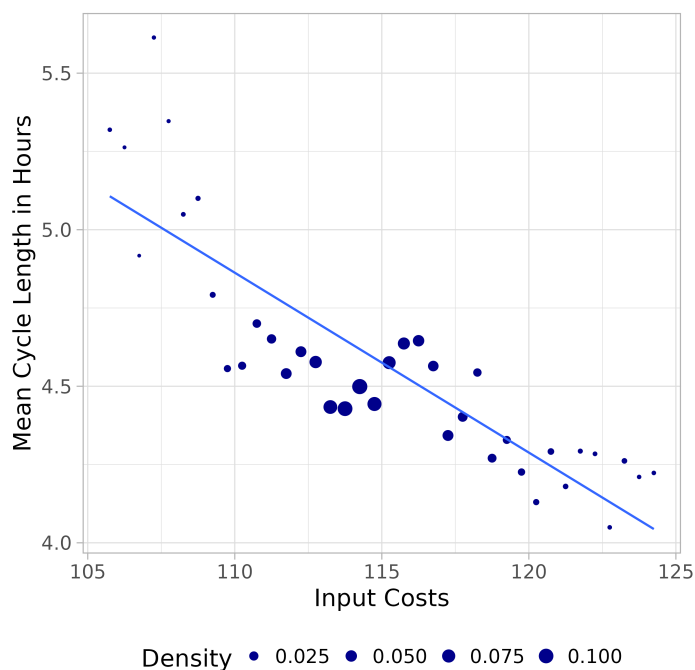


Figure 4: Mean Cycle Length by Input Cost Level

Note: This figure presents the correlation of mean price cycle length with station-date level input costs. Only stations with cycles on a date included. Monopolies not included. The circle size gives the share of observations in a certain bin. Fitted line in blue.

between (i) stations of brands with and without loyalty programs and (ii) whether stations belong to the largest five brands.

We calculate the share of cycles in a station's market that the station initiates. Figure 5 plots two outcomes of how likely a station is to initiate a cycle by brand affiliation and loyalty program. Panel (a) shows the share of cycles initiated by a station and panel (b) shows the share of station-date observations on which a station initiated at least one cycle. We find that big brand stations and stations with loyalty programs are more likely to initiate cycles. The share of increases for loyalty program stations is 31.2 p.p. (SE: 0.7 p.p., clustered at municipality level) higher than for non-loyalty program stations. For big brand vs. no big brand stations the difference is 30.6 p.p. (SE: 0.8 p.p., clustered at municipality level).³ A similar pattern is evident for the share of stations that initiated at least one cycle on a given date: big brand stations and those offering loyalty programs are more likely to have initiated at least one cycle on a given date. Hence, contrary to

³Note that differences in the number of competitors of markets do not mechanically drive the likelihood of being the cycle initiator. Loyalty/non-loyalty (Big brand/no big brand) stations on average have 3.11/3.44 (3.32/3.08) competitors.

