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How do Consumers Respond to Gasoline Price Cycles?*

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Abstract

This paper empirically studies how consumers respond to retail gasoline price cycles. Our analysis uses new station-level price data from local markets in Ontario, Canada, and a unique market-level measure of consumer responsiveness based on web traffic from gasoline price reporting websites. We first document how stations use coordinated pricing strategies that give rise to large daily changes in price levels and dispersion in cycling gasoline markets. We then show consumer responsiveness exhibits cycles that move with these price fluctuations. Through a series of tests we further show that forward-looking stockpiling behavior by consumers plays a central role in generating these patterns.

Keywords: Retail gasoline price cycles; Dynamic demand; Consumer search
JEL Codes: L11, L9, D22

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1 Introduction

The continued rise in gasoline prices over the past decade has seen anti-trust authorities increase their scrutiny over how companies set prices, and has heightened interest over the nature of competition in gasoline markets. A key finding from various policy and academic studies on gasoline pricing is that retail prices exhibit asymmetric cycles in many markets.[1] Figure 1 depicts an example of a cycling market from Kingston, Canada. In cycling markets like Kingston, retail prices experience large infrequent price jumps or *restorations*, and an *undercutting phase* that consists of small daily price cuts between consecutive price restorations.

While a number of researchers have examined retailers' pricing behavior in coordinating restorations and undercutting prices, there are virtually no empirical studies on whether or how consumers respond to price cycles. More generally, there is little evidence on how consumers respond to daily fluctuations in gasoline prices. The disproportionate amount of supply-side research reflects the fact that while daily retail price data is available to researchers, daily data on volumes of fuel sold at a station or in a market are generally confidential and unavailable to researchers. The lack of demand-side research is unfortunate given its relevance for policymakers concerned with consumer welfare and demand-side sources of market power in retail gasoline markets.

In this paper, we develop a novel empirical study of how consumers respond to gasoline price cycles. The study proceeds in two parts. We first examine firms' pricing behavior in cycling gasoline markets and provide new evidence that dominant retailers engage in price leadership in these markets. We then use a novel measure of daily market-level consumer responsiveness to study how consumers respond to daily fluctuations in price levels and dispersion arising from firms' pricing behavior, and to test for consumer stockpiling and search behavior.

Our analysis uses a new dataset of daily, station-level prices from Ontario, Canada from 2007-2008. The owners of GasBuddy Organization Inc. (GasBuddy), who run the most popular online gasoline price reporting websites in North America, provided us with these data. Users of these websites upload stations' prices from their local markets via the internet using mobile devices and computers. The dataset consists of every station-level price report submitted to GasBuddy's websites over the sample period.

[1] See Eckert (2013) and Noel (2011) for extensive reviews of the academic literature on retail gasoline pricing and cycles. A number of policy studies from the U.S., Canada, and Australia have also studied price cycles. See, for example, Federal Trade Commission (2011), Government of Canada (2003), and Australia Consumer and Competition Commission (2007).

In the first part of the paper, we study firm-specific pricing behavior, and their impact on daily retail price levels and dispersion in cycling markets. We show that stations run by major vertically-integrated brands systematically take on a leadership role in coordinating price restorations. In contrast, we find independent (non-branded) stations do not engage in such price leadership. We further show that branded retailers not only influence the level of prices when coordinating restorations, but also station-level price dispersion. In particular, market-level price dispersion collapses after a restoration price jump, and gradually rises as price undercutting ensues.

In the second part of the paper, we analyze how consumers respond to these daily fluctuations in price levels and dispersion. Like previous researchers, we do not have access to data on volumes of fuel sold for our analysis. Instead we exploit the fact that our data contain every price report submitted to GasBuddy's websites over the sample period. This allows us to construct a daily, market-specific measure of demand responsiveness in terms of the number of price reports these websites receive from price spotters for a given date and market. This price reporting-based measure of responsiveness essentially assumes that consumers are more actively shopping and sampling gasoline stations' prices on days when GasBuddy's websites receive more price reports for a given market.

The main advantage of this measure is we can match it to daily, market-level changes in price levels and dispersion. Such disaggregation is particularly helpful in studying consumer demand responses in cycling markets where retail prices exhibit large fluctuations on a daily basis. The main shortcoming of the measure is it only captures demand responses of consumers who actively report gasoline prices to websites. These individuals are unlikely to be typical consumers, and as such we interpret our results as corresponding to the behavior of highly informed/attentive consumers.

We use regressions to study how price reporting intensity varies with the level and dispersion of prices over the cycle. We find reporting intensity experiences a dramatic, statistically significant increase just before and during restorations, a period where both price levels and dispersion also rise dramatically.[2] The baseline estimates further establish that daily price dispersion is the main determinant of price reporting intensity across different days of the cycle.

We consider two non-mutually exclusive mechanisms in interpreting these patterns: stockpiling and

[2]The rise in price dispersion around restorations reflects our main findings in the first part of the paper. When branded retailers increase their stations' prices to coordinate restorations, they create large increases in price dispersion for one- or two days as rival stations adjust their prices upward from the bottom of the cycle.

consumer search.[3] The baseline results alone, while interesting, are not overly helpful in determining whether one or both of these mechanisms drive price reporting behavior. Forward-looking consumers could monitor daily changes in price dispersion, which varies in predictable ways over the cycle, to time their fuel purchases at the bottom of the cycle. Similarly, a costly search model would predict a rise in price reporting around restorations since the marginal benefit to searching for and reporting prices is higher when prices are more dispersed, and consumers are more likely to find a deal.

We try to disentangle stockpiling from search-based incentives in price reporting by investigating heterogeneous relationships between reporting intensity, price dispersion, and positive and negative price changes by day of the cycle. Interestingly, we find reporting intensity is strongly linked to price dispersion on days just prior to and during restorations; however, no such relationship exists the day immediately after a restoration. This can be explained by a model of stockpiling and demand accumulation: if GasBuddy's price spotters tend to time their purchases and fill their cars' fuel tanks at the bottom of the cycle, then one day after a restoration they will not be actively shopping for fuel, and hence not monitoring price dispersion to make another well-timed fuel purchase. In contrast, a search-based explanation of price reporting alone has a difficult time explaining why reporting intensity and price dispersion has a strong positive relationship on some days of the cycle but not others.

Our analysis also reveals heterogeneous relationships between price reporting and lagged retail price changes that further point to dynamic demand behavior. On most days of the cycle, price reporting is largely unrelated to lagged positive and negative retail price changes. There are, however, two key exceptions: on days when restorations are initiated, reporting intensity rises when lagged retail prices start to rise, or when lagged price cuts become increasingly small. We document that both small price increases and smaller price cuts during the undercutting phase of the cycle tend to signal a restoration price jump is about to occur. As such, we see these findings as being consistent with forward-looking consumers who use this information to anticipate restorations, and time their purchases at the bottom of the cycle.

As a final test of stockpiling, we examine daily price reporting in the context of rural gasoline markets. These markets are well-suited for testing stockpiling behavior for two reasons. First, price restorations and undercutting phases are also present in rural markets, as well as periods of price rigidity following

[3] In Section 4, we caveat how endogeneity issues arising from firms' optimal price decisions can affect the interpretation of our results. We also discuss how correcting for this source of simultaneity in our reduced-form regressions, say for example with instrumental variables, is prohibitively difficult if consumers are forward-looking.

restorations; in short, these markets exhibit "slow" price cycles. Thus, consumers in these markets have particularly strong incentives to time their purchases and stockpile fuel prior to restorations to avoid paying higher prices in the future. Second, the majority of rural markets in the sample have five or less stations that tend to be located in close proximity to each other. As such, there is little scope for search-based incentives to drive price reporting in these markets. Therefore, if stockpiling plays no role in price reporting, we should not find the jump in reporting intensity around restorations in rural markets that we found in the sample's (faster) cycling markets. Our empirical findings show this is not the case: price reporting exhibits a large, statistically significant rise when restorations are initiated in rural markets. The evidence further supports the hypothesis that dynamic demand incentives drive price reporting.

As we discuss in the paper's conclusion, our results have implications for price transparency policies that provide consumers with web-based information on daily, market-level retail price fluctuations; such policies have recently been considered and enacted by anti-trust authorities and policy makers in Australia and Canada. By providing some of the first "hard" empirical evidence of stockpiling behavior, this paper emphasizes the importance of policies that help consumers make well-timed retail fuel purchases. In this way, these policies can yield consumer welfare gains in gasoline markets, particularly in those with price cycles (Noel, 2012).

Related literature

The paper contributes to a large empirical literature on consumer demand in retail gasoline markets. Previous researchers have examined a number of issues such as identifying price elasticities with low frequency (monthly, quarterly) data (Small and Van Dender, 2008; Hughes, Knittel, and Sperling, 2008) and high (daily) frequency data (Lewis, Levin, and Wolak, 2012), spatial differentiation (Houde, 2012), and consumer search (Yatchew and No, 2001, Lewis, 2011; Lewis and Marvel, 2011; Chandra and Tappata, 2011).

Among these papers, we most closely relate to Lewis's and Marvel's (2011) study of asymmetric demand responses to positive and negative retail price changes. They also use daily GasBuddy web usage data to measure responsiveness, except their measure is based on web traffic (or 'hits') on GasBuddy's websites from the U.S., which entails visits by both price spotters and non-price spotters. They find aggregate web traffic is higher following price increases than decreases, and argue this evidence supports asymmetric search theories that provide a competitive explanation for "rockets and feathers" pricing.

Our analysis is complementary to theirs; while their responsiveness measure is not for a select group of consumers, it precludes any disaggregated analyses of market-level demand responses to changes in price levels and dispersion.

