Pricing strategy heterogeneity in retail gasoline markets*

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Abstract. Retail gasoline markets feature high cross-sectional price dispersion and asymmetric cycles in price dynamics, two puzzling phenomena that have gone unrelated largely because the literature defines price cycles at the market level. The aim of this paper is to identify different pricing strategies—indicated by cycling behavior—at the gas station level, measure their consequences for price-level variability, and explore their determinants. We use daily, station-level gas prices in the U.S., and propose a new cycling indicator that overcomes issues with the existing one. Our results uncover a high degree of heterogeneity in pricing strategies within retail gasoline markets, even among gas stations in close proximity, and regardless of the brand. We exploit this intra-market variation in cycling behavior as an identification strategy, before unavailable, for the estimation of a cycle-induced price gap of -3.43 cents, which makes the pricing strategy one of the most significant determinants of price dispersion. With respect to the reasons that motivate cycling behavior, we rule out conventional forms of collusion and show that some testable predictions of the theory of Edgeworth cycles do not hold. We contribute to the explanation of cycling heterogeneity by showing that a station's choice of a pricing strategy is related to the type of consumer targeted: non-cycling stations aim to attract inelastic consumers, while cycling stations target price-sensitive, search-intensive consumers.

Keywords: retail gasoline markets; firm strategy; collusion; Edgeworth cycles; price dispersion.

JEL classifications: D22, L20, L71, Q35, R32.

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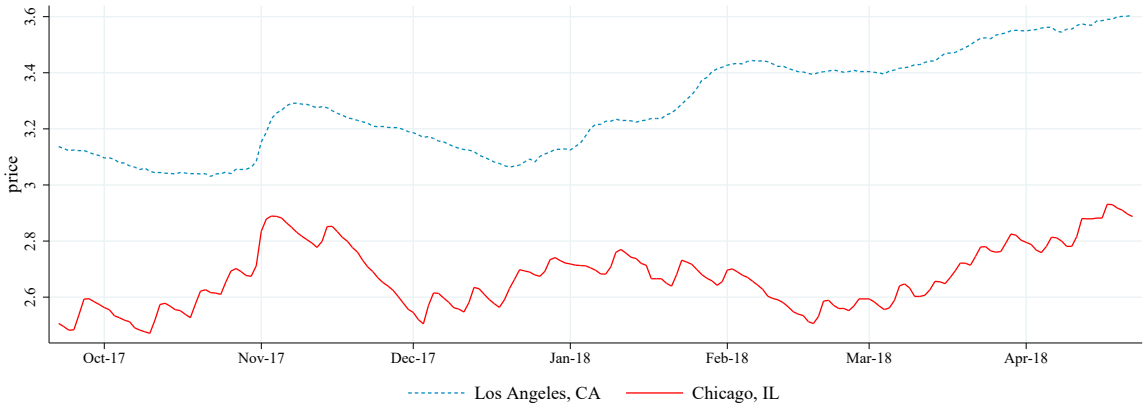
1 Introduction

The varying price of retail gasoline is in the psyche of American consumers. U.S. households spend a non-negligible share of their incomes in gasoline and their demand for it is very inelastic (Brons et al., 2008). Consumers are also exposed to gas prices regardless of their purchases because gas stations post their prices publicly for everyone to see, including the competition. One salient, well-documented feature of retail gasoline markets is the high degree of cross-sectional price dispersion: a price spotted for a gas station can differ sharply from another found just down the block (see, e.g., Figure 8b). This affects market efficiency and impacts welfare, as consumers have to allocate more resources to price-search activities. Studies that have attempted to identify the sources of price differentials across stations have focused on variables such as market structure, firm characteristics, gasoline brand, geographic differentiation, and market concentration (see, e.g., Eckert and West (2004) and Hosken et al. (2008)). But much of this intra-market variation in prices has gone unexplained even after controlling for all these determinants. In this paper, we show that gas station heterogeneity in pricing strategies accounts for a significant part of the price dispersion observed in retail gasoline markets.

The goal of this paper is to identify the existence of different pricing strategies across firms within retail gasoline markets, measure its consequences for price-level variability, and provide insights into the reasons behind the pricing strategy choices of gas stations. In order to detect types of strategies we inspect the price dynamic patterns they produce. We distinguish between two different patterns, according to the presence or absence of asymmetric price cycles. These type of cycles, where rapid price spikes are followed by slow reductions (see, e.g., Figure 1), have only been documented at the market level (Eckert, 2002; Noel, 2007a; Lewis, 2009); there is no empirical evidence of firm heterogeneity—or lack thereof—in cycling behavior. In this paper, we identify cycling and non-cycling pricing strategies at the station level. We establish that both strategies coexist within markets, even for stations in close proximity and regardless of brand or other station and location characteristics. This heterogeneity seems to be explained by consumers sorting through gas stations that target different price sensitivities, and results in a significant price gap between cyclers and non-cyclers.

We use a rich data set of daily, station level gas prices in the continental U.S. obtained from GasBuddy.com, a website that provides consumer-reported information on gas prices. In order to recognize the presence of cycles, we construct an indicator that exploits a definitional implication of the asymmetry by comparing the steepness of

Figure 1. Retail gasoline price dynamics: markets with and without asymmetric cycles.



increasing and decreasing cycle phases. The resulting classification of dynamic price schedules is robust to several data situations often faced when studying retail gasoline markets, including the presence of price trends and short sample periods. This new cycling indicator is a methodological contribution that improves on the standard measure used in the literature, the median change in price, that is based on the assumption that cycle asymmetry generates more periods with price decreases than periods with increases. The median price change indicator cannot identify cycles at the station level due to the large number of days were individual stations do not change their prices. Furthermore, the implication of the asymmetry it relies on may not hold if the decreasing stage of the cycles is under or overrepresented (e.g., under the data circumstances mentioned above), in which case it leads to misclassifications. Our new cycling indicator overcomes these drawbacks.

With our new cycling indicator, we classify the gas stations in our sample according to their cycling or non-cycling strategies. Our results indicate that, even though cycling stations are highly concentrated in the Midwest, several locations that have been viewed as non-cycling based on aggregate market price dynamics actually have remarkable concentrations of cyclers as well, most notably in Florida, Georgia, and Texas. This challenges the presumption in the literature that market-level cycles in the U.S. are a Midwestern phenomenon (Lewis, 2009; Doyle et al., 2010; Zimmerman et al., 2013). More generally, although most firms in cycling markets are cyclers and vice versa, both price strategies are to be found in any type of market, sometimes coexisting yards away from each other. The station-level heterogeneity in cycling behavior that we find contributes to the explanation of intra-market price variability: controlling for the variables normally associated to price levels in the literature, cycling gas stations charge 3.43 cents less than non-cycling ones. Therefore, the pricing strategy arises as

a newly-found significant determinant of cross-sectional price dispersion.

To assess the reasons behind these cycles and the variability in cycling behavior, we first revisit the validity of existing explanations of asymmetric cycles in retail gasoline markets. The overwhelming majority of previous studies align with the theory of Edgeworth cycles (Maskin and Tirole, 1988). This is one of the equilibria of the authors' duopoly model; it consists of a price war, in which firms undercut each other until they reach marginal cost, followed by a relenting phase with firms randomizing over whether or not to restore price and initiate a new cycle. It has been claimed that the theory does not offer testable predictions other than the asymmetric price cycle pattern. However, the random strategies played in the attrition war phase imply that it should not be possible to predict when firms leave the trough of the cycle. We establish that the probability of a cycling station to be at the last day of its cycle trough is highly concentrated on certain days of the week, undermining the ability of the standard Edgeworth cycle model to explain the asymmetric price cycles in retail gasoline markets. An alternative explanation of these cycles suggested by a new strand of literature is that they are the result of collusive behavior, based on the degree of coordination at the restoring stage (Byrne and de Ross, forthcoming; Foros and Steen, 2013). An observable consequence of any conventional form of collusion would be an increase in price level, but a convincing identification of the effect of cycles on prices has eluded the literature due to the presence of observable and unobservable confounders that cannot be controlled for when the cycles are defined at the market level. In this paper, we exploit station-level variability in cycling behavior as an identification strategy to estimate the cycle-induced price gap controlling for market-level confounders. We find that cycling stations charge on average lower prices, which provides evidence against conventional collusion hypotheses.

An explanation of cycling-behavior heterogeneity consistent with our data is a setting where gas stations choose a pricing strategy depending on the type of consumers they intend to target. Cycling stations aim to draw the attention of search-intensive consumers with frequent and sizable price changes. By concentrating lower prices on a few forecastable days, they attract price-sensitive consumers more willing to restrict their purchases to certain days of the week. In contrast, non-cycling stations divide up the pricing space in a different way. They use loyalty cards and cash discounts to target consumers that are willing to incur the hassles of carrying station cards or cash, and charge much higher prices to those that are not. Because of their low propensity to search, these consumers will also be attracted to non-cycling stations' fewer and milder changes in prices. We provide evidence of consumers sorting themselves through gas

stations according to the price schedule they offer by constructing a proxy for the frequency of price reporting, directly related to the level of search activity. Our results indicate that consumer search is indeed higher at cycling gas stations.

The rest of the paper is organized as follows. Section 2 reviews the related literature on retail gasoline markets, emphasizing our paper's contributions. Section 3 describes the database used in this study. Section 4 introduces the cycling indicator we construct to classify stations' strategies, describes its properties, and compares it to existing indicators. Section 5 provides an overview of the degree and nature of the station-level cycling heterogeneity found within U.S. markets. In Section 6 we reassess the validity of the reasons behind cycle asymmetry that have been suggested by the literature and offer an explanation of strategy heterogeneity consistent with our results. Section 7 concludes with a discussion of the contributions of this paper, its limitations, and implications for public policy and future work.

2 Related literature

Our paper relates to previous research on gasoline retailing that focuses on cross-sectional price dispersion and asymmetric retail price cycles, two well studied but previously unlinked topics in the literature.[1] Empirical work analyzing the determinants of station price levels has mainly considered the effect of location characteristics (e.g., station density), brand or contractual form, and station characteristics. The findings on location concentration have been mixed: while several studies report a negative relationship between price and station density (see, e.g., Barron et al. (2004) and Eckert and West (2004) for markets in the U. S. and Canada, respectively), others find no effect (e.g., Hosken et al. (2008) in Washington D.C.). Station amenities or physical characteristics (such as the availability of car wash or service station) have been found to have little effect (Eckert and West, 2004; Hosken et al., 2008). It has also been shown that station level prices are significantly affected by brand and vertical structure (Hosken et al., 2008). There is no previous work incorporating the role of different pricing strategies in station-level price variability, which is the contribution of this paper to the retail gasoline price dispersion literature.

Asymmetric price cycles in gasoline retailing were first documented by Allvine and Patterson (1974) in some southern and western U.S. cities. Castanias and Johnson (1993)

[1] See Eckert (2013) and Noel (2016) for extensive surveys of the literature on retail gasoline markets.

were the first to notice the resemblance between these cycles and an 'Edgeworth cycle' dynamic pricing equilibrium. Edgeworth cycles were proposed by Edgeworth (1925) and later formalized by Maskin and Tirole (1988) as one of the possible Markov perfect equilibria of their alternating price-setting duopoly model. In this Edgeworth cycle equilibrium, firms engage in a price war undercutting each other until the competitive price is reached; a relenting phase then starts where firms randomize between setting marginal cost and restoring price—in which case the other firm follows—to start a new cycle. Figure 2 displays the market-level price dynamics that are generated in this equilibrium; the similarity with the sawtooth-like patterns observed in retail gasoline markets is evident. As a consequence, Edgeworth cycles have been the theoretical foundation of the overwhelming majority of empirical work that arose since the early 2000 on asymmetric price cycles in gasoline retailing dynamics.[2]

Figure 2. Maskin and Tirole (1988)'s Edgeworth cycles.

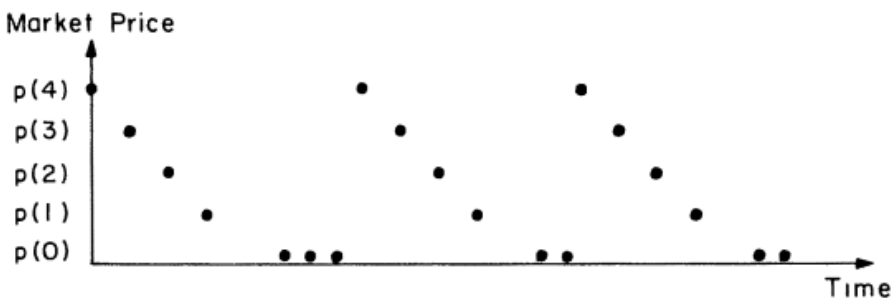


FIGURE 1.—Edgeworth cycles.

Source: Maskin and Tirole (1988).

The main contribution of this literature has been to establish the existence of asymmetric cycles, independent of changes in costs, in retail gas prices.[3] They have now been documented in most large and many medium-sized cities in Canada (Eckert, 2002; Noel, 2007b; Atkinson, 2009) and Australia (Wang, 2009) since the 1980s, and in some European cities (Foros and Steen, 2013; Siekmann, 2017). In the United States, the consensus is that these cycles reappeared in the 2000s only in several Midwest markets (Lewis, 2009; Doyle et al., 2010; Zimmerman et al., 2013). They have been shown to be

[2]A few articles suggest extensions of the model to generate more testable predictions. Eckert (2003) introduce firms of different sizes; Noel (2008) introduces different types of asymmetric equilibria (cost shocks, product differentiation, capacity constraints) and adds a third firm.

[3]Some papers relate this phenomenon with that of 'rockets-and-feathers', where retail gasoline prices adjust faster to cost increases than they do to cost decreases. Eckert (2002) shows that the speed of upstream prices passthrough depends upon the current position on the Edgeworth cycle. Noel (2009) decomposes the asymmetry into a component explained by price response asymmetry and a 'pure' Edgeworth cycle asymmetry. Lewis and Noel (2011) show that passthrough is faster in cycling than in non-cycling cities.

more likely to emerge in markets with low (Eckert, 2003; Noel, 2007a) or intermediate (Doyle et al., 2010) levels of concentration, as well as those with a large number of certain type of small retailers (Noel, 2007a; Doyle et al., 2010). Noel (2007a) shows how the length (found to be either monthly, weekly (Lewis and Noel, 2011; Foros and Steen, 2013), or sometimes daily (Noel, 2007b)) and amplitude of the cycles are affected by market characteristics.

The main contributions of our paper are in the topics within this literature related to individual station behavior, the effect of cycles on price levels, and the alternative explanation of these cycles as the result of collusive behavior. Previous work using station-level data focused on the analysis of price leadership and coordination (Noel, 2007b; Atkinson, 2009; Lewis, 2012), but there is no empirical evidence on the existence of cycling and non-cycling station-level behavior. The only paper that refers to asymmetric cycles as a station level decision is Doyle et al. (2010), but they use market-level data and several predictions of their model—which is an adaptation of Edgeworth cycles—are inconsistent with our findings, as we will explain later.