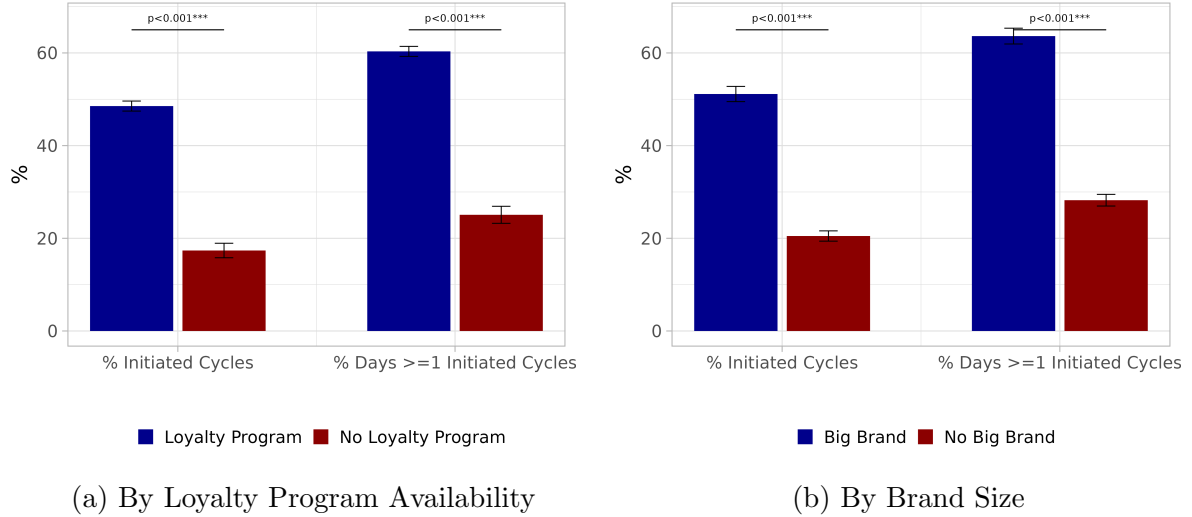


Figure 5: Likelihood of Initiating Local Market Cycle

Note: This figure shows the share of price cycles that were initiated by a given firm, and the share of days in which a given firm initiated at least one cycle. In panel (a), we show a breakdown by loyalty program availability, and in panel (b) a breakdown by brand size. Only non-monopolists included. Standard errors clustered at the municipality level and 95% confidence bands reported.

the predictions of earlier theories, there are systematic patterns regarding the identity of stations that re-initiate cycles.

As an additional investigation into station-level differences in the propensity to re-initiate cycles, we quantify the time difference between price increases at loyalty and non-loyalty stations, as well as between big-brand and non-big-brand stations. We do this by regressing

$$Time_{ict} = \alpha_c + \beta X_i + \epsilon_{ict} \quad (5)$$

where c is the index of the number of price cycles within a day and α_c is a cycle-number fixed effect. $Time_{ict}$ is the time of the cycle start of the c -th cycle of station i on date t . X_i gives station loyalty and brand status. Standard errors are clustered at the municipality level. By taking into account cycle fixed effects, we only exploit variation in the timing of the cycle.

We find that stations with a loyalty program on average increase prices by 18.7 minutes (SE = 1.09, $p < 0.001$, clustered at municipality level) earlier than their counterparts. Big-brand stations increase prices 13.8 minutes (SE = 1.77, $p < 0.001$, clustered at municipality level) earlier than their counterparts.

Our finding is in line with previous observations in the literature that large brands

typically act as price leaders and initiate cycles (e.g., Eckert, 2003, Kahl and Wein, 2025, Lemus and Luco, 2021, Lewis, 2012, Noel, 2007b, Siekmann, 2017). Taken together, the following result supports part (ii) of Prediction 2:

Result 2. (ii) *Firms with a larger captive consumer base (as proxied by loyalty programs and brand affiliation) are significantly more likely to lead the price cycles.*

Finally, we turn to pass-through, as dealt with in Prediction 3. Part (i) predicts that the pass-through of marginal cost changes to the lower bound of the price cycle is less than 100%. To test this, we run a regression of station-level daily minimum prices on input costs. Pooling all stations, we find a pass-through rate of 92.2%, with a 95% confidence interval ranging from 90.4% to 94.0%. Note that also Montag et al. (2023) and Dimitrakopoulou et al. (2024) found pass-through rates below 100% (specifically, around 80%), albeit for a VAT change instead of pass-through of marginal costs. Their findings were established in Germany and Greece.

We therefore document the following result, supporting part (i) of Prediction 3:

Result 3. (i) *The pass-through of marginal costs to the lower bound of the price cycle is significantly less than 100%.*

Part (ii) of Prediction 3 concerns heterogeneity of pass-through rates to the lower bound of the price cycle that varies with the size of the captive consumer base. To capture this aspect we regress prices on marginal costs with an interaction term of a loyalty program indicator, and separately with a big brand dummy. There are pronounced and statistically significant differences between the groups with and without loyalty programs (with pass-through rates of 91.7% vs 95.8%, respectively), and similarly between brand size (91.0% vs 94.7%).⁴ In line with our interpretation that stations with loyalty program, and those which are affiliated with a large brand, have a higher captive consumer base, this leads to the following finding, supporting part (ii) of Prediction 3:

Result 3. (ii) *Firms with a higher captive consumer base have a significantly lower pass-through rate to the lower bound of the price cycle.*

⁴A graphical depiction of these regressions is in Figure A.3 in the Online Appendix.