Our emphasis on stockpiling is a further novelty of the paper within the literature on gasoline demand. Stockpiling behavior and anticipatory purchasing naturally arises in studying a market where: (1) consumers manage inventories of a storable good (gas in their cars' fuel tanks); (2) prices are displayed on large signs at retailers' stations that consumers observe during their day-to-day commute; and (3) prices exhibit regular cycles with weekly or bi-weekly price jumps. Thus, the paper more broadly relates to empirical research on dynamic demand (see, for instance, Erdem, Imai, and Keane, 2003; Hendel and Nevo, 2006a, 2006b).

This paper also adds to a body of research on retail pricing in gasoline markets with price cycles.[4] It is most closely related to Lewis (2012), who goes beyond studying pricing strategies from individual cycling markets, and instead studies station-level data from a cross-section of cycling markets in the U.S. Midwest. Our finding that dominant retailers engage in price leadership in cycling markets from a different period and context serve to re-affirm Lewis's previous findings. There is, however, an important difference between Lewis's results and ours: while vertically-integrated branded retailers coordinate restorations in our Canadian markets, the non-integrated independent retailer Speedway coordinates restorations in his U.S. markets. Unlike independents in Canada, Speedway is a dominant player who has large station-level market shares in many cities and towns across the U.S. Midwest. Thus, the branded/independent distinction appears to be irrelevant for predicting which retailer coordinates restorations, rather it is whether a retailer operates large networks of stations.

2 Data

The data used in this paper are drawn from a dataset developed in Byrne and Leslie (2013). Here, we briefly summarize the data used in this paper, and refer the interested reader to Byrne and Leslie (2013) for further details on the dataset.

The owners of GasBuddy provided us with daily station level retail gasoline price data for all markets

[4] A number of papers have analyzed firms' pricing strategies using station-level price data from individual cycling markets such as Vancouver, Toronto, and Guelph, Canada (respectively, Eckert and West, 2004; Noel, 2007b; Atkinson, 2009) and Perth, Australia (Wang, 2009; de Roos and Katayama, 2013)). Foros and Steen (2013) use station-level data from a cross-section of markets from Norway, finding evidence of price coordination among the dominant four gasoline companies in the country.

in Ontario, Canada from August 1, 2007 to August 12, 2008. These data represent the universe of price reports over this period from users of GasBuddy's websites including `www.gasbuddy.com`, `www.ontariogasprices.com`, `www.ottawagasprices.com`, and other city-specific sites. GasBuddy's users build profiles by uploading prices observed in their local markets to these websites using personal computers and mobile phones. In addition to the individual price observations, these data list each station's location and brand. In total, the dataset consists of 602,604 station-price-day observations across 137 markets in Ontario. The prices are for regular unleaded gasoline and are reported in terms of Canadian cents per liter (cpl).

Keeping with convention in the literature, we label vertically integrated gasoline retailers "brands" and all other station-types "independents." There are four dominant brands in Ontario: Esso, Shell, Petro-Canada, and Sunoco. The companies respectively operate 20%, 16%, 15% and 10% of the stations across the province in our sample.

Given the self-reported nature of these data, the station level prices are likely to exhibit selection bias. In particular, stations in high-traffic areas and branded stations are likely to receive a disproportionate number of price reports (Atkinson, 2008). When we aggregate up to daily market level average prices, the resulting market-level price series tend to exhibit minimal biases when compared to other independently collected price series (Byrne and Leslie, 2013; Atkinson, 2008).[5] Given the findings from these previous robustness checks, we only caveat results based on the station-level price data in Sections 3.3 and 3.4 below.

We also use daily wholesale ("rack") price data from MJ Ervin and Associates. Rack price series from 12 locations are used: Toronto, Ottawa, Kingston, Windsor, London, Sudbury, Sault Ste. Marie, Thunder Bay, North Bay, Timmins, Hamilton, and St. Catharines. Rack price locations are matched to GasBuddy locations according to the rack price location that is closest to a given GasBuddy location in terms of great-circle distance.

2.1 Classifying price dynamics

Figure 1 highlights the three types of pricing regimes observed in the data. In the nomenclature of Noel (2007a), Kingston (pop. 117,250; 44 stations), Hamilton (pop. 504,560; 93 stations), and Kapuskasing (pop. 8,510, 3 stations) exhibit *price cycles*, *cost-based pricing*, and *sticky pricing*. Price cycles have

[5] Specifically, the Appendix of Byrne and Leslie (2013) shows that daily average price data from GasBuddy track closely with independently constructed market-level price series from MJ Ervin and Associates over the sample period. Atkinson (2008) shows that average daily prices for Guelph, Canada constructed using station level data from GasBuddy and from the author (collected bi-hourly from individual stations) closely follow each other over time.

an asymmetric "sawtooth" pattern characterized by infrequent *price restorations* where retail prices experience large discrete jumps, and *undercutting phases* that occur between restorations, where prices experience small daily price declines. Byrne and Leslie (2013) examine these urban-rural differences in price dynamics and the determinants of pricing regimes across markets. In short, they find large urban markets exhibit cost-based pricing, and rural, highly concentrated markets that are far from wholesalers' petroleum terminals have sticky pricing. Price cycles tend to exist in the intermediate-sized markets between these two extremes within Ontario during our sample period.[6]

Since the focus of this article is on cycling gasoline markets, we must classify which markets exhibit price cycles in the sample. We follow Lewis's (2009) simple classification scheme: a market has price cycles if the median of its daily price change is negative.[7] Intuitively, cycling markets tend to have negative daily median price changes since the relative infrequency of price restorations to undercutting phase days implies these markets have many more daily price decreases than increases. In contrast, cost-based and sticky markets have similar numbers of price increases and decreases over time. Further, sticky markets have many days with no daily price change. Cost-based and sticky markets therefore tend to have median daily price changes of 0.

Using our cut-off rule, we classify 33 of the 137 markets as exhibiting price cycles. On average, our cycling markets have populations of 52,873 individuals and 16 gasoline stations. Table 1 shows the smallest and largest cycling markets are Val Caron and Windsor, with populations of 4,036 and 216,470 people, and station counts of 4 and 53.[8]

3 Price leadership and coordination

This section investigates supply-side pricing behavior in cycling markets. Fundamentally, firms' pricing strategies are what generate daily fluctuations in the level and dispersion of gasoline prices, which consumers potentially respond to. As such, this section's analysis provides context for our investigation into demand-side responses to price cycles in Section 4.

[6] It is not clear how generalizable the finding that intermediate-sized markets tend to exhibit price cycles is. Clark and Houde (2012a) note asymmetric price cycles exist in Montreal; Australian Consumer and Competition Commission (2007) documents price cycles in major Australian cities like Sydney and Melbourne which similar in size to Hamilton and Toronto, Ontario.

[7] This type of cut-off rule for classifying cycling markets is used in a number of recent papers including Lewis (2009), Lewis (2012). Our results throughout are robust to cut-offs for defining cycling markets between 0 cpl and -2.5 cpl.

[8] Figure A.1 in the Appendix of Byrne and Leslie (2013) maps out the locations of cycling and non-cycling markets in the province. Clusters of cycling markets exist in eastern Ontario around Kingston and Brockville, in southwestern Ontario towards Windsor, and in the Niagara region. Northern cities along the Trans-Canada highways such as North Bay, Sarnia, and Thunder Bay also tend to exhibit price cycles.

We first describe how we identify restoration events in the data and present summary statistics that characterize what a typical price cycle looks like. We then investigate the roles brands and independents play in coordinating price restorations and undercutting market prices between restorations.[9] The section closes by discussing competitive and collusive mechanisms that could give rise to the observed pricing behavior.

In general, we expect branded retailers are more likely to take on a leadership role in coordinating price restorations for two inter-related reasons. First, brands in Ontario have regional managers who centrally set prices across their networks of stations.[10] Therefore, these firms are well-positioned to increase prices at their many stations and signal the start of restorations to their competitors. Moreover, because they operate relatively large station networks, brands realize the largest benefits from having high price-cost margins. This implies they also have the largest incentives to periodically coordinate restorations.

In contrast, we expect locally-run independents to be aggressive in undercutting prices and to play a minor role in initiating restorations. These firms have relatively small station networks, and therefore are less able to signal restorations to their competitors. Moreover, given their small size relative to brands, independents have large business stealing incentives and thus should be more aggressive in undercutting brands' prices following restorations.

3.1 Identifying restorations

To study the pricing strategies of firms we must first identify price restoration events. We use a cutoff rule to do so: a restoration day occurs if a market's median gasoline price increases by 1.5 cpl over consecutive days or over two days.[11] Under this definition, a single restoration period is either one- or two days. This allows for the possibility that some retailers restore their prices on day t, while others restore their prices when they open their stations on day $t+1$.[12] A station is classified as participating in

[9] We restrict our empirical analysis to conservative daily frequencies. Sample selection issues from GasBuddy spotters likely undermines any "real-time" analysis of identifying exactly which stations are the first to initiate price jumps during restorations or undercut rivals' prices within a given day.

[10] Our discussions with individual station owners and employees from two of the major brands confirm this to be the case. Improvements in information technology over the past few decades have seen brands move away from lessee-dealer arrangements to having firm-run retail chains with centralized pricing. The regional clusters of cycling markets across the province, presented in figure A.1 in Byrne and Leslie (2013), may correspond to regional definitions for managers of branded stations. Atkinson (2009) similarly finds evidence of regional pricing strategies among brands in southern Ontario in 2005.

[11] We use the inter-day changes in the median rather than the mean gasoline price within markets to avoid the impact of extreme price observations in identifying restoration events.