Attempts to find an association between asymmetric cycles and price levels have been mostly limited to cross-section comparisons between markets with and without cycles (Noel, 2002; Doyle et al., 2010), although these papers warn against causal interpretations. Zimmerman et al. (2013) propose a difference-in-differences approach using the start of the Midwest cycles in 2000; the decreasing price associated with the cycles, however, may be biased by confounding changes in market structure of those cities (e.g., the expansion of some large independent chains). Noel (2015) exploits the variability generated by a fire in a Canadian refinery that arguably made asymmetric cycles in some markets halt, which led to increased prices; the external validity issues associated with this natural experiment exercise indicates that this result needs to be interpreted cautiously. A valid identification strategy for the estimation of the effect of cycles on price levels would also be helpful to shed light on the claim that these asymmetric cycles are collusive in nature. Byrne and de Ross (forthcoming) and Foros and Steen (2013) argue that the level of coordination in the synchronization of price restorations is an indication of anti-competitive behavior in Perth (Australia) and Norway, respectively.[4] However, there is no evidence linking cycles to the expected result of any traditional form of collusion on the price level, nor is there a valid and general strategy available to identify it.

[4]Both markets posses institutional features that may make the cycles in this cities different in nature than those in North America, a price transparency program in Perth and recommended prices in Norway.

In summary, our paper primarily contributes to the literature with the identification of asymmetric cycles at the station level. The intra-market variability found in cycling behavior, in turn, provides the literature with a new identification strategy for the cycle-induced price gap, which helps disentangle various collusion hypotheses. Additionally, it contributes to the discussion of what explains cross-sectional price-level variability in retail gasoline markets, by uncovering a novel determinant—station's cycling strategies.

3 Data

We use a novel database of daily regular gasoline prices at the station level in the continental United States. We gathered these data from GasBuddy.com, a website that provides information on gas prices reported by consumers through a smartphone app. Consumers use this app to check prices at stations nearby and find good deals, but they also have cash incentives to report or update prices as they spot them. The use of this type of consumer-reported data is not new in the academic research on retail gas prices,[5] although most previous work analyzes Canadian markets.

We retrieved these data every day at 10:00 pm during the 7-month period between September 22, 2017 and April 22, 2018. For each day and gas station in our sample we observe the latest price reported, how long ago it was reported (we keep only prices reported in the last 24 hours), station location, station brand, and other station features (convenience store, cash discounts, etc.). See Hurtado (2018) for an extensive explanation of the database.

In our analysis, we work with gas stations that have prices reported for at least 100 (out of 213) days, to ensure that we correctly capture the patterns in their price dynamics. We further limit our sample to cities with a representative amount (at least 70%) of stations with more than 100 reports[6] in order to be able to accurately characterize competition at the market level. Our final database consists of 10,134,059 observations, from 58,618 gas stations in 313 metropolitan statistical areas (MSA).

[5]See Atkinson (2008) for a description of the advantages and potential issues.

[6]This last restriction only reduces our sample size to be 80% of all stations with more than 100 observations.

4 A new cycling indicator

The first step in our analysis is to classify gas stations according to their price strategy. We do so by inspecting the firm-level price dynamics that these strategies produce; in particular, we determine whether or not a station engages in asymmetric cycles. Figure 3 displays representative examples of the different types of price dynamics at the station level. To tell them apart in our data, we need a measure able to identify the presence of the distinctive sawtooth-like pattern in Figure 3b. In this section, we develop such an indicator, discuss its properties and robustness, and compare it with measures used in previous work.

Figure 3. Station-level price dynamics for two selected gas stations in Chicago, IL.

(a) Non-cycling gas station.

(b) Cycling gas station.

We propose a cycling indicator that exploits a definitional implication of the cycle asymmetry. In the presence of asymmetric price cycles, sharp price jumps are followed by gradual decreases. As a consequence, the rate at which prices go up is faster than the

rate at which they go down. We construct a measure of that discrepancy, the Cycling Ratio, defined as the average change in increasing stages divided by (the absolute value of) the average change in decreasing stages:

$$\text{Cycling Ratio}_s = \frac{\overline{|\Delta_+ p^s|}}{\overline{|\Delta_- p^s|}} = \frac{\dfrac{\Sigma_{t=1}^T |\Delta_t p^s| \times 1(t \in \tau_+^s)}{\Sigma_{t=1}^T 1(t \in \tau_+^s)}}{\dfrac{\Sigma_{t=1}^T |\Delta_t p^s| \times 1(t \in \tau_-^s)}{\Sigma_{t=1}^T 1(t \in \tau_-^s)}} \tag{1}$$

where $\Delta_t p^s = p_t^s - p_{t-1}^s$, τ_+ is the subset of dates in the sample at which station s experienced an increasing-price stage, and τ_- is the subset of dates at which the station experienced a decreasing-price stage.[7]

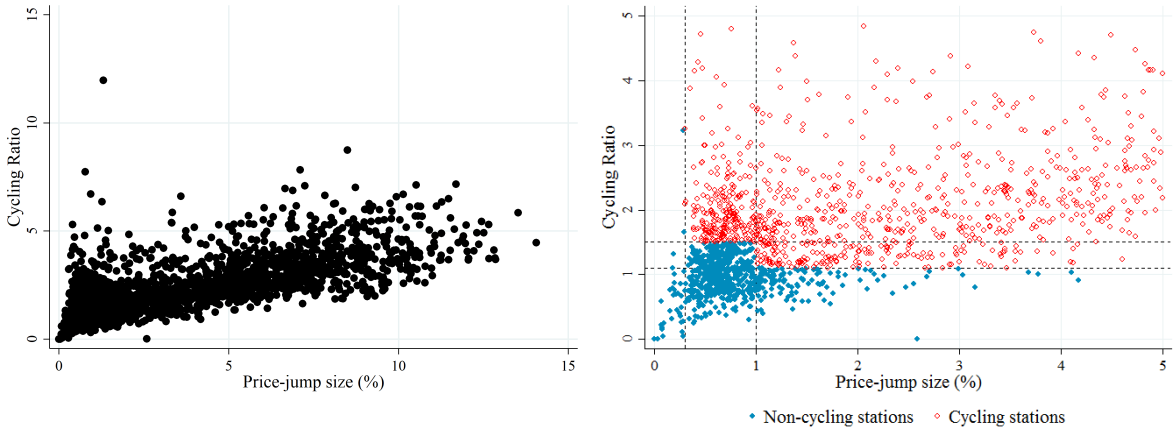
A Cycling Ratio sufficiently larger than one indicates that prices go up significantly faster than they go down, suggesting the presence of cycling behavior. In order to minimize the use of an arbitrary threshold above which a gas station should be considered a cycler, we augment this measure by combining it with another regularity of asymmetric cycle patterns: the presence of sizable price jumps. Figure 4a illustrates the strong positive correlation between cycle asymmetry, as measured by the Cycling Ratio, and the size of the price increases, which we measure with the average percent price increase. We classify most gas stations with a Cycling Ratio of 1.5 or higher as cyclers: for these, the price increases were on average more than 50% faster than the decreases. For Cycling Ratios higher than 1.1 but lower than 1.5, we demand more evidence of cycle asymmetry by requiring an average price jump of at least 1% for the gas station to be classified as cycler.[8] A graphical depiction of the definition of our cycling indicator is provided in Figure 4b; the indicator takes on a value of one for gas stations classified as cyclers according to the previous description, and is zero otherwise. A more conservative approach is to only consider cyclers those that have a Cycling Ratio greater than 1.5 and non-cyclers those with a Cycling Ratio lesser or equal to 1 and percent price jump below 1%, discarding the rest (Figure A.2). The Appendix contains robustness analyses were the results of this paper are estimated using this restricted sample. In general, the patterns found with this more stringent classification are even more pronounced than those in our main analysis.

The Cycling Ratio constructed to measure cycle asymmetry is robust to the different realities usually found when analyzing gasoline price data. To illustrate, Figure 5

[7]See Figure A.1 for clarification of τ_+ and τ_- in the examples of Figure 3.

[8]We require a price jump of at least 0.3% for Cycling Ratios 1.5 or higher, mostly to correct for measurement error.

Figure 4. A new cycling indicator: Cycling Ratio and average percent price increase.



(a) Cycling Ratio and average price jump.

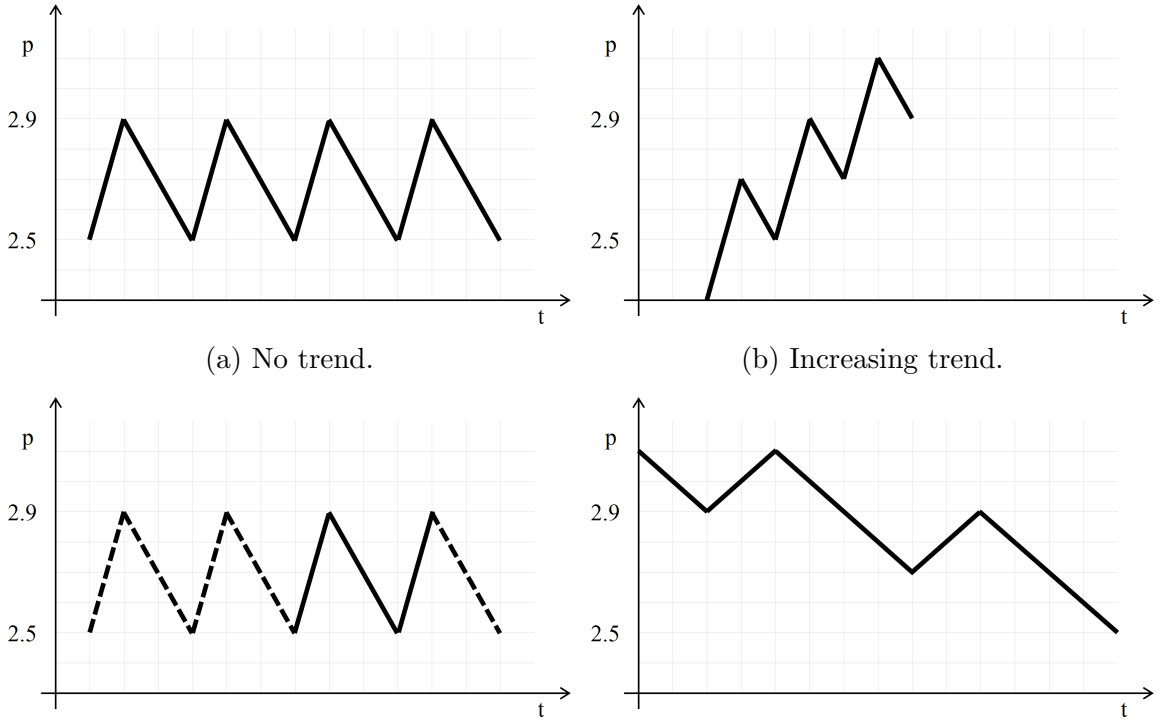
(b) Cycling indicator definition.

Note. A point in these panels represent a gas station according to its combination of Cycling Ratio and average percent increase in price (price jump). For the purposes of illustration, only gas stations in Chicago are displayed.

displays some simplified examples used to evaluate the accuracy of the Cycling Ratio in the presence of price trends and short data periods. The price dynamics in Figures 5a, 5b, and 5c come from the same asymmetric cycling data process, but represent different contexts of analysis: upward trends in Figure 5b and short-period data availability in Figure 5c. Regardless of those differences, however, the average (i.e., per period) price increase is always \$0.4 and the average price decrease is always -\$0.2, resulting in a Cycling Ratio of 2 that reflects the asymmetry of these cycles. In Figure 5d a non-cycling dynamic pattern is shown, with average price increases of \$0.1 and average price decreases of -\$0.1 for a Cycling Ratio of 1. The presence of a downward trend in Figure 5d did not prevent the Cycling Ratio from correctly identifying the absence of asymmetric cycles.

To conclude this section, we compare the performance of our new cycling indicator with the standard indicator used in the literature, the median change in price. Lewis (2009) used for the first time the median daily change in a city average price as a proxy for the extent of asymmetric price cycles. The measure reflects the following rationale: with cycle asymmetry, there would be more periods when the price decreases than periods when it increases, and then the median first difference of the price would be negative. This indicator has been extensively used in the literature ever since to identify cycling cities (Lewis, 2009; Doyle et al., 2010; Lewis, 2012; Zimmerman et al., 2013). The cutoff threshold below which a market is categorized as cycler varies across studies; Doyle et al. (2010) applies a cutoff of -0.5 cents, that was later adopted by Zimmerman et al. (2013) as well. Whereas the median change in price was used to classify cycling and non-cycling cities before, in this study we intend to classify patterns of the price

Figure 5. Indicators' performance in the presence of price trends or short data span.



(a) No trend. (b) Increasing trend.

(c) Short data span. (d) Decreasing trend.

Note. The Cycling Ratio is robust to the presence of price trends and short data periods: it equals 2 for panels (a), (b), and (c) regardless of those circumstances because the patterns come from the same asymmetric-cycling data process. If the decreasing phase of the cycles is under of overrepresented, the median price change can falsely reject (panels (b) and (c)) or falsely confirm (panel (d)) the presence of asymmetric cycles.

dynamics of firms instead. Unlike market-level prices, which as an average of its stations will most certainly change daily, one feature of the price dynamics of individual gas stations is the large number of days when there are not changes in prices. As a result, the median price change has no power to identify cycling from non-cycling station-level strategies (for example, in Figure 3 both stations have a median price change of zero).

The inability of the median change in price to classify gas stations, however, is not its primary drawback: it may incur misclassifications at the market level under certain conditions. The implication of the cycle asymmetry that its accuracy relies on does not hold whenever the decreasing stages are under or overrepresented, which happens in practice under the circumstances of retail gasoline markets mentioned before. For instance, if prices trend upwards, the undercutting phases will be cut short, which generates a lower count of days with negative changes in price. In this case, the median price change will tend to misclassify cycling markets as non-cyclers (e.g., in the case of Figure 5b, the median price change is \$0.1). On the other hand, with downward trends, the decreasing stages will be artificially long, making the median price change prone to misclassify symmetric dynamic patterns as asymmetric cycles (in the example of Figure 5d, the median price change is -\$0.1). But even if the decreasing price stages reach down to the same, steady marginal cost every time, if the available data span a relatively short sample period undercutting stages might be underrepresented, leading to false rejection of cycling behavior (e.g., the median price change is \$0.1 for Figure 5c). Even though adjusting the cutoff threshold can sometimes mitigate this issues,[9] those changes would necessarily be arbitrary and would heavily depend on visual inspection.

The cycling indicator proposed in this paper is suited to identify cycling asymmetry in station-level price dynamics and overcomes the misclassification drawbacks of the median change in price. Because it leverages changes in steepness of the stages instead of their different duration, its accuracy does not depend on a constant marginal cost or a lengthy data set. The main use we make of our new cycling indicator in this paper is the classification of all the stations in our sample as cyclers or non-cyclers; however, the new indicator can be applied to price dynamics at the market level as well. In Table 1 we compare the split of the 313 cities in our data in cyclers and non-cyclers, according to both the new indicator and the median price change (using the -0.5 cent threshold). For most markets the indicators coincide; however, almost a quarter of the cities are non-cyclers according to the median change in price but cyclers according to the new indicator. This can be in part due to the cutoff used being too stringent, but, as we will explain in the next section, it is mostly due to the misclassification issues of

[9] Noel (2015) mentions the need to determine the cutoff considering the price trends.

the median price change that our new indicator improves upon.