4 Discussion

In our model, firms are assumed to be myopic (they each have a discount factor equal to zero). Theories involving tacit collusion and focal points typically require sufficiently patient firms (δ close to 1). In these models, firms have a short-run incentive to deviate, and the threat of costly punishment deters them from deviating in case they are sufficiently patient. In principle, also in our framework such a form of tacit collusion at monopoly prices, or partial collusion below monopoly prices, could arise if *all firms* are sufficiently patient. In that case, a folk-theorem type of argument implies that many equilibria are possible. Notably, our equilibrium still exists in these situations.

Price cycles are frequently viewed with suspicion and linked to concern of anti-competitive conduct, see, e.g., Byrne and De Roos (2019). In our model, some stations' prices are below monopoly levels all the time, and all stations' prices above marginal costs all the time. Nevertheless, relative to an outcome involving tacit collusion, price levels are certainly lower in our cycling equilibrium.

Maskin and Tirole (1988) show the possible existence of Edgeworth cycles in Markov-perfect equilibria when firms are sufficiently patient. If these equilibria exist, they typically co-exist with several other equilibria, which makes it difficult to obtain predictions and comparative statics. Equilibria with cycles typically involve mixing at the bottom of the cycle, which implies that we should expect that firms stay at the bottom of the cycle for an extended time period. Moreover, the identity of the firm relenting first should be random. Both contrast with empirical reality, where we typically observe that firms with common characteristics initiate the cycle, and that the time spent at the bottom of the cycle is very short. Additionally, the framework of Maskin and Tirole is directly applicable to two symmetric firms only. In contrast, our framework has very clear empirical predictions regarding the firm expected to initiate the cycle. Moreover, we allow differentiation between arbitrarily many firms both in costs and in their popularity among consumers.

Taken together, these theories are at odds with Result 1 (ii), Result 1 (iii) and Result 3 (ii), and cannot even speak to Result 2 and Result 3 (i), whereas our theory is consistent

will all of these results.

Byrne and De Roos (2019) point out that dominant firms use price leadership as a means of establishing a focal point, suggesting potentially collusive motives. While their finding that dominant firms act as price leaders aligns with our Result 2 (ii), our interpretation differs fundamentally. In our framework, firms with larger captive consumer bases also lead price increases (i.e., relent first), but this behavior arises from short-term profit maximization rather than dynamic coordination. Moreover, our model allows for additional comparative statics and firm-level pass-through analysis, which are beyond the scope of Byrne and De Roos (2019).

5 Conclusion

This paper complements theoretical and empirical research on the determinants of price cycles and is novel in providing an understanding of how consumer search affects price cycles. We provide a simple yet powerful framework with which we are able to shed more light on price cycling behavior observed in the German retail gasoline market. Our model shows that cycles need not be driven by collusive behavior. By modeling firms as myopic oligopolists operating in an alternating-moves framework, we demonstrate how undercutting and relenting behaviors naturally generate recurring price cycles. Our model yields sharp predictions regarding price patterns, comparative statics, and pass-through.

We apply our predictions to the German retail gasoline market and thereby gain new insights on pricing that have been generated by our model. In particular, price cycles are not initiated at random, but are more likely to be initiated by firms with larger captive consumer bases. Price spells are of similar length across the cycle, but shorter when input costs are high. Additionally, we find incomplete pass-through of input costs at the cycles' bottom, particularly among firms with more captive consumers. These patterns are difficult to reconcile with existing theories based on mixed-strategy equilibria or tacit collusion, which typically predict full pass-through, extended durations at the cycle bottom, and lack clear comparative statics.

While our analysis is not designed to fully capture the inner workings of every gasoline

station in Germany, it offers valuable insights into several key dimensions of their operations. Future research could build on our framework by incorporating factors such as algorithmic pricing, firm heterogeneity, and regulatory interventions. Investigating how cycles evolve in the presence of pricing algorithms or strategic learning could yield insights into the persistence and variation of these cycles across different markets.

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