[12] We observe a small number of three-day restorations; however, we drop them in the empirical analysis.

a restoration if its price is greater than or equal to the market's median price on either day one- or two of a given restoration period.[13] The first restoration day of a given restoration period is set as day zero of a given cycle. The length of a cycle is the number of days between the last restoration day of the previous restoration period and the first restoration day of the next restoration period. The restoration price is computed as the maximum daily median price for two-day restoration periods.[14]

Figure 2 illustrates how daily changes in median prices and our 1.5 cpl cut-off rule identify price restorations for Kingston. Restorations correspond to the positive spikes in the daily median price that are sufficiently large to pass the 1.5 cpl horizontal cut-off line. A concern in identifying restorations with changes in the median price is that large daily changes in rack prices may generate large changes in retail prices and hence the median retail price. An alternative metric that accounts for this issue is the daily change in the median margin between the retail and rack price across stations.[15] We plot this series in Figure 2 as well. As expected, large changes in the median price and margin tend to occur on the same day. However, there are many instances where large negative changes in the rack price generate large margin differences that do not correspond to restoration-driven daily increases in the median price. We have exhaustively investigated changes in the median price and margin along these lines, and find changes in the less volatile median price is generally better at identifying restorations.[16]

3.2 Characterizing price cycles

Table 1 reports summary statistics that characterize a typical price cycle for each of the 33 cycling markets in our sample. In total, our 1.5 cpl cut-off rule identifies 429 unique cycles across our cycling

[13]Lewis (2012) p.17 uses a different restoration definition that also permits restorations to occur over one- or two days. He requires a minimum share of stations in a market to increase their prices by either 5 US cents per gallon (or 8 US cents in a robustness check) over a one- or two-day period for a restoration to be established. In terms of CAD cpl, these cut-off price changes are 1.41 cpl and 2.25 cpl (similar conversions as above). We do not use a minimum participation rate in identifying price restorations since we are concerned with potential measurement error due to sample selection issues with our Internet-collected GasBuddy data. Rather, we elect to use a conservative restoration identification rule based on daily changes in the median gasoline price with a market over time.

[14]To make concrete the definition of restoration events and the participation of firms in restorations, consider the following examples. Suppose the median price on days 0, 1, 2, 3 is 90 cpl, 93 cpl, 91 cpl and 90 cpl. In this case, a one-day restoration event occurs on day 1, the restoration price is 93 cpl, and any station that sets its price at or above 93 cpl on day 1 is classified as participating in the restoration. Suppose instead on days 0, 1, 2, 3 the median price is 90 cpl, 91.5 cpl, 92 cpl and 91 cpl. In this case, the price restoration event lasts for two days (days 1 and 2), the restoration price is 92 cpl, and any station that sets its price at or above 92 cpl on either day 1 or day 2 is classified as participating in the restoration. Our results are unchanged if we define the restoration price as the minimum daily median price within a two-day restoration period.

[15]Denoting this difference as a margin is a slight abuse of language since we do not observe individual stations' rack price, only the average rack price of independents (as reported by MJ Ervin), implying we cannot compute the true median margin.

[16]The results throughout the paper are unchanged under alternative cut-off rules based on 1 cpl, 2 cpl, and 2.5 cpl. We have also confirmed our results hold under all combinations of these price restoration cut-off rules, and alternative classifications of cycling markets based on median daily price change cut-off levels of -0.025 cpl and -0.075 cpl. All of these results are available upon request.

markets. Across all cycles and markets, the average restoration price jump is 5.51 cpl (s.d. = 2.38), while the average cycle duration 8.97 days (s.d. = 5.71). Brockville has the highest average restoration price jump of 8.71 cpl across the cycling cities. The average cycle duration ranges from 5.31 days in Thunder Bay to 14.88 days in Renfrew. Restorations largely occur during the middle part of the week: across all restorations and markets, 547 (70%) of our restorations occur on a Tuesday, Wednesday, or Thursday.

In Table 2 we summarize how the level and dispersion of retail prices varies over the cycle. The top panel reports sample averages for the difference between stations' daily prices and the last restoration price within their market. For example, the first entry in the second column says that on average across all stations and markets, the price cut one day after the start of the restoration is 0.591 cpl below the previous restoration price. Looking down the column, we see the magnitude of the average price cut continually grows over the undercutting phase, rising to 2.786 cpl by day seven of the cycle.

In the third and fourth columns we report analogous sample averages for branded and independent stations. Comparing the columns, we see that independents are statistically significantly more aggressive in undercutting, and that their prices tend to fall faster than those of branded stations over the undercutting phase.

Columns six and seven provide further preliminary evidence of heterogeneity in price undercutting intensity, this time among independent stations only. We classify two types of independents, "large" and "small", where an independent retailer is classified as large if it has 20 or more stations across the province. These include larger retailers such as Pioneer and Ultramar who have a relatively large number of stations in various markets across the province.[17] The difference in the average price cuts among large and small independents is statistically insignificant for days one to four of the cycle, implying that all independents tend to immediately undercut restoration prices in a similar manner. However, from days five through seven of the cycle, large independents start to exhibit relatively larger price cuts. This difference may reflect larger independents' ability to obtain lower wholesale fuel costs through bulk purchasing discounts, which allows them to establish themselves as lower-priced competitors relative to their small independent counterparts (which are often locally-owned service stations).

The bottom panel of Table 2 reports the average daily inter-quartile range by day of the cycle across

[17] Pioneer and Ultramar respectively have 125 and 68 stations across 67 and 50 markets in our sample. In percentage terms, 4.6% and 2.5% of all stations operate under the Pioneer or Ultramar name. To put this perspective, three-quarters of all independent operators have 2 or less stations in total.

all the cycling markets.[18] The main take-away from the panel is that retail price dispersion for all station-types is relatively high one day after a restoration starts, immediately drops on days two and three of the cycle, and then gradually rises as the undercutting phase ensues. That is, restorations appear to coordinate market prices, and then dispersion rises as stations engage in price undercutting. Lewis (2012) finds similar patterns in price dispersion over the cycle in cycling markets across the U.S. Midwest.

A secondary finding from the second and third columns is that price dispersion tends to be higher among branded stations than independents. Thus, independents' aggressiveness in undercutting prices appears to result in relatively lower price dispersion across their stations.

3.3 Initiating restorations

To investigate firm-specific differences in price leadership in initiating restorations, we estimate the following linear-in-probability model:

$$1\{\text{Stn}_i \text{ participates in Rest}_\tau\}_i = \beta_{0\tau} + \sum_{j=1}^{J} \beta_{1j} 1\{\text{Firm}_{ij}\} + \epsilon_{i\tau} \quad (1)$$

where $1\{\text{Stn}_i \text{ participates in Rest}_\tau\}_i$ is an indicator function equalling 1 if station i participates in restoration τ, $\beta_{0\tau}$ is a restoration τ fixed effect, and $1\{\text{Firm}_{ij}\}$ is an indicator function equalling 1 if station i is run by gasoline company j. We include firm-specific indicator variables for each of the four brands and seven independents that have sufficiently many stations across markets to estimate a firm-specific effect (Canadian Tire, Ultramar, Pioneer, Olco, 7-Eleven, MacEwen, Mac's). The remaining stations correspond to other independent firms in the sample, which serve as our baseline group. The inclusion of restoration-specific intercepts implies that we identify the coefficients of interest, $\beta_{1j} \ldots \beta_{iJ}$, off of within-restoration variation in firms' restoration participation rates. Thus, our estimates are robust to time and market-specific unobserved heterogeneity in restoration participation rates.

The estimation results in Table 3 indicate that major brands actively participate in initiating restorations, while independents do not. We present results for three separate cut-off rules for daily price changes of 1.5, 2, and 2.5 cpl for defining restorations events. All three columns yield similar results which indicates our results are robust to the chosen cut-off rule. Focusing on the results from the 1.5 cpl cut-off, we see that if a station operates under a Esso, Shell, Petro-Canada, or Sunoco brand name, then

[18] We report the inter-quartile range instead of standard deviation or sample range because it is the main dispersion measure used in the econometric analysis in Section 4 below.

its restoration participation rate rises by 29%, 26%, 33% and 21%. This marginal effect is large relative to the baseline station-level restoration participation rate of 30.8%. We similarly find that stations run by Canadian Tire, one of Canada's largest retailers, also exhibit significantly higher restoration participation rates.

In contrast, the independent stations are not significantly more likely to participate in restorations (Ultramar, Olco, 7-Eleven), or are significantly less likely to participate (Pioneer, MacEwan, Mac's). Overall, these results are consistent with our hypothesis that brands take on a leadership role in coordinating market prices during restorations.

3.4 Undercutting intensity

We now study firm-specific differences in undercutting intensity over the cycle. Such differences in pricing behavior potentially contribute to the rise in price dispersion over the undercutting phase that we documented in Table 2. The analysis is based on the following regression equation:

$$\text{PriceDiff}_{it\tau} = \beta_0^{t-\tau} + \sum_{j=1}^{J} \beta_{1j}^{t-\tau} 1\{\text{Firm}_{ij}\} + \epsilon_{it}; \quad \tau < t < \tau + 1 \tag{2}$$

where the dependent variable, $\text{PriceDiff}_{it\tau}$, is the difference between station i's price on date t and the last restoration price observed on date $\tau < t$: $\text{PriceDiff}_{it\tau} = \text{Price}_{it} - \text{RestPrice}_{\tau}$. As before, $1\{\text{Firm}_{ij}\}$ is an indicator function equalling 1 if station i is operated by firm j. Thus, $\beta_{1j}^{t-\tau}$ is an estimate of how much firm j–run stations undercut the last restoration price on average across cycling cities $t-\tau$ days following a restoration.

Our estimates, which are presented in Table 4, highlight important differences in the undercutting aggressiveness of brands and independents. In short, we find that independents are aggressive in undercutting prices while brands are not. For example, the Table's Day 1 column indicates that Esso, Petro-Canada, and Sunoco stations have 0.69, 0.64, and 0.34 cpl *higher* gasoline prices relative to the baseline 1.34 cpl price cut one-day after a restoration event. Meanwhile, independent stations run by Ultramar, Pioneer, MacEwen, and Mac's immediately undercut the last restoration price by an additional 0.76, 0.44, 0.40, and 1.27 cpl beyond the baseline 1.34 cpl Day 1 price cut.