Table 1. New vs Old indicator comparison at the market level.

	Old indicator		
New indicator	Non-cycler	Cycler	Total
Non-cycler	159	0	159
Cycler	73	81	154
Total	232	81	313

Note. The new indicator classifies cities according to their Cycling Ratio and percent price jump; the old indicator refers to the median price change, using -0.5 cents as cutoff.

5 Intra-market price strategy heterogeneity

Using the indicator described in Section 4, every gas station in our sample was classified according to its price strategy, concretely, based on whether it engages in asymmetric price cycle dynamics or not. In this section we present our findings on the heterogeneous cycling behavior found in retail gasoline markets, characterize this variability between and within cities, and explore its consequences for cross-sectional price dispersion.

5.1 Cycling heterogeneity: an overview

Every point in Figure 6 corresponds to a gas station in our data, and its color depends on the price strategy it was classified into.[10] Blue points represent non-cycling firms, whereas red and orange represent cycling stations. The distinction among cyclers accounts for differences in the degree of asymmetry or cycle intensity: orange is for cycling stations with a Cycling Ratio between 1 and 3, red for Cycling Ratios of 3 or higher (i.e., prices jump at least three times as fast as they go down). Figure 6 reveals two broad features of asymmetric price cycles in U.S. retail gasoline markets. First, even though cycling gas stations are highly concentrated in the Midwest, other metropolitan areas in the South and the West also have a high concentration of cyclers. Several previous studies have concluded that market-level cycles in the U.S. are a Midwestern phenomenon (Lewis, 2009; Doyle et al., 2010; Zimmerman et al., 2013); however Figure 6 shows a significant agglomeration of cycling firms in typically considered non-cycling areas, suggesting there might be asymmetric price cycles at the market level in these areas too. We test this by applying our cycling indicator to the average

[10]Figure A.3 provides a version of this map in grayscale.

price dynamics of every city in our sample (see Table 1), which confirmed the existence of asymmetric cycles in some non-Midwest markets in the states of Florida, Georgia, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Utah. In some of these cases, the median price change classifies them as cyclers as well; it might have been the case, then, that previous work did not find cycle asymmetry there because the cycles were indeed not present during the time period that their data spanned. In other cases, the median price change is not negative enough (considering the usual cutoffs) to detect price cycle asymmetry; this reinforces the advantages and the identification power of our new cycling indicator.

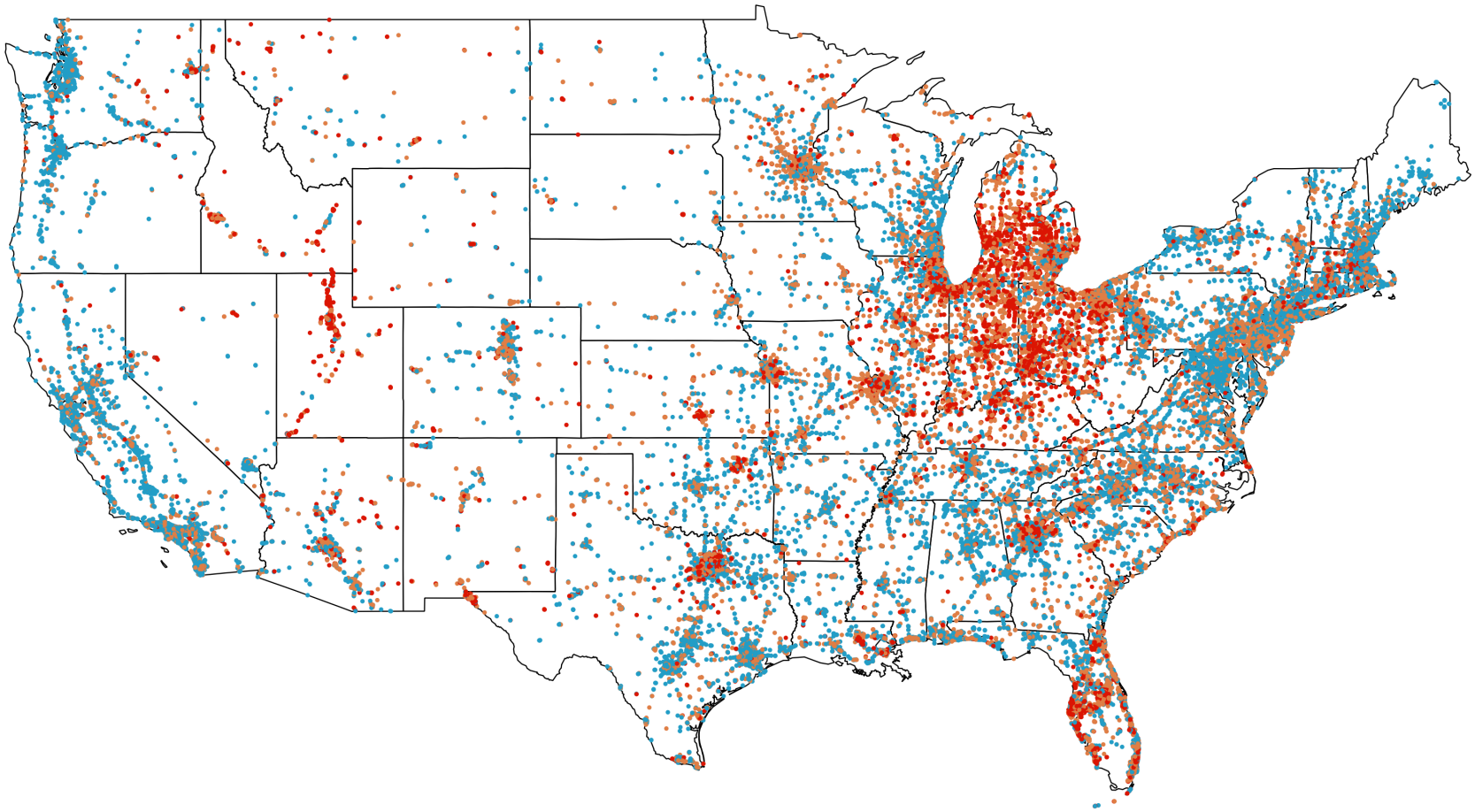
Figure 6 also highlights that, even though there is concentration of cyclers and non-cyclers in different markets, gas stations with both types of price strategy turn up to a greater or lesser extent all around the country. To better illustrate this result, Figure 7 shows a closer look at some selected markets. The cities of Chicago in Figure 7a and Dallas in Figure 7b are overall cycling markets, while both Boston in Figure 7c and Los Angeles in Figure 7d are non-cycling markets. Although most firms in cycling markets are cyclers and vice versa,[11] both price strategies are found in each type of market, sometimes coexisting yards away from each other (Figure 8a). Figure 9 depicts the average price dynamics of cycling and non-cycling stations separately for our two examples of cycling cities; clearly, the overall cycling nature of these markets is inherited from the dynamic patterns of their large proportion of cycling stations.

We also explore whether gas stations stick always to the same price strategy or instead change it over time. To do this, we constructed daily station-level indicators using price dynamics within a two-month rolling window.[12] As explained in Section 4, the robustness of our cycling indicator to short data periods allows us to perform this exercise accurately. Based on this daily indicator, we calculated the share of cycling and non-cycling stations in the U.S. for every day in our sample period, shown in Figure 10a. The fluctuation of this share reveals that firms in U.S. retail gasoline markets do switch pricing strategies over time; only 26% of the gas stations in our sample stick to either a cycling or non-cycling strategy during the whole period (Figure 10b). In that sense the full-sample cycling indicator we use throughout the paper summarizes the price strategy that each gas station most predominantly followed.

[11]The share of cycling stations does not seem to uniquely determine cycling at the market level. Preliminary results show that there is a non-linear relationship between the two, and it interacts with station-type concentration; for the cycling pattern to show up in average prices, cycling stations do not only need to be enough, but also effectively coordinate cycle peaks and troughs.

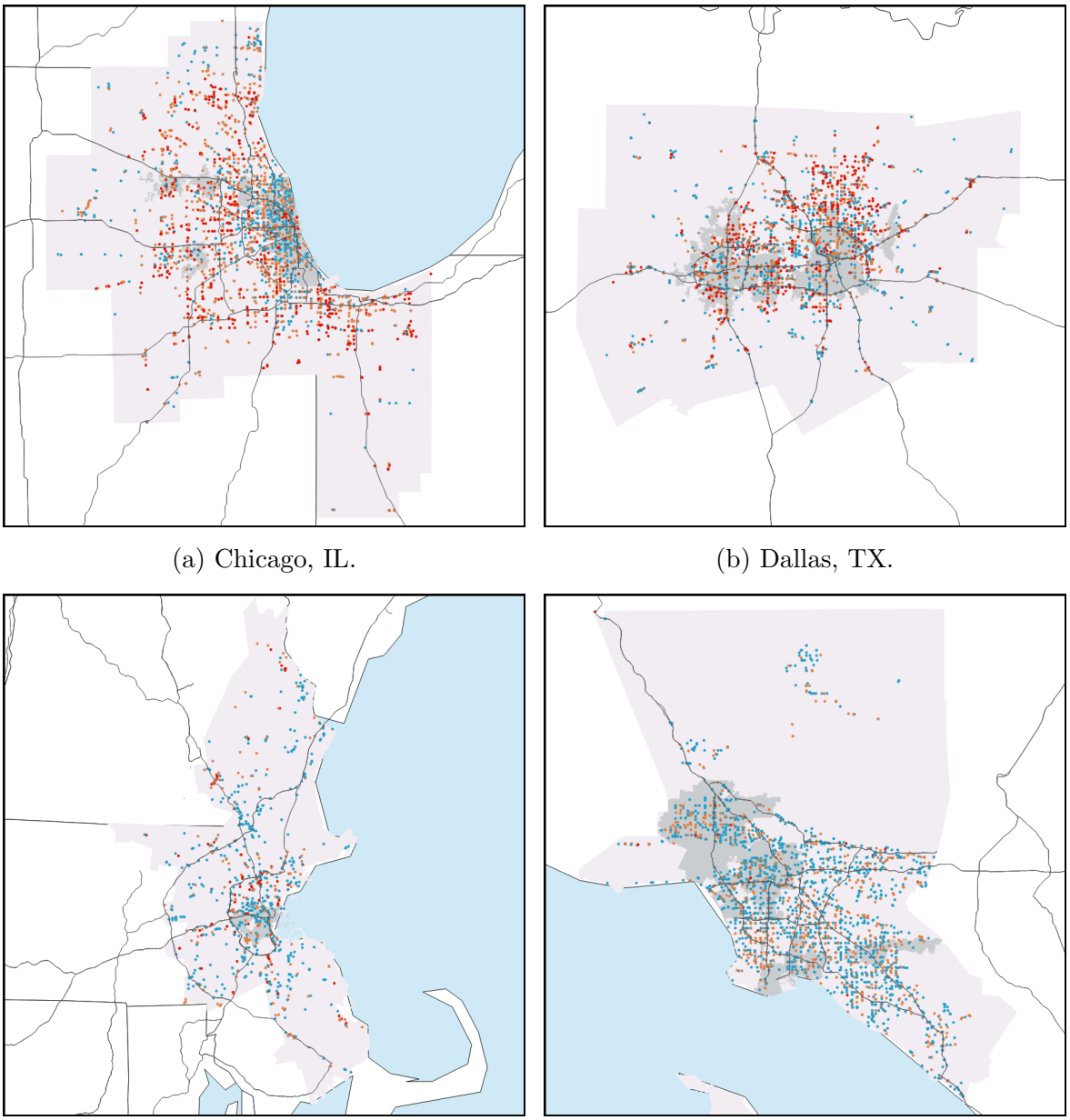
[12]We also tried an alternative window of 4 months with very similar results, see subsection 6.1.

Figure 6. Station cycling behavior heterogeneity in the U.S.



Note. Blue points represent non-cycling gas stations. Red and orange indicate different levels of cycling asymmetry.

Figure 7. Heterogeneous price strategies within markets.



(a) Chicago, IL.

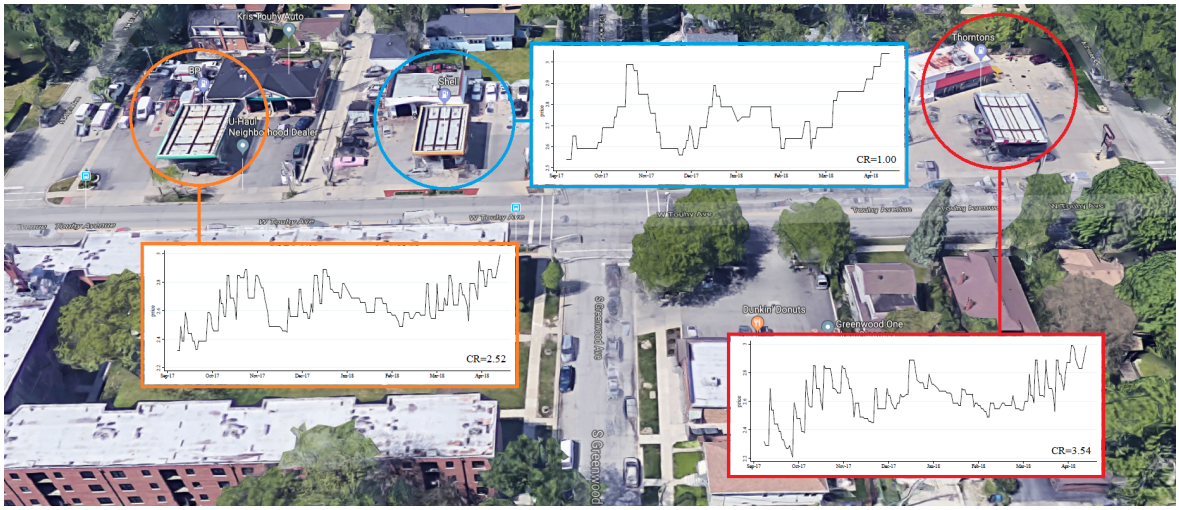
(b) Dallas, TX.

(c) Boston, MA.

(d) Los Angeles, CA.

Note. Blue points represent non-cycling gas stations. Red and orange indicate different levels of cycling asymmetry.

Figure 8. Close-by gas stations with different price strategies.

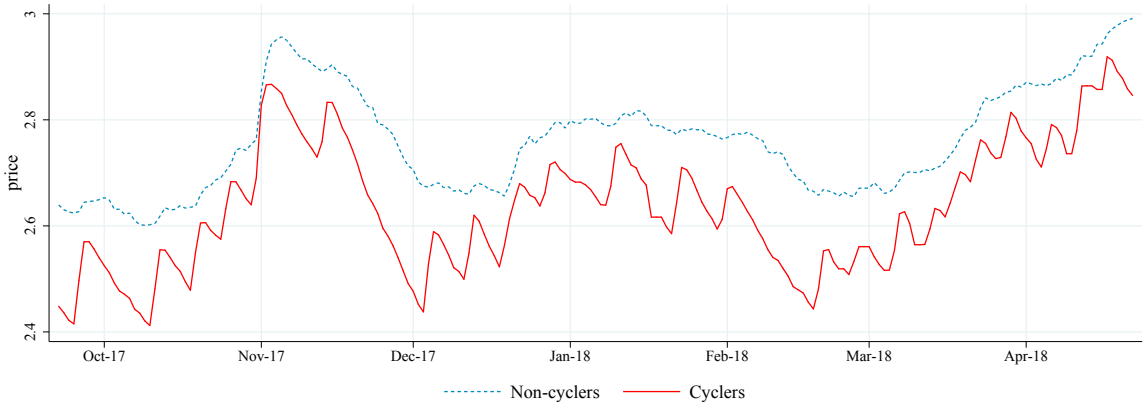


(a) Two cycling stations and one non-cycling station yards away in the Chicago area.

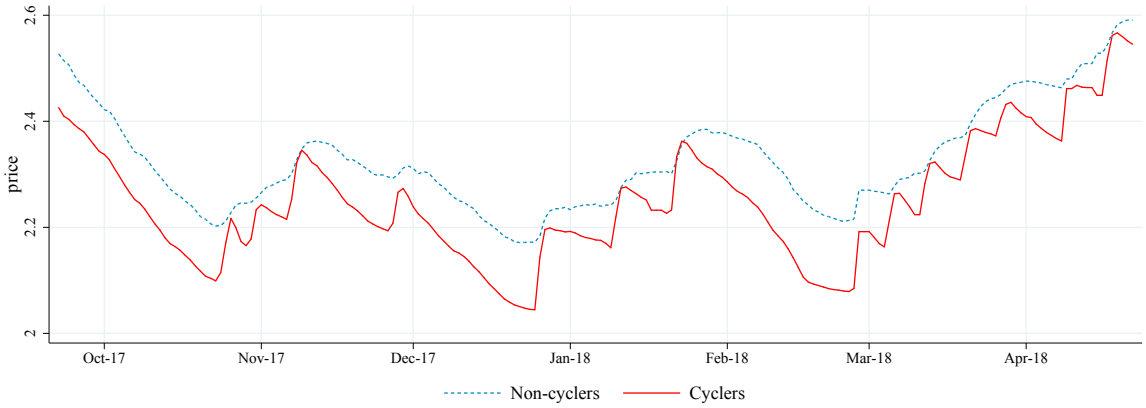
(b) Price differential between gas stations with different price strategies.

Note. Images were screenshotted from Google Maps and Street view (captured in November 2017). Panel (a) shows heterogeneous price dynamics types of three gas stations in Park Ridge IL, located yards away from each other. Panel (b) shows very different posted prices for two of these stations at the same time.

Figure 9. Price dynamics of cycling and non-cycling stations within markets.

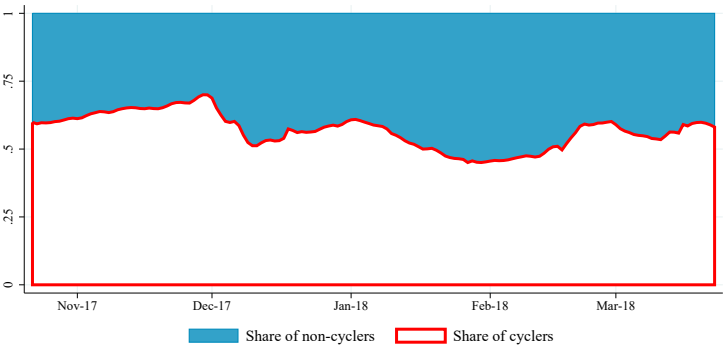


(a) Chicago, IL.



(b) Dallas, TX.

Figure 10. Varying pricing strategies.



(a) Share of cycling stations across time, U.S.

	# stations
Always no-cycler	4,988
Mostly no-cycler	24,918
Mostly cycler	22,906
Always cycler	11,990
Total	64,802

(b) Station strategy switching.

Note. For each gas station, cycling indicators were calculated at every day in the sample using a two-month window. Panel (a) shows the resulting share of cycling and non-cycling stations in the U.S. over time. Panel (b) breaks down the firms according to whether they changed strategies during the sample period or not.

5.2 What predicts cycling behavior?

In light of our findings in subsection 5.1, we explore which location characteristics and station features are associated with each type of pricing strategy (Table A.1 and Table A.3; the dependent variable is the cycling indicator). In Table A.1 the estimations include city-brand fixed effects, so the results aim to explain the variability in cycling behavior of same-brand stations within the same market. Non-cycling stations tend to be located in more densely populated areas. Furthermore, consistent with Doyle et al. (2010), we found a non-linear relationship with station density: cycling is more likely at intermediate levels of station concentration; it peaks at 6 or 7 gas stations in a 1-mile radius. However, once we control for the cycling behavior of neighbors, station density loses explanatory power, suggesting that Doyle et al. (2010)'s geographic differentiation vs. market power channel does not drive this result. A station's cycling indicator is strongly correlated with the cycling indicator of its closest neighbor—and with the average cycling behavior of neighboring stations in general—although that influence fades away the more isolated the station is. This result implies that gas stations following the same pricing strategy are on average expected to be found bunched together.

Table A.3 looks at the association between cycling and station brand size and features. Stations with convenience stores are more likely to be cyclers, regardless of their brand size. This result complements the empirical findings of Doyle et al. (2010), who find a positive relationship between cycling markets and the presence of convenience stores, but only those operated by independent gas stations. Some of our results, however, contrast with the predictions of Doyle et al. (2010)'s model. In particular we find that complementary goods other than convenience store, such as service station or restaurant, are negatively correlated with cycling. Also, both the smallest and the largest brands are less likely to cycle, therefore their brand loyalty channel to explain non-cycling strategies finds no support. However, we do find evidence for one of the predictions of Doyle et al. (2010)'s model: stations with a higher proportion of consumers with propensity to not switch gas stations are less likely to cycle. We mentioned how both channels explored in Doyle et al. (2010) to test that prediction, geographic differentiation and brand loyalty, do not hold in our results. The richness of our station-level data allows us to identify a better way in which that prediction can be tested. We find that big-brand gas stations offering discounts, either through loyalty cards or cash discounts, are much more likely to be non-cyclers. These are very relevant predictors of cycling behavior; we will return to these results in section Section 6.

5.3 Pricing strategy heterogeneity and price dispersion

As mentioned in Section 2, vast attention has been paid in the literature to cross-sectional price variation within markets. In examining the determinants of price levels or price dispersion, studies have considered several types of variables associated with these price differentials: location characteristics, station features, local concentration of stations, brand, etc. Researchers have not previously related price levels or price dispersion to asymmetric cycling in gasoline markets, because cycle asymmetry is a phenomenon so far only documented at the market level. In this paper, we introduce a new dimension of station heterogeneity within markets, the cycling vs. non-cycling pricing strategy, whose effect on price levels—compared to other determinants—we explore in this subsection.

Table 2 presents a simple analysis of the effect of previously-considered determinants and the pricing strategy on station-level prices. The results are fairly consistent with previous findings: stations charge higher prices in higher income neighborhoods and when located on a highway, and they charge lower prices overall the higher the station density. Prices are also related to the presence of certain station characteristics, after controlling for city-brand fixed effects. The effect of the pricing strategy is included through the indicator variable 'Cycler', that takes value one for stations engaging in asymmetric cycles and zero otherwise (column (2) uses our more stringent version of the cycling indicator defined in Section 4). We find that cycling stations charge prices 3.43 cents lower than non-cycling stations on average. The magnitude of this effect is considerably higher than almost every other determinant, whose coefficients rarely exceed one cent in absolute value. Interestingly, two of the station characteristics with reasonably large coefficients, loyalty card and cash discounts, are also negatively correlated with cycling behavior. Table 3 shows that gas stations that neither offer cash discounts nor loyalty cards are much less likely to be cyclers and, among them, the cycling price gap is significantly higher. This reflects that non-cyclers in this group charge price premiums both for the discount features and for the non-cycling strategy. When the restricted sample is used in column (2) of Table 2 the coefficient associated with cycling behavior is 80% larger, becoming by far the dominant explanatory factor for price levels. The interpretation of the cycling coefficient, as well as the issues needed to be tackled in order to identify it, will be discussed in detail in subsection 6.1. At this point, these results reveal that the difference in pricing strategies is a significant determinant of price variability within markets that has not been considered before.

Table 2. Contribution of cycling heterogeneity to cross-sectional price level variability.

	(1)	(2)
Pricing strategy		
Cycler	-3.429***	-6.157***
	(0.007)	(0.010)
Location characteristics		
Income (log)	0.206***	0.242***
	(0.010)	(0.011)
Population density	-0.022***	-0.011***
	(0.001)	(0.001)
On highway	0.184***	0.188***
	(0.010)	(0.012)
No. of neighboring stations	-0.241***	-0.151***
	(0.003)	(0.004)
No. of neighbors (sq)	0.008***	0.003***
	(0.000)	(0.000)
Station characteristics		
Offers loyalty discount	0.586***	0.375***
	(0.010)	(0.012)
Offers cash discount	3.535***	3.488***
	(0.011)	(0.014)
Has convenience store	-0.115***	-0.163***
	(0.010)	(0.012)
Has restaurant	0.341***	0.207***
	(0.010)	(0.011)
Has car wash	-0.304***	-0.312***
	(0.008)	(0.009)
Has service station	1.730***	1.726***
	(0.012)	(0.015)
Has truck stop	-0.587***	-0.547***
	(0.020)	(0.023)
R^2	0.9599	0.9620
Observations	10,113,008	7,184,024
Date-Zip FE	Yes	Yes
City-Brand FE	Yes	Yes
Sample	Full	Rest.

Note. Dependent variable: price of regular gasoline, in cents; the observation level is a station-day combination. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Cycling behavior, cycling price gap, and discounts.

	Loyalty card: No		Loyalty card: Yes	
	% cyclers	cycling-gap	% cyclers	cycling-gap
Cash discount: No	61%	-3.14	55%	-3.46
Cash discount: Yes	39%	-3.33	36%	-4.42

6 Explaining asymmetric price cycles

We have so far documented the existence of different pricing strategies among gas stations within cities in the U.S. retail gasoline industry. Concretely, we provided evidence that some firms engage in asymmetric price cycle dynamics while others do not, even stations of the same brand in the same local markets. We illustrated some of the consequences of that heterogeneity in terms of cross-sectional price dispersion. In this section, we attempt to shed some light on the reasons behind the cycles and the variability in cycling behavior. We begin by reassessing the validity of previous explanations mentioned in Section 2, collusion and Edgeworth cycles. Our results indicate that neither of these theoretical foundations of asymmetric cycles finds full support in light of our new evidence. Lastly, in subsection 6.3 we exploit the richness of our station-level strategy results in order to take the explanation of cycling asymmetry in a new direction, related to targeting of consumers with different price sensitivity.

6.1 Are cycles collusive?

Beyond the popular Edgeworth cycle explanation, which we will look into in subsection 6.2, the issue of whether there are collusive components behind these asymmetric cycles or not has recently caught the attention of a new strand of literature. As mentioned in Section 2, these authors argue that the high levels of coordination found among firms in the increasing stages are evidence of the collusive nature of the cycles. One testable prediction if these asymmetric cycles were the result of some traditional form of collusion is that the existence of cycles should lead to higher prices. A convincing identification of the effect of cycles on prices, however, has eluded the literature so far. Since asymmetric cycles have been considered a market-level phenomenon, previous attempts have relied either on price comparisons of markets with and without cycles, or on market-level price differences before and after cycles appear or disappear. The results from most of these strategies, as the literature warns, should not be given a

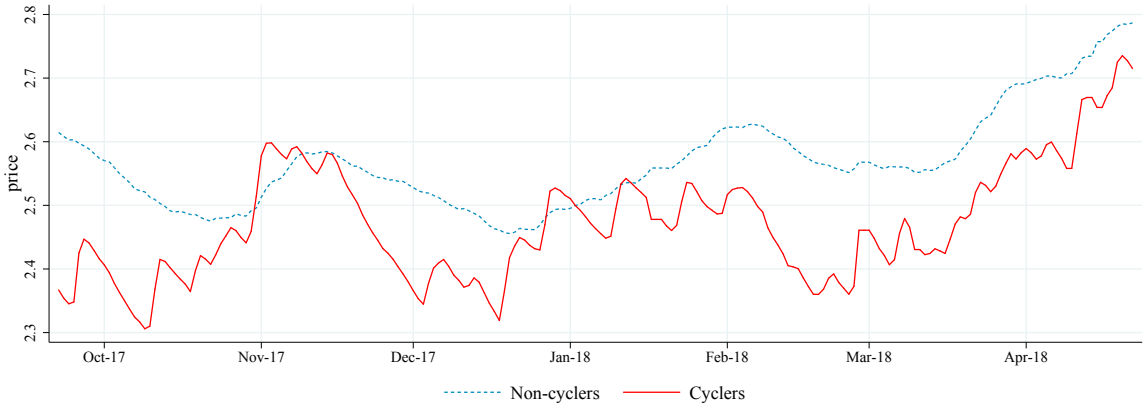
causal interpretation due to the presence of market-level confounders, either unobservable characteristics or observable features of the market structure that are very closely correlated with the presence of cycles.[13] In this paper, we provide a new dimension of asymmetric cycle variability—the intra-market heterogeneity in cycling behavior—which we exploit as an identification strategy to better estimate the cycle-induced price gap.

Figure 11 illustrates the comparison between the previously available source of variability and the new identification strategy that we utilize for the estimation of the effect of asymmetric cycles on price levels. As mentioned before, most previous work measured this effect by comparing cycling and non-cycling markets; Figure 11a replicates that comparison for the markets in our data. Consistent with the literature, non-cycling markets have higher prices than cycling markets, on average. This price gap, however, cannot be attributed solely to the lack of cycles, because these markets might be different in ways other than the cycling patterns. With cycling variability at the market level, these differences cannot be reliably controlled for, because they are either unobservable or perfectly correlated with the existence of cycles. To address these identification issues, we exploit a different level of variability in cycling behavior: the within-market heterogeneity in cycling strategies. In Figure 11b we overlap the price dynamics of the gas stations of Figure 8; noticeably, the non-cycling station's prices are in general higher than those of the cycling stations. Since these firms are located close to each other, they face the same local market characteristics; this in turn implies that the market-level confounders are controlled for in this comparison. In what follows, we use this source of identification to measure the effect of asymmetric cycling behavior on price levels.