Looking across the Day 2 through Day 7 columns, we see that the coefficients for the four brands are statistically insignificant. This implies branded stations do not aggressively undercut market prices over days 2 through 7 of the undercutting phase. In contrast, most of the coefficients for Ultramar, Pioneer, and MacEwen are negative and statistically significant, implying these firms are aggressive in undercutting prices. The magnitude of the coefficients for these independents rises between the Day 2 and Day 7 columns, indicating these firms become increasingly aggressive in undercutting market prices. Collectively, these increasing differences in undercutting aggressiveness between independents and brands by cycle day partly explain why we see rising price dispersion over the undercutting phase of the cycle.

Overall, the results show larger independents like Ultramar and Pioneer are particularly aggressive in undercutting in Ontario. In particular, we have jointly tested the equality of the seven coefficients across firms and rejected the null at the 5% level when comparing Ultramar or Pioneer to each of the other independents. Again, as relatively large independents, Ultramar's and Pioneer's ability to obtain lower wholesale fuel costs potentially explains their ability to establish themselves the lowest-price competitors. Indeed, Ultramar explicitly states this intention through its national "Low Price Guarantee" policy for matching the lowest price in a market at a point in time. For Pioneer, the results reflect findings from previous studies (Atkinson, 2009; Eckert and West, 2004) who similarly find its stations to be particularly aggressive in price setting.

3.5 Caveats

The price leadership and undercutting results correspond to previous findings from individual gasoline markets in Canada (Atkinson, 2009) and Australia (Wang, 2009), as well as multi-market studies from the U.S. and Norway (Lewis, 2012; Foros and Steen, 2013). This gives us confidence in claiming that we have identified firm-specific differences in brands' and independents' pricing behavior. Nevertheless, given potential selection biases in our GasBuddy data at the station-level (Atkinson, 2008), we raise caution over the interpretation of the magnitude of our estimates.

To the extent that GasBuddy price spotters are more likely to report branded stations' prices during restorations over independents' prices, our estimated restoration participation rates among brands will be biased upward.[19] Under this sample selectivity, stations run by brands will have too large an influence in determining the daily median price relative to a random sample of stations' prices for a given market-date. As a result, we will be more likely to observe instances where the prices of branded stations are set at or above the median price during restoration periods. This implies brands will be classified as

[19] Price spotters could over-sample branded prices either because of pure branding effects/biases, or because branded stations are more likely to be located in high traffic areas while independents are located low traffic areas.

restoration participants too often compared to a random sampling approach.

It is less clear how sample selection affects the magnitude of our price undercutting findings. It is unclear the extent to which GasBuddy spotters over- or under-sample stations' prices that are above or below the city-wide average price; one could make a case for either. To the extent that brands (independents) truly undercut market level average retail prices, over-sampling of higher prices set by branded stations would tend to push up (down) the magnitude of brands' (independents') undercutting estimates in equation 2. Over-sampling independents' lower prices would tend to push down (up) independents' (brands') undercutting estimates.

3.6 Is the pricing behavior competitive or collusive?

While the main objective of the above empirical analysis is simply to provide context for our examination of demand responses to price cycles, we briefly stop here to consider what mechanisms could underly the observed pricing patterns. Numerous studies have put forth a competitive explanation for price cycles, namely that they correspond to the Edgeworth Cycle equilibrium from the Maskin and Tirole (1988) duopoly model (Eckert, 2013). The association was first made by Castanias and Johnson (1993), who noted the remarkable similarity between the cycling behavior seen in the data and that predicted by the model.

An important set of theoretical results for this explanation comes from Noel (2008), who considers various extensions of the model. In one extension he allows for triopoly, and shows restoration failures can occur in equilibrium where one firm attempts to initiate a restoration, but the other two fail to follow. Such restoration failures provide a theoretical basis for the desire to have a market leader to co-ordinate market prices during restorations, which we might expect to be major brands who can readily do so with their large networks of stations.

The role of independents as aggressive undercutting players is predicted through another extension of the model by Eckert (2003). He introduces firm size asymmetry into the model, and shows that if the asymmetry (and hence the business stealing incentives) between the two firms is sufficiently large, then the Markov Perfect strategies in the Edgeworth Cycle equilibrium sees the smaller "independent" firm aggressively cut prices in each period during the undercutting phase. In contrast, the larger "branded" firm is non-aggressive in undercutting and simply matches the price cuts of the small firm period-by-period.

An alternative interpretation of price cycles is that they arise from collusion. Given restoration events often occur independently of daily wholesale price movements and involve a large degree of price leadership and coordination (as we have documented), it is natural to suspect some form of tacit or even explicit collusion is present in cycling markets. Competitive theories of the cycle are less useful for predicting these empirical patterns. While the Maskin and Tirole (1988) model can be use to motivate the need for price leadership to avoid restoration failures, it does not yield predictions over whether a particular firm will consistently take on a leadership role during restorations, nor which firm it will be. Moreover, as Foros and Steen (2013) note, the model says nothing about why price restorations tend to occur on particular days of the week, such as Mondays in their sample, or the middle of the week in ours.

Recent events from Canada provide direct evidence of collusion in cycling markets. In an on-going investigation, Canada's Competition Bureau has uncovered cartels in cycling markets across Ontario and Quebec. In fact, operators of stations in two of the cycling markets in our sample (Kingston and Brockville) have plead guilty to price fixing from May to November 2007, which falls within our sample period.[20] Based on this evidence alone we cannot rule out a collusive explanation for price cycles in our context.

The Bureau also uncovered cartels in cycling retail gasoline markets across Quebec through its investigation. As Clark and Houde (2012a) and (2012b) document, the collusive arrangement saw market leaders explicitly communicate with their rivals to determine the order in which stations would raise their prices to initiate restorations, and cut prices during the undercutting phase.[21] Against this backdrop, the authors offer a novel collusive interpretation of the cycle: by systematically varying the timing of price increases and decreases among stations over the cycle, (heterogenous) cartel members effectively can make inter-temporal market share transfers to sustain collusion.[22]

Our empirical results do not lend themselves to making a definitive statement about whether the cycling markets in our sample strictly reflect competitive or collusive behavior.[23] Regardless of the supply-

[20]The cartels involved Pioneer, Canadian Tire, and Mr. Gas stations. In total, these companies were respectively fined $985,000, $900,000, and $150,000 for their anti-competitive conduct. For additional details, see http://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/03447.html (accessed July 7, 2013)

[21]Wang (2008) similarly provides evidence from a price fixing case from the cycling gasoline market of Ballarat, Australia. He documents how retailers explicitly coordinated on the timing of restoration price increases to shorten the length of time spent at the bottom of the cycle.

[22]Slade (1987) and (1992) offers a slightly different collusive interpretation. She links price cycles in Vancouver's retail gasoline market to tacitly collusive behavior, where unanticipated demand shocks infrequently result in price wars that resemble post-restoration undercutting behavior. Wang (2009) also offers a tacit collusion-based interpretation of price restorations in Perth, Australia's cycling gasoline market.

[23]That is, we stop short of attempting to detect collusion in cycling gasoline markets empirically. Such an ambitious task is

side pricing mechanism, the degree to which consumers respond to daily movements in price levels and dispersion induced by firms' pricing behavior is an important piece of the puzzle for interpreting such conduct, and predicting any welfare effects of anti-competitive behavior. We now turn to these important, yet less understood demand-side issues.

4 Consumer demand responses to price cycles

In this section we investigate how consumers respond to price cycles. We first describe our measures of demand-side responsiveness and price dispersion used in the empirical analysis. With these measures, we then estimate econometric models that characterize how consumers respond to changes in price levels and dispersion over the cycle.

4.1 Measuring demand responsiveness and price dispersion

Demand responsiveness

Given price restorations and undercutting continually occur at daily frequencies, an analysis of demand-side responses to price cycles should ideally be based on daily station- or market-level data on prices and volumes of gasoline sold. Unfortunately, like almost all other researchers (except Lewis, Levin, and Wolak, 2012), we do not have high-frequency data on volumes sold.

In light of these data limitations, we construct a high-frequency measure of consumer responsiveness to daily price changes based on Internet usage data from GasBuddy's websites. In particular, we exploit the fact that our GasBuddy data contain the universe of price reports submitted to the company's websites for the cycling markets in our sample.[24] This allows us to tabulate the number of GasBuddy price reports for each day and market in the sample. Our measure of consumer responsiveness, Report_{mt}, is the number of GasBuddy price reports in market m on date t.

The main benefit of this responsiveness measure is that we can match it to daily average prices for a given market. By examining market-level demand responses and retail prices, we can directly study how consumers respond to daily fluctuations in market-level prices and price dispersion around restorations and the undercutting phase of the cycle. Fundamentally, this analysis assumes that price spotters obtain station-level price observations from their local markets and upload it to one of GasBuddy's websites. This assumption is empirically supported by Byrne and Leslie (2013) and Atkinson (2008) who show that

well-beyond the scope of this paper, and is clearly an important area for future research.

[24] Unfortunately, we do not have information on the identity of individual price spotters in these markets.

daily GasBuddy price data correspond to independently-collected price data across markets in Ontario. That is, price spotters appear to report actual prices from stations in their local markets.

The selectivity of consumers who report prices to GasBuddy is the main drawback of the Report_{mt} measure. This limits the interpretation of our results as strictly corresponding to this group of particularly attentive consumers who actively spot prices in their local markets and report them online. Ideally, we would like to have market-level Internet traffic statistics for GasBuddy's websites from all people looking for information on a given market's prices (which would include both price spotters and non price spotters). Such disaggregated web-use data are, however, unavailable.