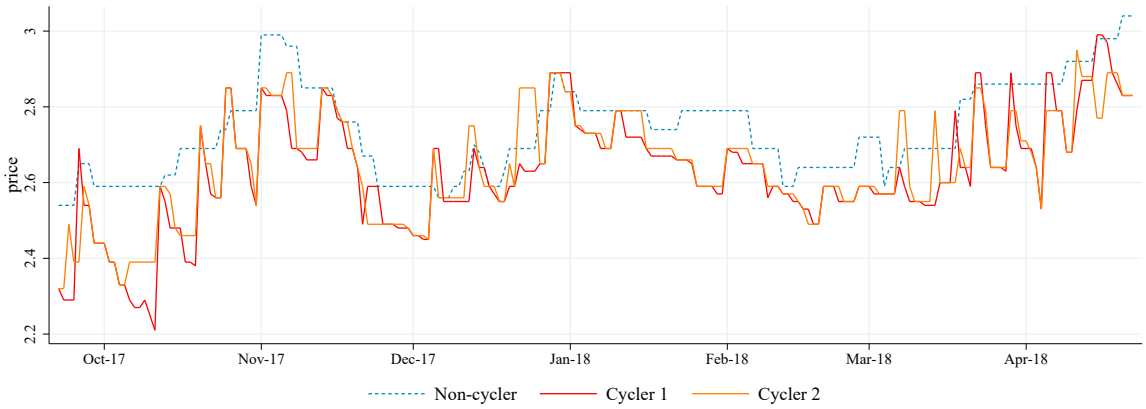
The results are presented in Table 4. The dependent variable is the daily, station-level price of regular gasoline in cents, and the main explanatory variable is the pricing strategy of the gas station, measured with the full-sample cycling indicator presented in Section 4 (other price-level determinants are also controlled for, as in Table 2). In column (1) the price gap was obtained without local market fixed effects; not accounting for the market confounders gives an average difference in price of 11 cents between cycling and non-cycling stations. Once the daily market environment is controlled for by including date-zipcode fixed effects in column (2), the price gap decreases by almost 70%. This discrepancy reveals the extent of bias in the estimation of the price gap when one does not control for local conditions by exploiting within-market

[13] One exception could be Noel (2015)'s natural experiment approach, although, by construction, it lacks external validity.

Figure 11. Identification strategies for the estimation of the cycle-induced price gap.



(a) Average market price of cycling and non-cycling markets, U.S.



(b) Cycling vs. non-cycling stations in the same market, Chicago IL.

heterogeneity in cycling behavior. If the effect on price of the different brands by city is further canceled out, we reach our main specification result: gas stations that exhibit asymmetric cycling patterns in their price dynamics charge on average 3.43 cents less for regular gasoline than stations that follow non-cycling pricing strategies (this is the price gap reported in column (1) of Table 2). In other words, under the same market structure, same-brand firms offering identical amenities and with equal location characteristics charge on average a significantly lower price if they are cyclers. There is a baseline effect of 2.7 cents, and then the gap increases the higher the cycling intensity (i.e., the more asymmetric the cycles, indicated by a higher Cycling Ratio). This result holds for premium and midgrade gasoline as well (see Table A.6). As shown in Table 2, the magnitude of the coefficient almost doubles if the results are estimated using the restricted sample (Table A.5).

Table 4. The effect of asymmetric price cycles on gasoline price levels.

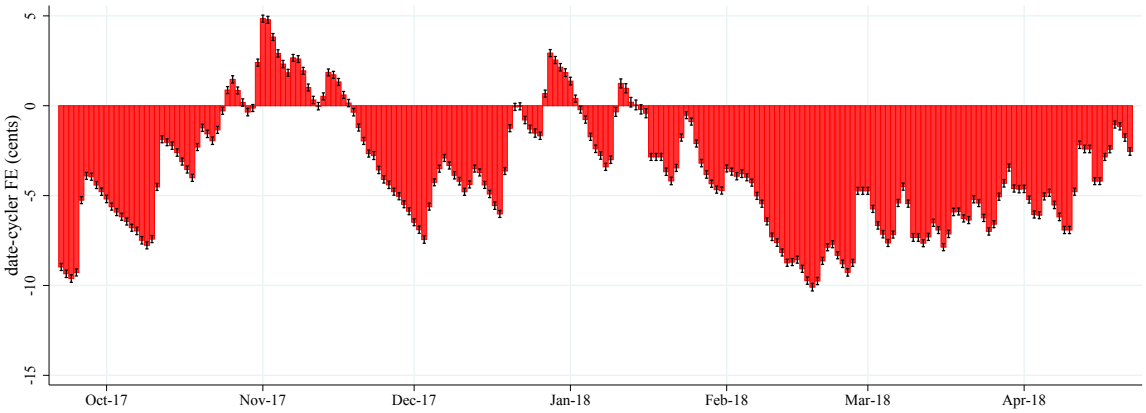
	(1)	(2)	(3)	(4)	(5)	(6)
Cycling indicator	-11.446***	-4.910***	-3.429***	-2.710***		
	(0.019)	(0.008)	(0.007)	(0.010)		
Cycling intensity				-0.315***		
				(0.003)		
Varying cycling ind.					-0.576***	-0.442***
					(0.006)	(0.007)
Varying cycling int.						-0.047***
						(0.001)
R^2	0.2594	0.9359	0.9599	0.9600	0.9862	0.9862
Obs	10,113,008	10,113,008	10,113,008	10,113,008	7,141,398	7,141,398
$\bar{Y}$	256.080	256.080	256.080	256.080	254.119	254.119
Date FE	Yes					
Date-Zip FE	No	Yes	Yes	Yes	Yes	Yes
City-Brand FE	No	No	Yes	Yes		
Station FE	No	No	No	No	Yes	Yes

Note. Dependent variable: price of regular gasoline, in cents; the observation level is a station-day combination. Cycling indicator is the full-sample indicator of cycling behavior; cycle intensity is the full-sample Cycling Ratio. Varying cycle indicator and intensity are the date-level versions of those two variables. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The up-and-down nature of cyclers' price dynamics would suggest that the average gap previously estimated changes systematically over time. The main specification of column (3), but interacting the cycling indicator with the date fixed effect, yields the coefficients plotted in Figure 12. It can be noticed how the price gap shrinks, sometimes even becoming positive, in periods of cycle peaks.

The results shown so far use the full-sample cycling indicator, which classifies gas stations according to the price strategy that they most predominantly followed. As described in subsection 5.1, we also constructed daily station-level cycling indicators

Figure 12. The effect of cycles on price level over time.



Note. The coefficients plotted are the date-cycler fixed effect on price, controlling for zipcode and brand.

using the price dynamics of a two-month rolling window around each day. Accordingly, an additional test for the existence of a price gap induced by cycling behavior would be to compare a gas station price level in periods when it engages in cycles and in periods when it does not.[14] The results of such exercise are reported in columns (5) and (6) of Table 4, where the estimation used the varying cycling indicator and included gas station fixed effects. The decreasing effect of asymmetric cycling strategies on prices survives even when looking into the dynamics of an individual firm: the prices charged by a gas station are relatively lower on average when the station cycles than when it does not.[15]

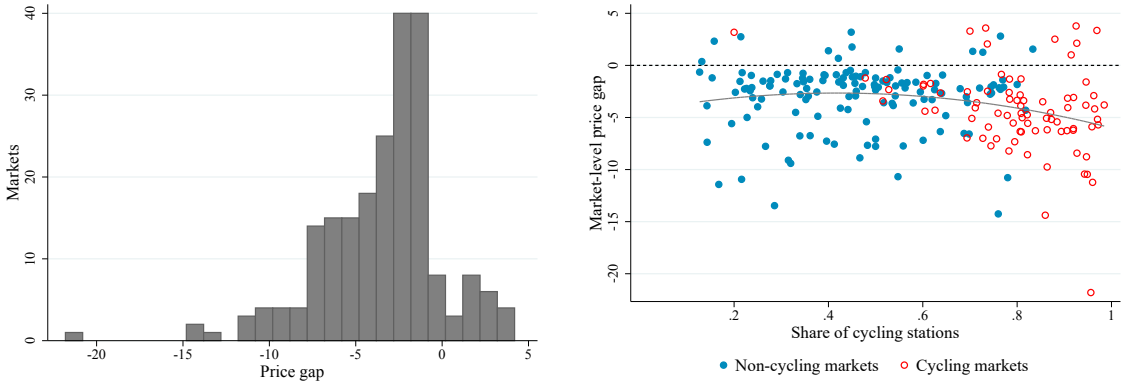
Lastly, in Figure 13 we explore how this cycling price gap differs across markets in our sample. The distribution of price gaps is shown in Figure 13a. Although more research remains to be done to explain the variability in market price gaps, we suggest one possible direction in Figure 13b. On the one hand, the cycling classification of the market-level price dynamics does not seem to be systematically related to the existence of a positive price gap, nor to the magnitude of negative price gaps. On the other hand, there seems to be a non-linear relationship between the share of cycling stations and the price gap: the price differential between cycling and non-cycling stations seems to be bigger in markets where cycling stations are either relatively very few or they are the big majority.

The results presented in this subsection demonstrate that gas stations engaging in

[14]Figure A.5 in the Appendix displays the Cycling Ratio distributions for periods of cycling and non-cycling.

[15]Other robustness checks of Table 4 using a four-month rolling window (Table A.7) and controlling for neighbors cycling behavior (Table A.8) are presented in the Appendix.

Figure 13. Cycling price gap across markets.



(a) Ditribution of market price gaps. (b) Market price gap and share of cyclers.

Note. The market price gap is the coefficient of the market-cycler fixed effect, controlling for date, zipcode, and brand.

asymmetric cycles charge on average lower prices than non-cycling gas stations. This finding can naturally be interpreted as evidence against the hypothesis posed by some previous work that cycles in retail gasoline markets are the result of traditional forms of collusion. In this sense, the coordination of firms in the restoring stage of the cycles seems to be the realization of some specific form of firm interaction rather than involving collusive behavior in the conventional sense. The remainder of the paper is devoted to understanding the nature of those interactions. We first assess to which extent Edgeworth cycles can explain the cycling pattern found in our data. Finally, we suggest insights on why cycle heterogeneity arises within markets.

6.2 Edgeworth cycles revisited

As mentioned in Section 2, the overwhelming majority of empirical studies of price cycles in retail gasoline markets align with the theory of Edgeworth cycles (Maskin and Tirole, 1988). In this subsection, we document ways in which the standard version of that theory and its available extensions are inconsistent with our new findings. The first and foremost limitation is the assumption underlying virtually every previous work on Edgeworth cycles that all firms in a cycling market engage in cycling patterns and vice versa. As we documented in Section 5, there is a high degree of heterogeneity in cycling behavior within markets, sometimes even within yards distance, which entirely rules out the accuracy of that assumption. The only contribution that steps into the right direction in that sense is Doyle et al. (2010)'s. In their model, they aim to explain why some markets display cycles while others do not by treating cycling

behavior as a firm-level decision, driven by some station characteristics. However, they test their model with aggregated data and are silent about the possibility of cycling heterogeneity within local markets. We also discussed earlier in subsection 5.2 how the station features that should predict cycling according to their model—i.e., brand loyalty, geographic differentiation, and complementary goods—do not necessarily find support in our firm-level results. For the theory of Edgeworth cycles or its extensions to be able to explain the observed patterns in the retail gasoline industry an adaptation rendering cycling strategy heterogeneity at the station level would be needed. We address a way in which that can be accomplished in subsection 6.3.

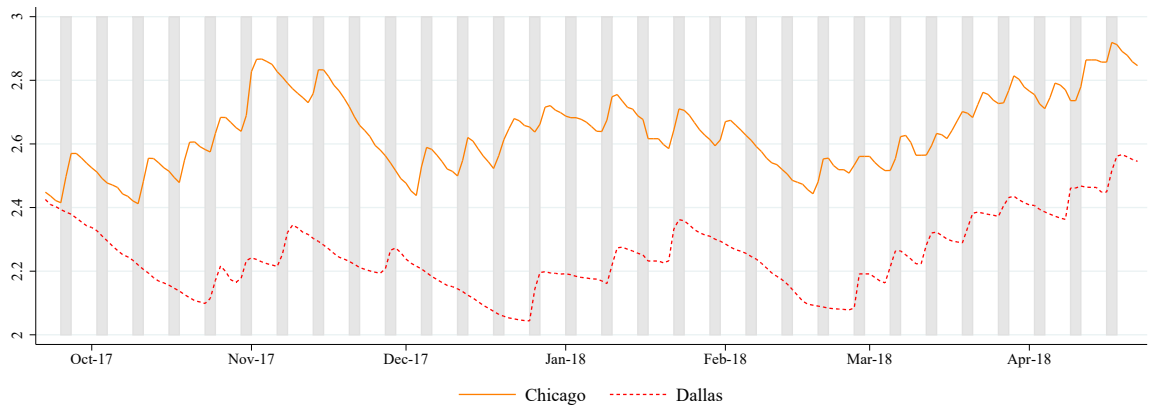
Apart from these limitations, another drawback of Edgeworth cycles as an explanation of the asymmetric cycles in retail gasoline prices comes from the fact that one testable prediction of the model is decidedly contradicted by our data. The main empirical prediction of the theory is the asymmetry of the cycles in price dynamics; the resemblance of the asymmetric cycles in retail gasoline markets to the pattern of Edgeworth cycle dynamic pricing equilibrium was what linked the observed phenomenon to Maskin and Tirole (1988)'s explanation in the first place. Even though it has been claimed that the theory does not offer any other testable predictions, there is an additional feature of Edgeworth cycles that can be tested in the data. In Maskin and Tirole (1988)'s Edgeworth cycle equilibrium, the decreasing phase of the cycle has firms undercutting each other until they reach marginal cost. At the trough of the cycle, the firms enter a war of attrition in which they randomize between restoring price or not; once one of them does relent, the other follows and a new cycle is initiated. One consequence of that mechanism is that the cycle length should be random; in particular, it should not be possible to predict when firms leave the trough of the cycle. However, we find strong weekly patterns in the asymmetric cycle dynamics,[16] revealing that the timing of price relenting could be predicted by day of the week.

To illustrate this claim, Figure 14 overlaps the price dynamics of cycling stations in our cycling market examples of Chicago and Dallas with weekly markers; the shaded areas indicate Monday-Tuesday-Wednesday intervals. One regularity to notice is that when a new cycle starts it does so at the beginning of the week, and then a cycle peak occurs certainly within a couple of days. On the other hand, the time span between cycle troughs is always weekly, biweekly, triweekly, and so on. These two observations imply that the duration of the cycles can be approximately measured in multiples of

[16] Weekly patterns in asymmetric retail gasoline price cycles have been documented before (see, e.g., Lewis and Noel (2011)); however, they have not been analyzed as a contradiction of the fundamentals of Edgeworth cycles.

weeks, and that which multiple depends on whether a price jump is triggered in that market early in the week or not. In what follows we look into each of those regularities.

Figure 14. Weekly patterns in asymmetric price cycles, Chicago and Dallas.

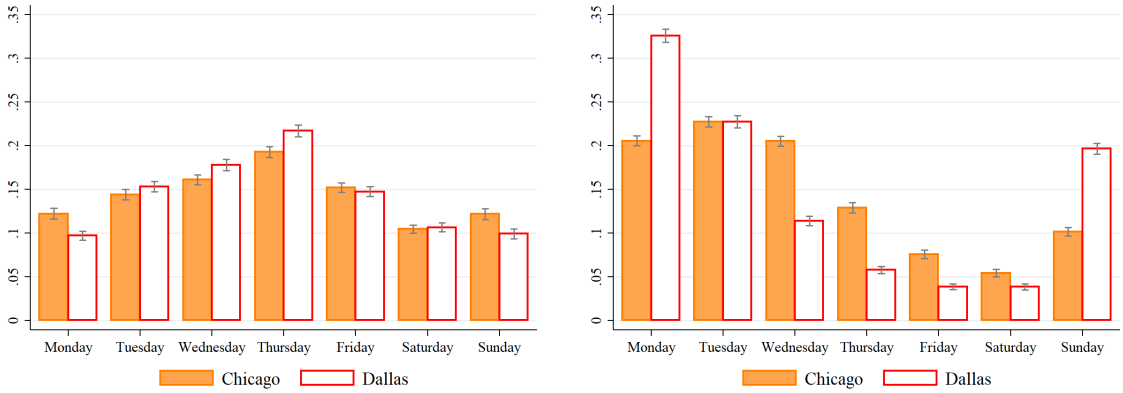


Note. These price dynamics correspond to the average price of cycling stations in each market.

We first explore which days of the week are more likely to be cycle peaks or troughs. For each cycling gas station, we calculated the empirical probability distribution of peaks and troughs across days of the week, in terms of the relative frequency; then, we averaged the day-of-the-week probabilities of peaks and troughs at the market level. Figure 15 shows the results for our two example markets. Both Chicago's and Dallas' gas stations are more likely to have cycle peaks on Thursdays (Figure 15a). As for the troughs, gas stations in Chicago are more likely to reach cycle troughs quite similarly either Monday, Tuesday, or Wednesday; in Dallas, gas stations' probabilities of trough are concentrated on Monday, followed by Tuesday and Sunday (Figure 15b). Comparing Figures 15a and 15b, even though peak probabilities are better lined up on Thursday for both markets, the distributions are flatter (i.e., there is a mode on Thursday but the average probability does not differ greatly among days of the week). Contrarily, Chicago and Dallas market average probabilities of trough are shifted apart, but these distributions are much more concentrated than peak distributions.

The findings just described for our example markets hold for our entire sample as well. We calculated these average empirical probability distributions of peaks and troughs for each market in our sample. Based on that, we defined the market peak (trough) as the day of the week with highest probability of being a peak (trough); for example, Figures 15a and 15b imply that Chicago's peak and trough are Thursday and Tuesday, respectively, while Dallas' are Thursday and Monday. Figure 16a summarizes the results; it shows how many markets have their peak and trough at each day of the

Figure 15. Distribution of troughs and peaks across day of the week, Chicago and Dallas.



(a) Peaks. (b) Troughs.

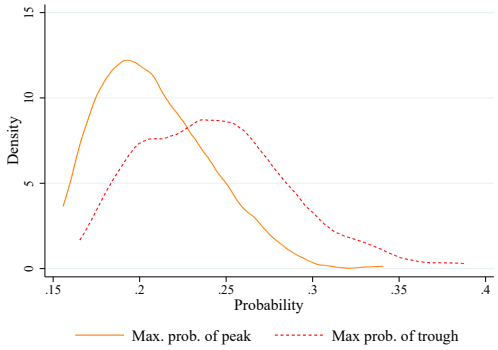
Note. For each cycling gas station, the relative frequency of peaks and troughs by day of the week was calculated. Depicted is the average of those empirical probabilities at the market level.

week.[17] The majority of the cities in our sample (59%) are more likely to have cycle peaks on Thursdays. Even though the market troughs are not that centered around one day of the week, Monday, Tuesday, and Wednesday contain over 85% of market troughs.

Figure 16. Market-level peaks and troughs.

Day-of-week	Peaks	%	Troughs	%
Monday	27	9.22	78	26.62
Tuesday	34	11.60	103	35.15
Wednesday	21	7.17	72	24.56
Thursday	173	59.04	27	9.22
Friday	17	5.80	2	.68
Saturday	4	1.37	1	.34
Sunday	17	5.80	10	3.41
Total	293	100.00	293	100.00

(a) Peaks and troughs by day of the week.



(b) Max. prob. of peaks and troughs.

Note. (a) 293 markets broken down according to the day of the week they more likely have peaks and troughs. (b) The maximum probability of peak (trough) is the probability of peak (trough) of the market day-of-the-week peak (trough).

We explore the flatness of peak (trough) distributions using as a measure the maximum probability of a peak (trough), that is, the average empirical probability of the market peak (trough) as define above. For example, from Figures 15a and 15b the maximum peak probability in Dallas is 0.2172 and in Chicago is 0.1930; the maximum trough

[17] The total number of markets is 293—instead of 313—because we excluded markets with less than 10 cycling gas stations, as their average empirical probabilities were very noisy.

probability is 0.3258 for Dallas (the average probability of the market trough, which is Monday for Dallas) and 0.2275 for Chicago. Figure 16b depicts the densities of market maximum probabilities of peaks and troughs. Just as in the Chicago and Dallas example, peak distributions are more similar but flatter (maximum probability density has a higher mode, but is centered at a low probability value), whereas the trough distributions can be more or less concentrated in different markets (e.g., it is more concentrated in Dallas than in Chicago) but are in general more concentrated than peak distributions (the density of the maximum probability of troughs is shifted to the right with respect to peaks).

These results indicate that, for a given market, the day of the week for the occurrence of cycle troughs is easier to predict than for peaks. The importance of these results for the overall predictability of cycle peaks and troughs is nonetheless played down by the fact that cycles reach their peaks certainly within a couple of days after a trough, whereas troughs do not necessarily occur a certain number of days after a peak. The distance between troughs, however, can be always measured in multiples of weeks. This stresses the importance of understanding the nature of cycle troughs, rather than the emphasis on cycle peaks commonly found in the literature.

The issue of why price restoring is triggered at the beginning of some weeks and not others should be investigated thoroughly. We aim to contribute to that discussion by showing the relationship between price relenting and changes in costs. As it is well documented in the literature, the cycle asymmetry in retail gasoline prices is not inherited from asymmetry in upstream price dynamics. In our data period, for example, the Cycling Ratios of two common proxies for costs, crude oil prices and New York gasoline futures, are 0.85 and 0.82, respectively (see Figure A.6). Instead, in Table 5 we explore whether changes in wholesale prices are likely to trigger retail price restorations of cycling gas stations. The observation level is a cycling station-day combination; the dependent variable takes a value of one if the gas station had a trough that day, and zero otherwise. Our results indicate that an increase in costs either that day, the day before, or two days ago is associated with a higher chance that the gas station relents (we proxy for cost with the price of crude oil[18]). We control for city-day of the week fixed effects, therefore the interpretation holds on average for any given market-level probability of trough each day of the week. Most importantly, an increase in cost is twice more likely to trigger a price restoration on the day of the week that corresponds to the market trough. The results are more pronounced when run only for cycling

[18]Table A.9 in the Appendix explores the same analysis using New York gasoline futures instead, with similar results.

markets, where there are many well-synchronized cycling gas stations. This suggests that whether or not firms face changes in wholesale costs close to the market-level trough might be a key factor in determining which weeks will mark the beginning of a cycle in a given market.

Table 5. Price restoration and changes in cost for cycling stations.

	Full sample	Cycling markets
$\Delta cost_t > 0$	0.023***	0.034***
	(0.000)	(0.000)
$\Delta cost_{t-1} > 0$	0.020***	0.030***
	(0.000)	(0.000)
$\Delta cost_{t-2} > 0$	0.013***	0.019***
	(0.000)	(0.000)
Market trough=1 $\times$ $\Delta cost_t > 0$=1	0.023***	0.029***
	(0.001)	(0.001)
Market trough=1 $\times$ $\Delta cost_{t-1} > 0$=1	0.026***	0.040***
	(0.001)	(0.001)
Market trough=1 $\times$ $\Delta cost_{t-2} > 0$=1	0.002**	-0.002
	(0.001)	(0.001)
R^2	0.1006	0.1027
Observations	5,820,508	3,313,895
Week-Zip FE	Yes	Yes
Brand FE	Yes	Yes
City-dow FE	Yes	Yes

Note. Dependent variable: 1(station-level trough); the observation level is a cycling station-day combination. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In this subsection we provided evidence that the standard Edgeworth cycle theory cannot account for one key feature of asymmetric cycles in retail gasoline markets, which is the n-week duration of the cycles with troughs systematically aligned by day of the week. We documented which days of the week are more likely to be peaks and troughs, and discussed some reasons why new cycles begin some weeks and no others. Left to be addressed is why Monday, Tuesday, and Wednesday are the days of the week when troughs occur in almost every market. Possible explanations can be associated with different price elasticity of consumers within a week.[19] Cycling firms may decrease prices to attract price-searching consumers; when the week starts and demand becomes more inelastic (e.g., because consumers less-flexibly need gasoline for work commuting) is when they can afford to temporarily charge higher prices. In line with this reasoning, below we provide evidence on the relationship between cycling behavior an consumer price search.

[19]This phenomenon has been proven to exist in other industries; see Puller and Taylor (2012) for an example of day-of-the-week price discrimination by U.S. airlines.

6.3 Consumer search and price sensitivity

We have shown so far that asymmetric cycling strategies seem to be the realization of some form of imperfect competition rather than the result of collusion. We also showed that Maskin and Tirole (1988)'s theory of Edgeworth cycles and its few available extensions are inadequate to fully account for the patterns found in our results: n-week duration of the cycles and high degree of cycling heterogeneity within markets. In this last subsection, we contribute to the discussion of what explains these cycles and their heterogeneity with new evidence indicating that gas stations might be dividing markets up by choosing pricing strategies that target different types of consumers.

Some of the results from previous sections hint in the direction of cycling and non-cycling stations following different strategies to attract consumers. The negative cycling price gap and the fact that cycling stations concentrate lower prices in certain days of the week could be the result of these stations targeting price-sensitive consumers more inclined to price search or willing to restrict their gas purchases to particular days. If this were the case, one would expect non-cycling stations aiming at more inelastic consumers. In subsection 5.2 we showed how non-cycling stations are strongly more likely to offer cash or loyalty discounts, which indicates that they may actually be dividing up the pricing space in a different way. These discounts work as a laid-back search strategy for consumers not willing to actively search for low prices, but willing to incur the hassles of carrying station cards or cash. For consumers not willing to do so, they charge much higher prices. Because of their low propensity to search, these consumers will also be attracted to non-cycling stations' fewer and milder changes in prices. In contrast, cycling stations aim to attract attentive, price-sensitive consumers, also drawn by cyclers' frequent and sizable changes in price. In what follows, we provide evidence in favor of this source of heterogeneity in cycling behavior. First, some scattered indications of the relationship between price search and cycling behavior are presented; we then delve into a more systematic measure of that relationship.

Table 6 contains findings that align with the hypothesis of cycling stations targeting more elastic consumers. In Table 6a, cycling stations are shown to be less likely to be found on state borders, but if in the border they tend to locate on the lower-state tax side. Gas stations have been proven to bunch on the lower side of the border (Hurtado, 2018); consumers using those gas stations will be comparatively more prone to be looking for cheaper prices. Table 6b analyzes the surcharge for premium (or midgrade) gasoline applied by gas stations when facing different demand preferences. The results indicate that cycling stations charge a lower price differential for premium

or midgrade gasoline in higher income neighborhoods. Wealthier consumers are more prone to search for cheaper premium (or midgrade) gas prices,[20] since they are more likely to actually demand that product; then, the finding in Table 6b can be the consequence of cycling gas stations intending to capture those high-income, search-oriented consumers.

Table 6. Some evidence on station cycling behavior and propensity of consumer search.

	Cycling indicator
In border	-0.064***
	(0.011)
Lower-tax side	0.003
	(0.008)
In border=1 × Lower-tax side=1	0.031**
	(0.015)
R^2	0.3826
Obs	58,497
Location char.	Yes
Station char.	Yes
City-Brand FE	Yes

(a) Cycling behavior at the state border.

	Premium	Midgrade
Cycler=1	0.602***	0.520***
	(0.085)	(0.075)
Income (log)	-0.017**	-0.005
	(0.007)	(0.007)
Cycler=1 × Income (log)	-0.040***	-0.042***
	(0.008)	(0.007)
R^2	0.8469	0.7110
Obs	7,130,388	6,943,466
$\bar{Y}$	20.561	10.744
Date-Zip FE	Yes	Yes
City-Brand FE	Yes	Yes

(b) Premium/midgrade surcharge.

Note. (a) Dependent variable: cycling indicator; the observation level is a gas station. In border = 1(station located within 5 miles of the state border). For measures of state taxes see Hurtado (2018). (b) Dependent variable: premium and midgrade price differentials with respect to regular gasoline price, in percentage points; the observation level is a station-date combination. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To assess the relationship between firm cycling strategies and consumer price sensitivity in U.S. retail gasoline markets in a more definite and systematic fashion, we construct a measure of search activity using the nature of our data. As described in Section 3, we use consumer-reported data retrieved at the same time every day and we observe how long ago each price was reported. Gas stations with prices reported more frequently will tend to have lower 'how long ago' values; therefore, a measure of reporting frequency would be inversely related to that variable. We define such a measure simply as 24-'how long ago'[21] and use this 'popularity' index as a proxy for the level of search activity, since price reports are the result of consumers searching for cheap prices through the app.[22]

The average popularity of U.S. cycling and non-cycling stations over our sample period is presented in Figure 17. For both types of gas stations, the reporting frequency seems to drop in general right before the shaded areas, that is, during the weekends. Most

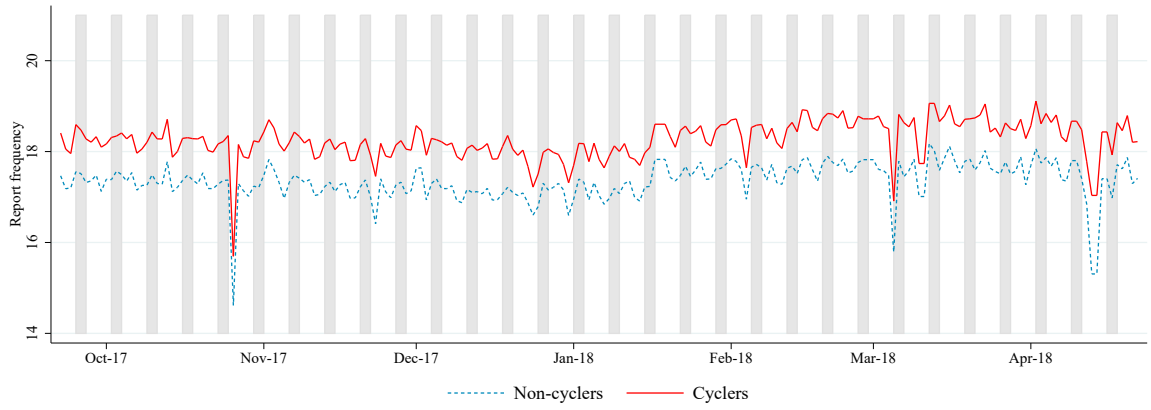
[20] We confirm that relationship using the measure of price search frequency that we introduce later.

[21] We chose that measure because 'how long ago' is expressed in hours, and we preferred a linear transformation. The value of the variable itself does not have a meaningful interpretation, but its usefulness comes from its direct relationship with reporting and search.

[22] See Byrne et al. (2013) for another example of the use of report frequency as a proxy for search intensity.

interestingly, in this raw comparison cycling gas stations have arguably more reports than non-cycling ones. Some identification concerns need to be addressed, however, before claiming that this purely reflects more price-searching of cycling station's consumers. First, users of the app might be more prone to report the price of the gas station they actually end up buying gas from, which will most likely be the one with the lowest price. Since we found that cycling gas stations generally charge lower prices than non-cycling ones, part of the difference in reporting from Figure 17 may merely reflect that difference in price and not the cycling strategy itself. Second, users can report a price they spot both if it is different than in the app (i.e., correct or update a price), as well as if it is unchanged (i.e., check or confirm a price). If they are more likely to report in the former case, this would bias the effect of cycling on consumer search behavior upwards, because cycling gas stations change their prices more often.