It is useful to highlight some summary statistics for Report_{mt} to provide a sense of how many price reports GasBuddy's websites receive for a typical market and day. The sample average of Report_{mt} is 39 (s.d. = 52). Our cycling markets have at least one report for 321 out of a possible of 378 days on average; more than half of the markets have a positive number of reports for 360 days or more.[25]

Price dispersion

We considered three different measures of price dispersion for our analysis: range, inter-quartile range (IQR), and standard deviation. Given our demand response measure is a function of the number of price reports (or observations) for a given day and market, a natural concern is that our measures of demand responsiveness and price dispersion may be correlated by construction. For example, the expected price range of a random sample will increase with the number of observations since there is a higher probability of obtaining extreme price observations in larger samples. Days with only one price report are problematic since they entail the smallest values for both reports and dispersion. Thus, the correlation between these price dispersion measures and our demand response measure will be higher by construction for days with few price observations.

In Appendix A we investigate how these dispersion measures vary with sample size. We run Monte Carlo simulations where we: (1) simulate datasets that reflect the market- and date-specific sample sizes and price distributions observed in the data; and (2) compute the three dispersion measures with the simulated data and see how they vary with sample size. As expected, the results show a positive relationship between price range and sample size. For small sample sizes of seven or less, there is a similar

[25] On days where $\text{Report}_{mt} = 0$, we cannot construct a daily average retail price for a market. As a robustness check on whether having markets in the sample with many zero-reporting days in our sample affects our results, we have replicated our findings using a sub-sample of 21 (out of 33) markets that have at least one report for 340 (90%) of the 378 days in the sample. The estimates are nearly identical to what we report below.

positive relationship between sample size and the IQR and standard deviation. Beyond these small samples, however, the expected values of these latter dispersion measures are uncorrelated with sample size.

Given these findings, we conduct our analysis based on samples where each market-date is restricted to have eight or more price reports. As a robustness check, we also present estimates based on a cut-off of 12 price reports (which cuts our sample-size down by a third). If a spurious positive relationship between sample size and dispersion is driving our results, then there should be a larger positive relationship between our demand responsiveness and dispersion measures in the less restricted sample. Our main results are based on the IQR measure of price dispersion.[26]

Nevertheless, these sample restrictions do limit the scope of our analysis. For instance, there may be some selection bias in our results relative to what we might find if we had a random sample of price reporting intensity that included days with less than eight reports, and an unbiased estimate price dispersion at the market-date level for these days.[27] Further, we cannot examine any decisions on the extensive margin, such as whether a day has zero or a positive number of price reports. Again, this is because we cannot obtain unbiased estimates of price dispersion on days with few price reports, and because we cannot estimate price levels or dispersion on days with zero price reports as we have no price data on these days. For the reasons, we cannot use Tobit models to correct for sample selectivity in the following regression analyses. We can, however, investigate the impact that truncating Report_{mt} at eight has on our results using truncated regression models.

4.2 Consumer demand responses over the cycle

Figure 3 provides some preliminary evidence on the relationship between our demand responsiveness measure, price dispersion, and restoration events. The figure's left and right panels plot the sample averages and their 95% confidence intervals for Report_{mt} and the inter-quartile range of prices across stations by day of the cycle. The left panel shows price reporting intensity is higher just before and during restoration events, and immediately falls following a restoration. The right panel highlights a similar pattern of rising then falling price dispersion around price restoration events. This reflects our discussion from Section 3 that market-wide price restorations typically happen over one or two days. During

[26] In Appendix A, we present results based alternative price dispersion measures (standard deviation, range), and for various alternative cut-off values/sample restrictions. The findings highlight how using the range as a price dispersion measure generates upward bias in our OLS estimate of the relationship between price dispersion and price reporting. In contrast, results based on the IQR (our main results) and standard deviation (in Appendix A) do not exhibit such biases for sufficiently large sample cut-off values.

[27] A priori, the direction of the bias is unclear given the potential demand-side mechanisms that we posit below.

this time, dispersion can experience a drastic jump if price-leading branded stations set a new restoration price while independents' prices are still at the bottom of the cycle.[28]

Our empirical analysis focuses on two non-mutually exclusive demand-side mechanisms that could potentially generate these patterns. The first is that forward-looking consumers strategically time their purchases at the bottom of the cycle just prior to restoration price jumps. To the extent that GasBuddy price reporting reflects the number of price sensitive consumers in a market day-to-day, such stockpiling incentives would result in higher price reporting around restorations. Such an explanation is quite plausible given that: (1) gasoline is a storable good that consumers manage inventories of in their cars' gas tanks; and (2) consumers can anticipate restorations since they regularly occur on a weekly or bi-weekly basis, with a disproportionate amount occurring during the middle part of the week.[29]

A second potential explanation, which has received considerable attention in the literature, is that consumers engage in search behavior.[30] A standard prediction from theories of costly search is that holding search costs fixed, a rise in price dispersion should be accompanied by an increase in search intensity since the marginal benefit from searching is larger with higher price dispersion (see Section 2 of Baye, Morgan, and Scholten, 2006). If GasBuddy's price spotters act according to these incentives in sampling prices from their local markets and reporting them online, then a search-based explanation of the patterns in Figure 3 is also plausible.

[28]On average, the price differential from the bottom of the cycle to the next restoration price is five to six cpl, or six to seven percent of the average after-tax retail price of 81.4 cpl.

[29]Using extracts from recorded conversations among explicitly colluding retailers in cycling gasoline markets in Quebec, Clark and Houde (2012a) document that cartel members frequently note that line-ups emerge at low-price stations around price restoration periods. In interpreting these conversations, the authors similarly point out the predictability of price restorations periods, and that restorations generate a significant amount of retail price dispersion. The authors further estimate that such anticipatory stockpiling behavior by consumers ultimately results in large short-run price elasticities of -30.

[30]Numerous studies have concluded that search behavior is an important feature of retail gasoline markets on the basis that search theories can be used to explain: (1) observed price dispersion across stations; and (2) asymmetric responses of retail price changes to wholesale cost shocks (i.e., "rockets and feathers" pricing). See Eckert (2013) for an overview of these studies.

Econometric model

We begin our formal investigation into the roles of stockpiling and search-based incentives in price reporting by estimating the following regression model:

$$\begin{aligned}\ln(\text{Report}_{mt}) = \alpha_0 + \sum_{\tau=-3}^{3} \alpha_{1\tau} d_{m\tau} + \alpha_2 \text{IQR}_{mt} + \alpha_3 \text{CycleDay}_{mt} + \alpha_4 \text{LagCycleLength}_{mt} \\ + \sum_{k=t}^{t-7} \alpha_{5k}^{+} 1\{\Delta p_{mt} > 0\} \cdot \Delta p_{mk} + \sum_{k=t}^{t-7} \alpha_{5k}^{-} 1\{\Delta p_{mt} \leq 0\} \cdot \Delta p_{mk} + \mathbf{X}_{mt}\beta \\ + \mu_{dow,m} + \mu_w + \mu_h + \epsilon_{mt} \qquad (3)\end{aligned}$$

where we use the natural log of Report_{mt} as the dependent variable because the distribution of Report_{mt} is right-skewed. The first covariate, $d_{m\tau}$, is an indicator variable that equals one if date t is τ days away from the start of a restoration in market m.[31] Thus, the $\alpha_{1\tau}$ coefficients allow us to establish whether there is a jump in reporting intensity around restorations like we saw in Figure 3, after controlling for other factors that may simultaneously predicted price reporting such as day-of-the-week effects, holidays, or the weather.[32]

IQR_{mt} is our price dispersion measure, the inter-quartile range of station-level prices in market m on date t. If price reporting corresponds to search behavior, then it is natural to interpret an $\alpha_2 > 0$ estimate as corresponding to the benchmark theoretical prediction that search intensity is higher when prices are more disperse. Forward-looking consumers with stockpiling incentives could, however, form expectations based on observed price dispersion in their local markets, since this tends to indicate that a price restoration is about to happen. Given this, one cannot simply attribute the α_2 estimate as strictly being driven by search behavior. Regardless of its interpretation, the α_2 estimate will, at the very least, provide evidence of whether gasoline consumers respond to daily changes in price dispersion. Such a direct, market-level examination of this relationship is, to our knowledge, novel, at least in the context of gasoline markets, if not more broadly.

[31] Date t is classified as a $\tau = 0$ day if its day zero of a cycle, where market-wide price restorations are initiated. Recall from Section 3.1 that day zero of a cycle is the first day of a restoration period where the daily change in the median price is greater than the 1.5 cpl cut-off. Days where $\tau = -3$ are those are three-days before a restoration is initiated, $\tau = 2$ is two days after a restoration is initiated, and so on.

[32] A secondary issue with these indicator variables is that a handful dates in the sample have two $d_{m\tau}$ dummies equal to one. For example, some days are both three days after the last restoration ($d_{m,-3} = 1$) and three days before the next restoration ($d_{m,3} = 1$). To ensure our $\alpha_{1\tau}$ coefficients estimates correspond to dates that fall strictly on one of the seven days within the restoration event window, we include fixed effects in all regressions for all ($d_{m,\tau} = 1, d_{m,\tau'} = 1$) pairs where $\tau \neq \tau'$. None of our main results hinge on the inclusion of these fixed effects.

The next two variables are intended to further account for stockpiling incentives. CycleDay_{mt} is the current day of the cycle, or alternatively, how far market m is currently into a price cycle on date t. We expect $\alpha_3 > 0$ because the longer a current cycle has gone on, the more likely the next restoration event is to occur, which would cause shopping/price responsiveness to rise. The second variable, $\text{LagCycleLength}_{mt}$, is the length of the most recent cycle observed within a market. If forward-looking consumers form expectations about the length of price cycles based on the length of recent cycles, then we might expect $\alpha_4 > 0$. This is because longer price cycles tend to have flatter undercutting phases, and hence longer periods of slightly higher prices following a restoration. Consumers' stockpiling incentives (and thus price reporting intensity) may therefore be higher for larger values $\text{LagCycleLength}_{mt}$.[33]

We also allow contemporaneous and seven lagged retail price changes to affect current price reporting intensity.[34] We denote $\Delta p_{mt} = p_{mt} - p_{mt-1}$ as the difference in market m's average retail price between dates t and $t-1$, and $1\{\Delta p_{mt} > 0\}$ is an indicator variable that equals one if $\Delta p_{mt} > 0$ and zero otherwise (and similar for $1\{\Delta p_{mt} \leq 0\}$. The + and − superscripts on the α_{5k}'s indicate that we allow for price reporting to respond asymmetrically to positive and negative retail price changes. This specification choice is largely motivated by previous studies that develop theories of asymmetric search behavior to explain the presence of asymmetric retail price responses to wholesale cost changes.[35]

Dynamic demand considerations also motivate the inclusion of lagged positive and negative price changes in the model since forward-looking consumers could form expectations on the timing or likelihood of price restorations based on recent price changes. For example, market-wide average price cuts tend to be largest immediately after restorations, and become progressively smaller as the undercutting phase continues.[36] This implies that, holding price dispersion and other factors fixed, observing particularly small price cuts can signal that a price restoration is likely to soon occur. If GasBuddy's price spotters act on this information in strategically timing their fuel purchases, then we might expect smaller price cuts around restorations to be associated higher price reporting.

[33]We have experimented with various definitions of $\text{LagCycleLength}_{mt}$, such as the mean cycle length of the last 2, 3, or 4 cycles. All of these slight variations on our specification yield similar results to what we report below.

[34]We find the inclusion of higher order lags up to 21 days have little impact on our findings.

[35]See, for instance, Yang and Ye (2008), Tappata (2009), Lewis (2011), and Cabral and Fishman (2012). Indeed, Byrne and Leslie (2013) find evidence of asymmetric price adjustment in the sample's cycling markets. However, an asymmetric search story is not necessary to explain these pricing phenomena in cycling markets. As Eckert (2002) shows, the Maskin and Tirole (1988) model can also predict asymmetric price adjustment between the restoration and undercutting phases of the cycle.

[36]This can be seen in Table 2 by comparing the change in the average price cuts between cycle days 1 and 2, 2 and 3, and so on. Visual inspection of the example price cycles from Kingston in Figure 1 (as well as from other cycling markets) also show that the slope of the undercutting phase is steep immediately after price restorations, and flattens prior to the next restoration.

The remaining right-hand side variables control for a number factors that could simultaneously explain variation in price reporting over time and across markets. The $\mathbf{X}_{mt}$ vector consists of additional controls. These include weather-related variables including the maximum and minimum temperatures, as well as the total rainfall and snowfall amounts in market m on date t.[37] We also include two dummy variables that equal one if total rainfall and snowfall equals 0. In some specifications, we include three lagged values of the dependent variable to control for autocorrelation in reporting intensity.[38] In a dynamic demand environment this is a potentially important control if market demand for gasoline accumulates over time prior to a restoration.[39]

The $\mu_{dow,m}$, μ_w and μ_h coefficients are market m-specific fixed effects for day-of-the-week dow, week of the year w, and whether date t is a holiday h. Collectively these fixed effects attempt to hold fixed day- and market-specific costs to price reporting that affect the propensity of GasBuddy's price spotters to sample and upload prices from their local market to one of GasBuddy's websites. Such unobserved heterogeneity might include a market having a particularly active price spotter, or market-specific day-of-the-week effects in price reporting arising from differences in weekly commuting patterns across markets. To allow for persistence in the ϵ_{mt} shocks, we cluster our standard errors at the market level.[40]

Supply-side simultaneity

Gasoline stations' optimal pricing decisions, which depend on the degree of consumer price sensitivity (and hence price reporting) within their market day-to-day, are an important source of simultaneity that potentially undermines any casual interpretation of OLS coefficient estimates from equation (3). For example, the timing of price restorations may depend on the fraction of consumers engaged in strategic stockpiling behavior on a given date. If few consumers are currently actively shopping for gasoline, then firms may choose to coordinate a price restoration which simultaneously affects price levels and dispersion. Moreover, if firms are forward-looking in making their pricing decisions (which they would be in a dynamic demand environment), then dynamic supply-side pricing decisions could also create

[37]We obtain these market- and date-specific weather variables by first matching each market in our sample to their nearest weather station. The location of these weather stations, as well as the weather data they record, is freely available from Environment Canada's National Climate Data and Information Archive online at `http://climate.weatheroffice.gc.ca`.

[38]The results are robust to the inclusion of various lag structures.

[39]If we think of the undercutting phase of the cycle as a "sale", then we may expect gasoline demand to accumulate (for example, as in Hendel and Nevo, 2006b) until a price restoration (which is the like an "anti-sale") occurs.

[40]We have also confirmed that the residuals from our estimated models in the section are white noise. Thus, the various fixed effects, as well as the other covariates based on price changes, cycle location, price dispersion, and weather account for any persistence in prices over time.

correlation between lagged price changes and current levels of demand responsiveness.

Simultaneity bias can also arise from search behavior. As consumers become more informed about the price distribution by searching for a reporting prices, competition among stations is heightened, which can result in lower market-level price dispersion (Sorensen, 2000, Section 2). In a dynamic setting, we can similarly expect supply-side pricing behavior to affect the correlation in price reporting and price levels and dispersion over time (see, for example, Chandra and Tappata, 2011).

Regardless of the supply-side mechanism, these dynamic pricing incentives suggest that almost all the variables on the right-hand side of equation (3) are potentially endogenous. Thus, if we were, for example, to pursue an IV identification strategy, we would need implausibly many instruments to identify causal effects of changes in price levels or dispersion on price reporting. For these reasons, we focus on the OLS estimates, and discuss the potential roles of demand- and supply-side forces play generating our results.

As a robustness check, we report a set of IV coefficient estimates where we instrument for contemporaneous positive and negative price changes; at the very least, these variables would be endogenous regardless of whether dynamic pricing incentives exist. We follow Lewis and Marvel (2011) and use seven lagged differences in positive and negative rack price changes as instruments. The exclusion restriction is that conditional on retail prices, GasBuddy's price spotters do not use recent changes in rack prices when deciding to sample and report prices from their local market to one of GasBuddy's websites.

Results

The estimation results are presented in Table 5. The column (1) estimates imply daily price reporting increases (approximately) by 6% the day before a restoration is initiated, and by 7% on days when restorations are initiated. Thus, the hump shape in price reporting around restoration events still emerges after controlling for weather and the various fixed effects.

The column (2) results show these coefficient estimates become statistically insignificant once we control for price dispersion, whereas the price dispersion coefficient is significant. Thus, it is not the cycle day itself, but rather the stark rise in price dispersion around restorations that is associated with the rise in reporting behavior. The effect of rising price dispersion is also economically meaningful: all else being equal, a one standard deviation increase in a market's IQR of 2.1 cpl is associated with a 4.1% increase in price reporting intensity. While these coefficient estimates on price dispersion may of interest on their own, recall that from our previous discussion that these positive relationship could stem from dynamic demand- or search-based incentives in price reporting.

The column (3) estimates shows that the inclusion of the additional stockpiling variables in the model have virtually no impact on the price dispersion coefficient estimate. The regression coefficients for these variables have their expected signs, but they are statistically insignificant. Looking ahead however to the column (5) estimates, we see that a significant positive relationship between the length of the most recent cycle and price reporting emerges when lagged price changes and price reporting levels are controlled for; this provides some initial evidence of dynamic demand incentives in price reporting.

The column (4) estimates show the price dispersion coefficient estimate is also robust to controlling for lagged positive and negative price changes. Interestingly, all of the lagged price coefficients are statistically insignificant except for lagged one and two day negative price changes.[41] The estimates imply that higher price reporting intensity is associated with smaller recent price cuts. These results are largely inconsistent with theories of asymmetric search that predict consumers respond more to price increases than decreases; if anything, our estimates indicate the opposite of this. In contrast, this finding is consistent with the hypothesis that consumers stockpile gasoline upon observing increasingly small price cuts at the end of the cycle prior to the next restoration.

The remaining columns (5)-(8) of the table show the price dispersion coefficient estimate is robust to: (1) controlling for lagged reporting intensity; (2) instrumenting for contemporaneous price changes; (3) accounting for truncating the dependent variable at eight reports with a truncated regression model[42]; and (4) using a more restrictive sample in terms of the minimum number of price observations a market-date needs to be included. The significance and magnitude of the coefficients on lagged cycle length and recent negative price changes vary somewhat across these robustness checks.

In the Appendix we report and discuss supplemental findings that further highlight the robustness of our results. In Table A.1 of Appendix A we report analogous estimates to those from Table 5 based on various sample restrictions in terms of the minimum number of station-level price observations for a market-date to be included in the sample. In Table B.1 of Appendix B we estimate models that use alternative dependent variables including Report_{mt} in levels, and Report_{mt} in levels but scaled by the

[41] For the sake of brevity we do not report all the coefficients on the lagged price changes. The other coefficients can be found in column three of Table B.4 in the Appendix.

[42] See, for example, Section 16.2.3 of Cameron and Trivedi (2005) for a discussion of truncated regression models that take a parametric approach to accounting for the truncation of the dependent variable. In our case, the truncation point is at ln(8), which corresponds to our cut-off value of $\text{Report}_{mt} = 8$ for a given market-date to be included in the sample.

average number of reports per day in market m. We also report results based on a Poisson count model that accounts for the discreteness Report_{mt}. We again find our main empirical results emerge under these different model specifications.

4.3 Heterogeneity in demand responses by day of the cycle

The data further permit an investigation into whether changes in price levels and dispersion have a heterogenous relationship with price reporting by day of the cycle. We again focus on a seven day window around restoration events, and estimate separate regression models for each day within this window.[43] The models are analogous to that described in equation (3), except we drop the d_{mt} cycle-day indicator variables. We report OLS estimates that are based on specifications that include lagged reporting levels in the set of controls.