Figure 17. Price reporting activity for cycling and non-cycling stations, U.S.



Note. Report frequency proxied for with a popularity measure constructed based on how long ago prices were reported.

Table 7 shows how much search activity differs for consumers of cycling and non-cycling stations, accounting for the identification issues previously pointed out. The day-of-the-week fixed effects included in the estimation are displayed in Figure A.7, where the drop in reporting activity during the weekends is confirmed. The results in Table 7 indicate that, indeed, consumer search is higher for cycling than for non-cycling stations, even after controlling for the price level and the frequency with which stations change their prices. We additionally considered if consumers change their report intensity in different stages of the cycle (peaks and troughs). We find that search activity is higher right before and during peaks, and lower at troughs. Since we control for day of the week and price level, this finding can solely be attributed to the awareness of consumers of when peaks and troughs are more likely to happen in each market, which in turn translates into the recognition of gains from search being higher (lower) at peaks (troughs). Notice also that this effect is intensified for cycling stations'

consumers, because they are more attentive and knowledgeable of the structure of the cycles.

Table 7. Price search and cycling strategies.

	Report frequency
Price	-0.012***
	(0.000)
% of $\Delta p = 0$	-4.389***
	(0.024)
Cycler=1	0.092***
	(0.010)
Peaks and troughs	
Peak today=1	0.019***
	(0.007)
Peak tomorrow=1	0.024***
	(0.007)
Trough today=1	0.000
	(0.007)
Trough tomorrow=1	-0.022***
	(0.007)
Cycler=1 × Peak today=1	-0.008
	(0.010)
Cycler=1 × Peak tomorrow=1	0.010
	(0.010)
Cycler=1 × Trough today=1	-0.034***
	(0.009)
Cycler=1 × Trough tomorrow=1	-0.023**
	(0.009)
R^2	0.2027
Obs	9,968,687
Day-of-the-week FE	Yes
Week-zip FE	Yes
City-Brand FE	Yes

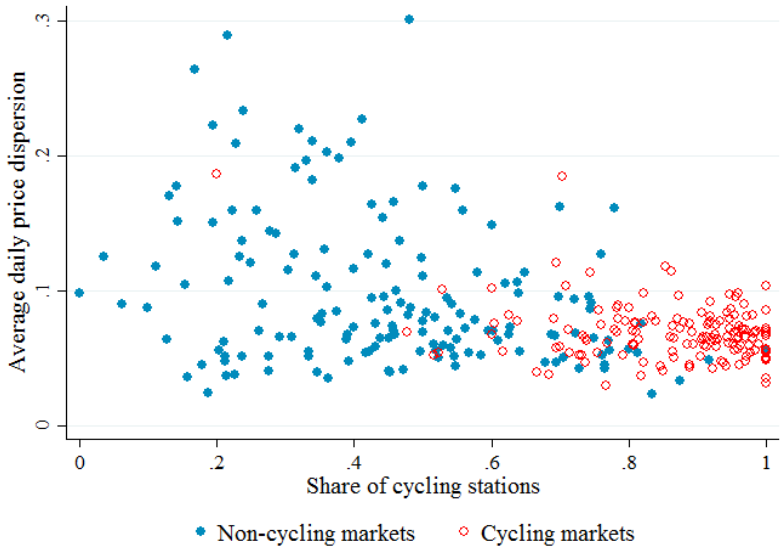
Note: p-values in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

7 Conclusions

This paper identifies the presence of asymmetric cycles in individual gas station price dynamics, and classifies firms in retail gasoline markets according to their cycling and non-cycling strategies. The cycling indicator we propose represents a methodological contribution since, unlike the one previously used in the literature, it is suited to the identification of cycles at the station level and it is robust to the presence of price trends

and short periods of data. The coexistence of both types of gas stations found within markets contrasts with previous work on asymmetric cycles in retail gasoline markets, where asymmetric cycles were regarded as a market-level phenomenon. In this sense, the focus on market-level price dynamics has so far prevented this literature from contributing to the explanation of the equally puzzling intra-market, cross-sectional price variability. Indeed, we find that cycling behavior is a significant determinant of gas stations' price level: stations that engage in asymmetric-cycle strategies charge on average 3.43 cents less than non-cycling stations. On the other hand, our results invite to revisit the discussion on asymmetric cycles and market-level price dispersion. It has been recently argued that these cycles are associated with high price dispersion (Noel, forthcoming). An exploratory analysis in Figure 18, however, suggests that markets with higher share of cycling stations—which tend to be cycling markets—present a relatively low and systematic daily overall price dispersion. Market-level price cycle asymmetry does not seem to induce price dispersion in the cross-section; if anything, a high share of well-synchronized cycling stations seem to guarantee relatively low levels of dispersion compared to an average non-cycling market. This issue deserves further and more careful research left for future work.

Figure 18. Market-level cross-sectional price dispersion and asymmetric cycles.



Note. Each point represent a market in our sample; price dispersion is measured as the average of daily standard deviations of prices.

In terms of the reasons behind these cycles and the heterogeneity in cycling behavior, a setting where gas stations choose a pricing strategy depending on the type of consumers they intend to target is consistent with our data. The Edgeworth cycle model that, with little exception, has served as the theoretical foundation of the empirical literature

in retail gasoline price cycles, finds no support in our results, as we find that one of the testable predictions of its standard version does not hold in light of our new evidence. Our negative cycle-induced price gap also rules out recent concerns that these cycles could be collusive in nature, which have led to investigations by competition authorities. Since the lack of a valid identification strategy for the estimation of the effect of cycles on price levels restricted the ability of previous work to test this fundamental empirical prediction of conventional forms of collusion, the intra-market variability in cycling behavior that we exploit for such estimation is also a valuable contribution in that sense. Our results indicate that the presence of asymmetric cycles in retail gasoline markets do not pose a threat to competition and therefore are not a public policy issue to be addressed. On the contrary, these cycles make price changes easier to predict and are associated with lower prices and lower market-level price dispersion, all of which benefit consumer welfare.

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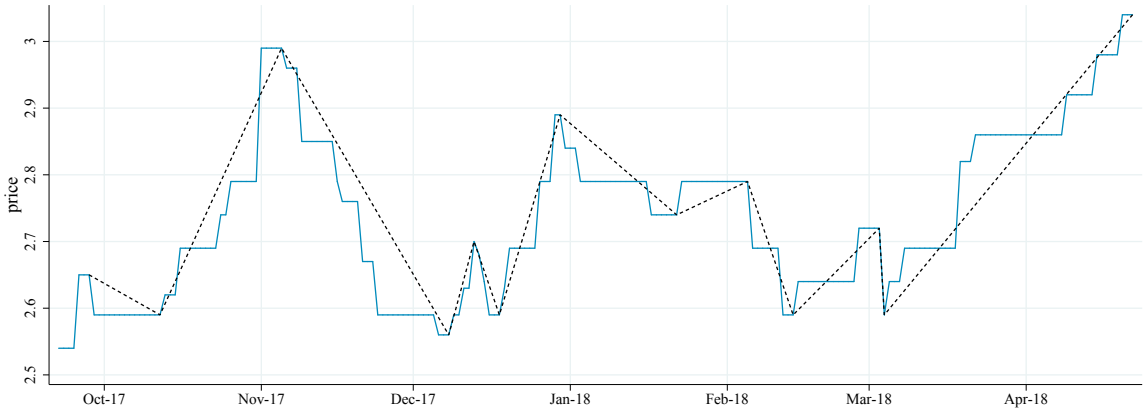
Appendix

Figure A.1. Increasing and decreasing stages in station-level price dynamics.



(a) Non-cycling station.

(b) Cycling station.

Note. Dashed lines delimit the dates included in τ_+ and τ_- for the station-level price dynamic examples of Figure 3.

Table A.1. Cycling, location characteristics, and neighbors' behavior.

	All	w/neighbors
Location characteristics		
Income (log)	0.004	-0.001
	(0.005)	(0.005)
Population density	-0.001***	-0.001**
	(0.000)	(0.000)
No. of neighboring stations	0.013***	0.002
	(0.002)	(0.002)
No. of neighbors (sq)	-0.001***	-0.000
	(0.000)	(0.000)
Neighbors' behavior		
Avg. neighbors' ind.		0.248***
		(0.009)
Closest neighbor's ind.		0.136***
		(0.007)
Dist. closest neigh. (100m)		0.004***
		(0.001)
Closest neighbor's ind.=1 × Dist. closest neigh. (100m)		-0.011***
		(0.001)
R^2	0.3821	0.4301
Observations	58,497	50,764
Station char.	Yes	Yes
City-brand FE	Yes	Yes

Note. Dependent variable: cycling indicator (linear probability model); the observation level is a gas station. Results in the first column include all the stations in our sample; second column includes gas stations with at least one neighboring station. Neighbors are defined as gas stations within a 1-mile radius. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2. Cycling, location characteristics, and neighbors' behavior. Restricted sample.

	All	w/neighbors
Location characteristics		
Income (log)	0.010**	0.004
	(0.005)	(0.005)
Population density	-0.001**	-0.000*
	(0.000)	(0.000)
No. of neighboring stations	0.013***	0.003
	(0.002)	(0.002)
No. of neighbors (sq)	-0.001***	-0.000
	(0.000)	(0.000)
Neighbors' behavior		
Avg. neighbors' ind.		0.234***
		(0.009)
Closest neighbor's ind.		0.124***
		(0.008)
Dist. closest neigh. (100m)		0.004***
		(0.001)
Closest neighbor's ind.=1 × Dist. closest neigh. (100m)		-0.011***
		(0.001)
R^2	0.3849	0.4334
Observations	41,033	35,787
Station char.	Yes	Yes
City-brand FE	Yes	Yes

Note. Dependent variable: cycling indicator (linear probability model); the observation level is a gas station. Results in the first column include all the stations in our restricted sample; second column includes (restricted sample) gas stations with at least one neighboring station. Neighbors are defined as gas stations within a 1-mile radius. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3. Cycling behavior, brand size, and station characteristics.

	All brands	Small	Med-small	Med-big	Big
Brand size					
Med-small	0.085***				
	(0.010)				
Med-big	0.151***				
	(0.008)				
Big	0.022***				
	(0.007)				
Station characteristics					
Loyalty discount	-0.044***	0.024	-0.017	-0.004	-0.048***
	(0.004)	(0.032)	(0.021)	(0.009)	(0.005)
Cash discount	-0.075***	0.001	0.007	-0.063***	-0.087***
	(0.006)	(0.023)	(0.025)	(0.016)	(0.007)
Convenience store	0.049***	0.064***	0.052***	0.064***	0.045***
	(0.005)	(0.019)	(0.019)	(0.009)	(0.008)
Restaurant	-0.029***	-0.007	-0.009	-0.002	-0.048***
	(0.006)	(0.026)	(0.023)	(0.012)	(0.007)
Car wash	-0.006	-0.030	0.019	0.002	-0.006
	(0.005)	(0.026)	(0.022)	(0.012)	(0.006)
Service station	-0.077***	-0.072***	-0.029	-0.158***	-0.072***
	(0.007)	(0.024)	(0.029)	(0.021)	(0.008)
Truck stop	0.014	-0.027	-0.025	0.036*	0.005
	(0.010)	(0.038)	(0.038)	(0.019)	(0.015)
R^2	0.2370	0.2077	0.2564	0.2249	0.2533
Observations	58,497	4,354	4,172	12,489	37,482
Location char.	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

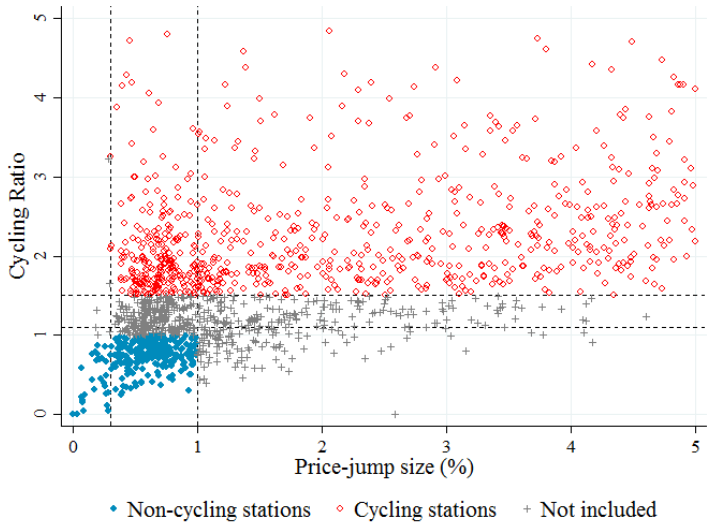
Note. Dependent variable: cycling indicator (linear probability model); the observation level is a gas station. Brand sizes are defined as follows: small, up to 10 gas stations; med-small, more than 10 and less than 100; med-large, more than 100 and less than 1000; big, more than 1000. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.4. Cycling behavior, brand size, and station characteristics. Restricted sample.

	All brands	Small	Med-small	Med-big	Big
Brand size					
Med-small	0.091***				
	(0.010)				
Med-big	0.139***				
	(0.008)				
Big	0.022***				
	(0.008)				
Station characteristics					
Loyalty discount	-0.046***	0.007	-0.018	-0.004	-0.051***
	(0.005)	(0.036)	(0.022)	(0.007)	(0.006)
Cash discount	-0.081***	0.045	0.036	-0.063***	-0.102***
	(0.006)	(0.028)	(0.026)	(0.015)	(0.008)
Convenience store	0.029***	0.081***	0.035*	0.022***	0.034***
	(0.006)	(0.022)	(0.020)	(0.008)	(0.009)
Restaurant	-0.029***	-0.027	-0.014	-0.001	-0.047***
	(0.006)	(0.029)	(0.023)	(0.011)	(0.008)
Car wash	-0.006	-0.036	0.008	0.001	-0.006
	(0.005)	(0.030)	(0.022)	(0.010)	(0.007)
Service station	-0.104***	-0.092***	-0.101***	-0.161***	-0.097***
	(0.008)	(0.028)	(0.029)	(0.019)	(0.010)
Truck stop	0.013	-0.010	-0.032	0.025	0.002
	(0.011)	(0.044)	(0.038)	(0.017)	(0.016)
R^2	0.2109	0.2315	0.2562	0.1948	0.2293
Observations	41,033	2,912	2,928	9,557	25,636
Location char.	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes

Note. Dependent variable: cycling indicator (linear probability model); the observation level is a gas station. Brand sizes are defined as follows: small, up to 10 gas stations; med-small, more than 10 and less than 100; med-large, more than 100 and less than 1000; big, more than 1000. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.2. Cycling Ratio and average percent price increase, Chicago IL. Restricted sample.