The estimation results, which are reported in Table 6, yield a number of additional insights. The first is that price dispersion has a heterogenous relationship with price reporting over the cycle. The day before and day of restorations, a one cpl rise in the inter-quartile range is associated with a 2.0% and 3.4% rise in the number of daily price reports. However, we find no relationship between price reporting and price dispersion the two days following a restoration. Together these results are consistent with demand accumulation and stockpiling story: consumers monitor market-level price dispersion to predict restorations and time their purchases at the bottom of the cycle, and then pay little attention to price dispersion the day after restoration events since their cars' gasoline tanks are filled.

Interestingly, we find three days after a restoration the dispersion coefficient are again statistically significant. Given price cycles are seven to eight days long on average, it is less likely these estimates reflect anticipatory stockpiling behavior. These estimates are more likely to reflect search-based behavior in price reporting during the initial parts of the cycle's undercutting phase. However, a search-based theory of price reporting has a more difficult time explaining why there is a significant relationship between dispersion and price reporting on some cycle days (columns $\tau = -1, 0, 3$) and not others (columns $\tau = -3, -2, 3$).

Rows two and three of the table again show the other two stockpiling variables, the length of the current and most recent cycle, generally have mixed and statistically insignificant relationships with price reporting. In contrast, the remaining rows of the table reveal some interesting relationships between

[43] To make the interpretation of the cycle-day specific estimates more transparent, we drop dates where more than one of the $d_{m\tau}$ dummies in equation (3) equal one.

lagged price changes and price reporting. In particular, looking down the $\tau = 0$ column, we see price reporting is 73.1% higher on restoration days when the lagged one day price change is one cpl higher. Working further down the column, we also see that a one cpl *smaller* price cut is associated with a 5.9% *increase* in price reporting. We see this collection of results as being best explained by a stockpiling story where consumers in cycling markets see smaller price cuts and any price increases around restoration periods as signals that market-wide prices are about to drastically rise.

In Tables B.2 and B.3 of Appendix B we reproduce the results from Table 6 except we replace the dependent variable to be Report_{mt} in levels, and Report_{mt} in levels but scaled by the average number of reports per day in market m. These robustness checks highlight similar relationships between price reporting and price dispersion on different cycle days (i.e., the significant results from the $\tau = -1, 0, 3$ columns in Table 6 remain). We also continue to find a robust positive relationship between price reporting and small lagged price cuts on days when restorations are initiated. In contrast, the relationship between price reporting and lagged price increases on restoration days is not robust to using Report_{mt} as the dependent variable.

Supply-side considerations

The above interpretations of our results need to be tempered by considerations of supply-side pricing behavior. Unfortunately, there is little guidance from theory regarding the joint dynamics of demand and pricing in cycling gasoline markets. One possibility is that the estimated positive relationships between price reporting, price dispersion, and price changes prior to and during restorations could capture GasBuddy price spotters being "caught off guard" by firms. If price spotters become inattentive over the undercutting phase, then stations could initiate restoration price jumps to earn higher profits for a day or two until price spotters become informed about the price distribution once again. We find this explanation less compelling than our demand-based interpretations of the OLS estimates, given that the timing and frequency price cycles largely appear to be predictable, non-random, and indeed quite regular.

4.4 Price cycles and demand responses in sticky markets

In this section we provide a further test for stockpiling, this time in the context of sticky markets. Recall from Figure 1 that sticky pricing tends to occur in rural markets such as Kapuskasing. In addition to having prolonged periods of price rigidity, these markets also exhibit restorations and undercutting. Examples of sticky market restoration events can be clearly seen in Figure 1 where prices frequently exhibit two to three cpl discrete price jumps.[44]

There are three reasons why sticky markets are good settings in which to test stockpiling behavior. First, because post-restoration undercutting is much slower in these markets, prices tend to remain higher for a longer period of time following restorations. This implies consumers have a particularly strong incentive to time their purchases and stockpile fuel prior to restoration price jumps. Second, to the extent that price reporting is primarily done by local consumers in these markets, we should expect search-based incentives in price reporting to be minimal.[45] This is because the rural towns in our sample with sticky pricing typically have few (five or less) gasoline stations that are located in close proximity to each other on the town's main street or near its highway exit. Third, the timing of restoration price jumps during the week is also predictable in these markets: 60% of the price jumps that we identify occur between Wednesday and Friday.

Similar to before, our examination of price reporting requires us to first classify which markets exhibit sticky pricing. Our classification scheme takes the set of markets that we classified as non-cycling in Section 2.1, and divides them into cost-based pricing and sticky-pricing markets based on the median of their retail price adjustment ratio:

$$\text{AdjustRatio}_m = \text{median}\Big(\frac{p_{mt} - p_{mt-1}}{w_{mt} - w_{mt-1}}\Big)$$

where recall p_{mt} is the average retail price in market m on date t and w_{mt} is the rack price.[46] Figure 4 presents a histogram of these market-level median adjustment ratios. It highlights a clear dichotomy: non-cycling markets tend to have median adjustment ratios that are either close to zero (sticky pricing) or one (cost-based pricing). Based on this figure, we classify a market as having sticky pricing if $\text{AdjustRatio}_m = 0$.[47] This classification scheme yields 61 sticky markets, or 45% of the total number of markets in the sample. On average, these markets have 4 gasoline stations and a population of 15,000 people. More than three-quarters of these markets have 5 or less stations.

Our analysis proceeds as before by identifying restoration events within our sticky markets. We again

[44] See Byrne and Leslie (2013) for a formal investigation into firms' pricing behavior and margin adjustments in sticky markets.

[45] We suspect a large share of price reports comes from local consumers, however, some fluctuations in a market's day-to-day price reporting levels may be due to highway drivers reporting retail prices at gasoline stations near highway exits.

[46] Clark and Houde (2012b) use a similar calculation to measure market-level responses of retail prices to daily wholesale price changes.

[47] Figure 4 indicates there are some markets with intermediate median adjustment ratios between zero and one. We have experimented with other non-zero thresholds such as 0.4 and 0.6, and obtain very similar results to what we report below.

use a threshold rule to do so: date t experiences a restoration if its median retail price increases by 1 cpl between dates t and $t-1$. The slightly smaller threshold reflects the fact that price jumps in sticky pricing markets tend to smaller than the large (and more frequent) price jumps in cycling markets.[48] Under this classification, we find that on average a sticky market experiences 1.4 restorations per month and restoration price jumps of 3.39 cpl. When compared to the cycle characteristics for the cycling markets in Table 1, these statistics highlight how sticky markets tend to experience relatively slower cycles with smaller price jumps.

With the restoration events in hand, we can examine how price reporting varies prior to and following price jumps in sticky markets. Given search incentives are likely to be minimal in these rural markets, if stockpiling plays no role in price reporting behavior, then we should not see a rise in price reporting around restoration events like we did for cycling markets. Figure 5 shows this is clearly not the case: price reporting in sticky markets experience a stark rise around restorations. As with Figure 3 from before, the figure plots the sample averages and their 95% confidence intervals for Report_{mt} by day of the cycle for market-dates that lie within a seven day window around a restoration event.

To formally test for this jump in price reporting around restorations, we estimate the following regression model:

$$\begin{aligned}\ln(\text{Report}_{mt}) = \alpha_0 &+ \sum_{\tau=-3}^{3} \alpha_{1\tau} d_{m\tau} + \sum_{i=1}^{4} \alpha_{2i} 1\{\text{Nday}_{i-1} \le \text{CycleDay}_{mt} < \text{Nday}_i\} \\ &+ \sum_{i=1}^{4} \alpha_{3i} 1\{\text{Nday}_{i-1} \le \text{LagCycleLength}_{mt} < \text{Nday}_i\} + \sum_{k=t}^{t-7} \alpha_{4k}^{+} 1\{\Delta p_{mt} > 0\} \cdot \Delta p_{mk} \\ &+ \sum_{k=t}^{t-7} \alpha_{4k}^{-} 1\{\Delta p_{mt} \le 0\} \cdot \Delta p_{mk} + \mathbf{X}_{mt}\beta + \mu_{dow,m} + \mu_w + \mu_h + \epsilon_{mt} \qquad (4)\end{aligned}$$

The specification is identical to that from equation (3) except for two key differences. The first is that the right-hand side of the equation does not include a price dispersion variable. Since we typically have a relatively small number of station-level price reports in sticky markets (with many days only having one price report), we cannot reliably measure daily price dispersion at a market-level. In contrast, because there are few stations in these markets that typically set the same prices day-to-day, we can approximate the daily market-wide price level with only a few station-level price observations. Beyond this, with many (79%) sticky markets having five or less geographically proximate stations, we suspect there will be little

[48] We have experimented with this cut-off rule and find little appreciable change in our results.

price dispersion in general. For these reasons, we do not include price dispersion as a covariate.

The other main difference in the specification is our choice of additional stockpiling variables, $1\{d_{i-1} < \text{CycleDay}_{mt} \leq d_i\}$ and $1\{d_{i-1} < \text{LagCycleLength}_{mt} \leq d_i\}$. The prior consists of four indicator variables that respectively equal one if on date t in market m it has been $11-17$, $18-24$, $25-31$, or >31 days since a restoration event has last occurred. The latter contains four indicator variables that respectively equal one if the length of the most recent price cycle in market m prior to date t was $11-17$, $18-24$, $25-31$, or >31 days long.[49] Similar to CycleDay_{mt} and $\text{LagCycleLength}_{mt}$ from equation (3), these two sets of indicator variables are meant to account for any effect that current and lagged cycle lengths have on consumers' expectations over future restoration events and cycle lengths. The main reason we use these indicator variables and not CycleDay_{mt} and $\text{LagCycleLength}_{mt}$ is that price cycles are less frequent and regular in sticky markets, which results in noisy CycleDay_{mt} and $\text{LagCycleLength}_{mt}$ variables.