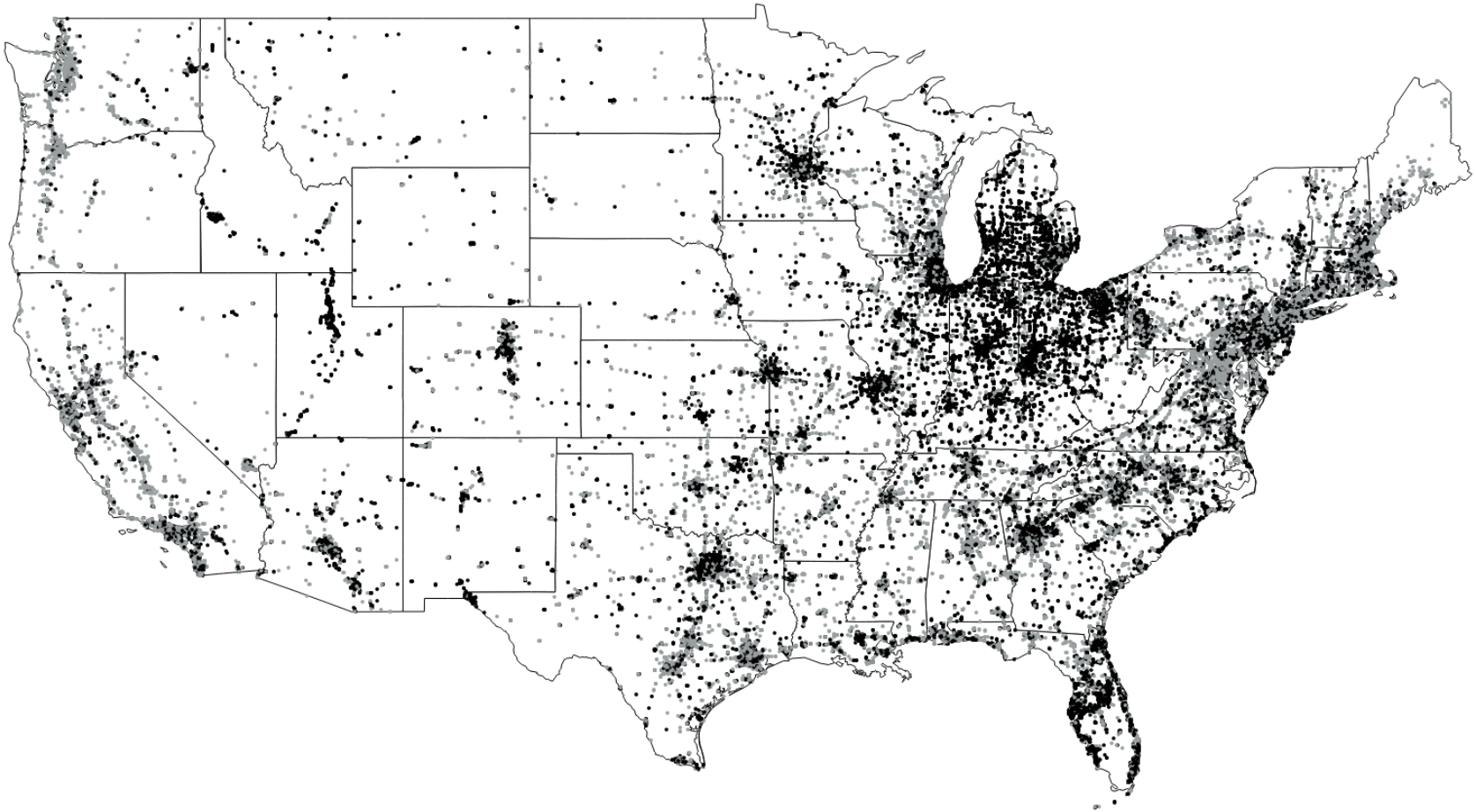
Note. Each Chicago gas station in our sample is represented by a point in these panels, according to their combination of Cycling Ratio and average percent increase in price (price jump).

Table A.5. The effect of asymmetric price cycles on gas price levels. Restricted sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Cycling indicator	-11.986***	-8.112***	-6.157***	-5.498***		
	(0.025)	(0.011)	(0.010)	(0.013)		
Cycling intensity				-0.282***		
				(0.003)		
Varying cycling ind.					-0.728***	-0.603***
					(0.009)	(0.010)
Varying cycling int.						-0.045***
						(0.001)
R^2	0.2572	0.9423	0.9620	0.9621	0.9873	0.9873
Obs	7,184,024	7,184,024	7,184,024	7,184,024	5,248,969	5,248,969
$\bar{Y}$	253.352	253.352	253.352	253.352	252.961	252.961
Date FE	Yes					
Date-Zip FE	No	Yes	Yes	Yes	Yes	Yes
City-Brand FE	No	No	Yes	Yes		
Station FE	No	No	No	No	Yes	Yes

Note. Dependent variable: price of regular gasoline, in cents; the observation level is a station-day combination. Cycling indicator is the full-sample indicator of cycling behavior; cycle intensity is the full-sample Cycling Ratio. Varying cycle indicator and intensity are the date-level versions of those two variables. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.3. Station cycling behavior heterogeneity in the U.S., in grayscale.



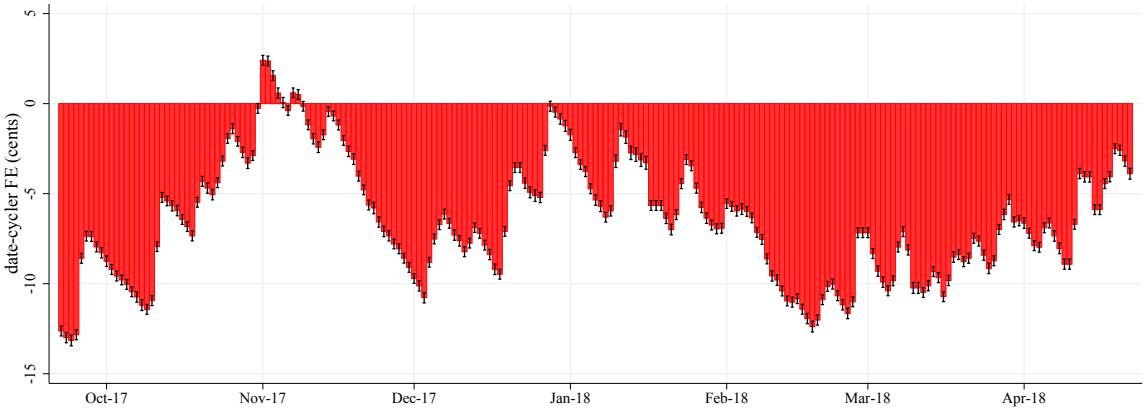
Note. Gray points represent non-cycling gas stations; black points represent cycling stations.

Table A.6. Cycling price strategy effect on price level. Premium and midgrade gasoline

	Premium	Midgrade
Cycler	-3.592***	-3.619***
	(0.013)	(0.012)
R^2	0.9057	0.9271
Obs	7,130,388	6,943,466
$\bar{Y}$	309.212	285.096
Date-Zip FE	Yes	Yes
City-Brand FE	Yes	Yes

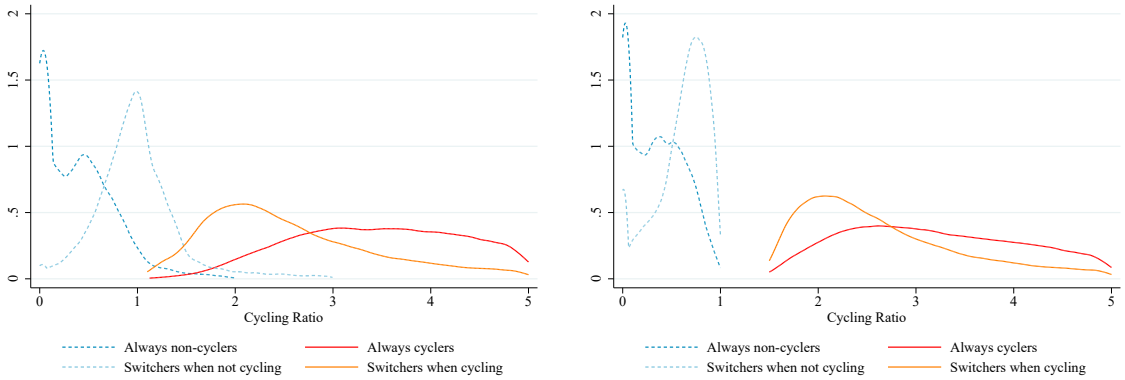
Note. Dependent variables: price of premium and midgrade gasoline, in cents; the observation level is a station-day combination. Cycler is the full-sample indicator of cycling behavior. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.4. The effect of cycles on price level over time. Restricted sample.



Note. The coefficients plotted are the date-cycler fixed effect on price, controlling for zipcode and brand.

Figure A.5. Cycling Ratio distribution and switching pricing strategies.



(a) Full sample.

(b) Restricted sample.

Table A.7. The effect of asymmetric price cycles on gas price levels. Four-month rolling window.

	(1)	(2)	(3)	(4)	(5)	(6)
Cycling indicator	-11.446***	-4.910***	-3.429***	-2.710***		
	(0.019)	(0.008)	(0.007)	(0.010)		
Cycling intensity				-0.315***		
				(0.003)		
Varying cycling ind.					-0.170***	-0.123***
					(0.006)	(0.008)
Varying cycling int.						-0.021***
						(0.002)
R^2	0.2594	0.9359	0.9599	0.9600	0.9862	0.9862
Obs	10,113,008	10,113,008	10,113,008	10,113,008	7,129,088	7,129,088
$\bar{Y}$	256.080	256.080	256.080	256.080	254.100	254.100
Date FE	Yes					
Date-Zip FE	No	Yes	Yes	Yes	Yes	Yes
City-Brand FE	No	No	Yes	Yes		
Station FE	No	No	No	No	Yes	Yes

Note. Dependent variable: price of regular gasoline, in cents; the observation level is a station-day combination. Cycling indicator is the full-sample indicator of cycling behavior; cycle intensity is the full-sample Cycling Ratio. Varying cycle indicator and intensity are the date-level versions of those two variables. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8. The effect of asymmetric price cycles on gas price levels. Controlling for neighbor strategies.

	(1)	(2)	(3)	(4)	(5)	(6)
Cycling indicator	-8.209***	-4.940***	-3.418***	-2.728***		
	(0.022)	(0.009)	(0.008)	(0.011)		
Cycling intensity				-0.302***		
				(0.003)		
Varying cycling ind.					-0.594***	-0.456***
					(0.006)	(0.007)
Varying cycling int.						-0.048***
						(0.001)
R^2	0.2777	0.9370	0.9612	0.9613	0.9866	0.9866
Obs	8,863,627	8,863,627	8,863,627	8,863,627	6,217,738	6,217,738
$\bar{Y}$	256.366	256.366	256.366	256.366	254.370	254.370
Date FE	Yes					
Date-Zip FE	No	Yes	Yes	Yes	Yes	Yes
City-Brand FE	No	No	Yes	Yes		
Station FE	No	No	No	No	Yes	Yes

Note. Dependent variable: price of regular gasoline, in cents; the observation level is a station-day combination. Cycling indicator is the full-sample indicator of cycling behavior; cycle intensity is the full-sample Cycling Ratio. Varying cycle indicator and intensity are the date-level versions of those two variables. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.6. Cost proxies dynamic patterns during the sample period.

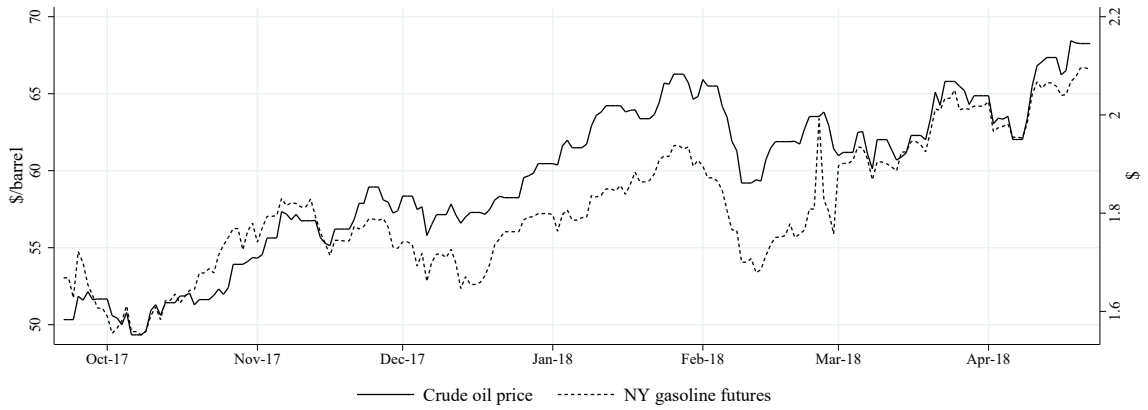
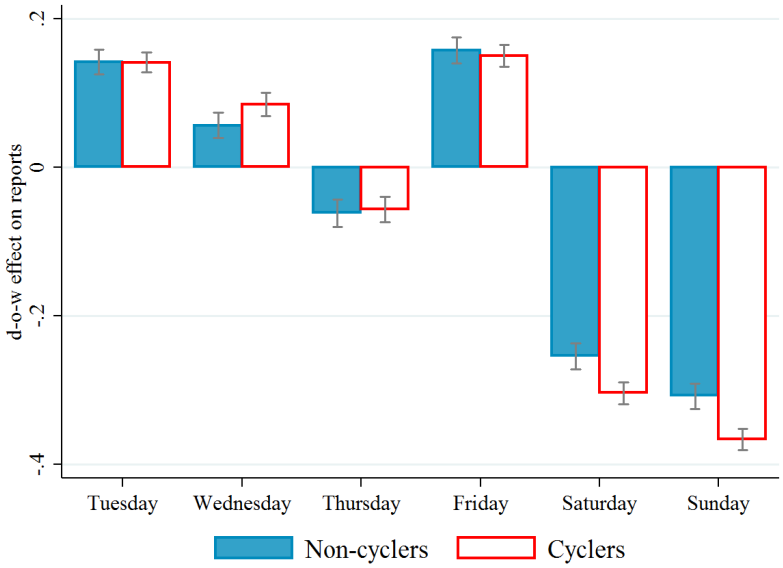


Table A.9. Price restoration and changes in cost for cycling stations. New York gasoline futures.

	Full sample	Cycling markets
$\Delta cost_t > 0$	0.013***	0.020***
	(0.000)	(0.000)
$\Delta cost_{t-1} > 0$	0.023***	0.033***
	(0.000)	(0.000)
$\Delta cost_{t-2} > 0$	0.005***	0.008***
	(0.000)	(0.000)
Market trough=1 $\times$ $\Delta cost_t > 0$=1	0.012***	0.016***
	(0.001)	(0.001)
Market trough=1 $\times$ $\Delta cost_{t-1} > 0$=1	0.032***	0.043***
	(0.001)	(0.001)
Market trough=1 $\times$ $\Delta cost_{t-2} > 0$=1	-0.004***	0.001
	(0.001)	(0.001)
R^2	0.1007	0.1024
Observations	5,820,508	3,313,895
Week-Zip FE	Yes	Yes
Brand FE	Yes	Yes
City-dow FE	Yes	Yes

Note. Dependent variable: 1(station-level trough); the observation level is a cycling station-day combination. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.7. Price reporting activity by day of the week.



Note. Plotted are the day-of-the-week fixed effects on reporting frequency from the estimation of Table 7.