Columns (1)-(5) in Table 7 reports the resulting OLS coefficient estimates.[50] Column (6) reports results from a truncated regression model that corrects for sample truncation at $\text{Report}_{mt} = 1$.[51] We see that once lagged price changes and reporting levels are accounted for in columns (4)-(6) of the table, we find a statistically significant and large 9-13% rise in price reporting on restoration days. The estimates further show that the somewhat persistent rise in reporting intensity following a restoration depicted in Figure 5 is not present under any specification of the model. In light of our previous discussion, we see these results as additional evidence in favor of a stockpiling explanation for daily changes in price reporting intensity over the cycle.

In Table B.4 of Appendix B we present various robustness checks that use alternative dependent variables (levels of Report_{mt}, levels scaled by market-level means for Report_{mt}) and econometric models (Poisson, Ordered Probit). The estimates across the specifications continue to indicate a jump in price reporting on restoration days, though we lose statistical significance in the regressions where the dependent variable is Report_{mt} in levels and in levels scaled market-level means of Report_{mt}. This partly due to the fact that Report_{mt} is noisier in rural markets; by taking its natural log we mitigate this noise and are able to obtain a better model fit and smaller standard errors in our baseline specification from equation

[49] As before, we measure price cycle length as the number of days between restoration events.

[50] The final estimation sample was based on 46 of 61 sticky markets that had five or more restorations over the year. Markets with fewer than five restorations tended to have many missing daily price observations and were therefore dropped.

[51] We have also attempted to instrument for contemporaneous retail price changes with lagged wholesale price changes; however, we found these instruments to be weak and unreliable. This is perhaps not surprising given the large degree of price rigidity observed in sticky markets at daily frequencies.

(4). This can be seen by comparing the magnitudes of both the standard errors for the restoration day dummy variable (relative to their coefficient estimates), and the R-Squared's across the various models in Table B.4.

5 Summary and discussion

In this paper we have undertaken a novel study of how consumers respond to retail gasoline price cycles. To provide context for the analysis, we first examined firms' pricing behavior in cycling gasoline markets. We found branded retailers exploit their large networks of stations to coordinate large weekly or bi-weekly price jumps/restorations in these markets, and that in doing so create large daily fluctuations in the level and dispersion of retail prices. While these results largely confirm previous findings from the U.S. by Lewis (2011), they do re-affirm his results by providing further evidence of price leadership by dominant retailers in cycling markets from a different time and context.

We then studied how consumers respond to these daily fluctuations price levels and dispersion using a unique market-level measure of daily demand responsiveness. We found demand responsiveness rises around price restoration periods, and, through a series of tests, show that forward-looking stockpiling behavior by consumers likely plays a central role in generating these patterns.

By emphasizing the importance of dynamic demand incentives in retail gasoline purchasing behavior, our study helps motivate pro-competitive policies and technologies like GasBuddy that aim inform the consumers about daily retail price fluctuation to help them make well-timed fuel purchases. Such price transparency policies have been proposed in Canada with Ontario's Gas Price Notices Act (Bill 228, 2007), a law that would require retailers to give 72 hours advanced notice on price increases. The Australian Competition and Consumer Commission (ACCC) has gone a step further, and implemented a national online price reporting system that provides consumers with daily information on prices and the timing of restorations.[52] Given most urban centres in Australia exhibit price cycles, it is perhaps not surprising that the ACCC has been one of the first authorities globally to enact such a policy. These policies can lead to non-negligible cost savings for consumers, and reductions in market power among firms, if they encourage purchasing strategies that see consumers buy fuel at the bottom of the cycle (Noel, 2012).[53]

[52]See `http://www.accc.gov.au/content/index.phtml/itemId/280309` (accessed January 10, 2013) for the url for this online price reporting system.

[53]This conclusion is, at the very least, valid in the short run. A caveat is that price transparency policies may eliminate price

The overall usefulness of price transparency policies, as well as the extent of firms' market power, crucially depends on the degree of (un)informedness among consumers in the population who purchase fuel.[54] While we have established that web-savvy consumers in cycling gasoline markets appear to be forward-looking and exploit web-based price information to time their fuel purchases (which in itself is a finding that supports the provision of online price reporting schemes such as GasBuddy or the ACCC's), we have nothing to say about how relatively uninformed consumers behave (such as the "only-fill-up-the tank-when-empty" consumer types). We also have nothing to say about the relative proportions of informed and uninformed consumers in a market. Survey evidence from the ACCC (2007) suggests that 60% of consumers follow retail prices day-to-day in timing their purchases; however, no formal econometric estimates of this figure exists. We therefore see investigations into the extent of consumer (un)informedness and myopia in gasoline markets and their determinants as being an important area of future research.

cycles altogether. This does not appear to be the case from the Australian experience since price cycles still exist in many cities despite the national price reporting policy. Price cycles continued to exist in Perth even after the introduction of FuelWatch, a policy that requires stations to submit their prices 24 hours in advance of posting them, and that publicly announces these prices to consumers each day.

[54]A related and more broad question for future research is if private companies like GasBuddy have an incentive to provide online price reporting infrastructure, then why should governments get directly involved in providing retail price information online to consumers? Why not develop private-public partnerships in informing the public about gasoline prices?

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Figures

Figure 1: Mean Retail and Rack Prices in Local Retail Gasoline Markets

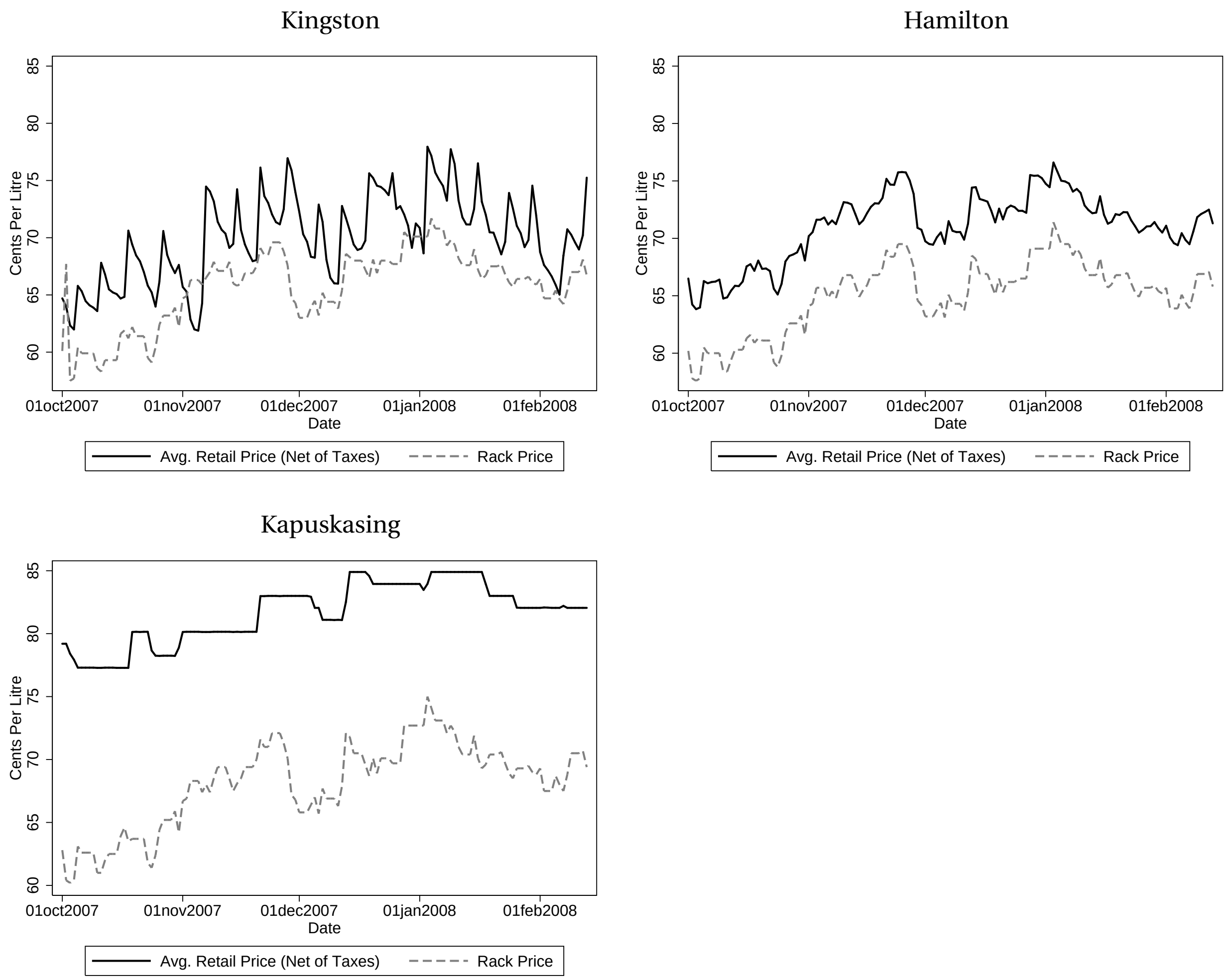


Figure 2: Daily Difference in Median Retail Price and Median Margin in Kingston

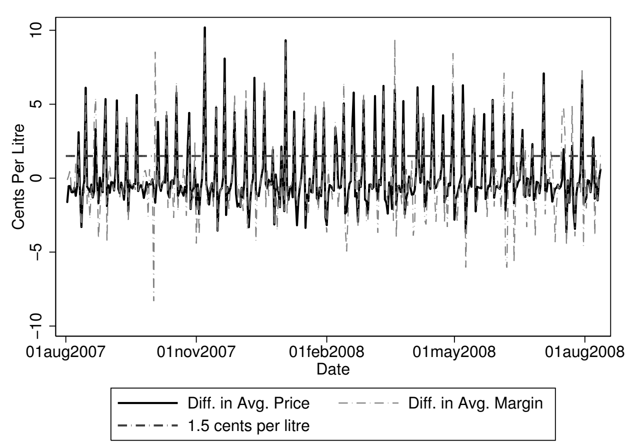


Figure 3: Price Reporting and Pricing Dispersion Around Restoration Price Jumps

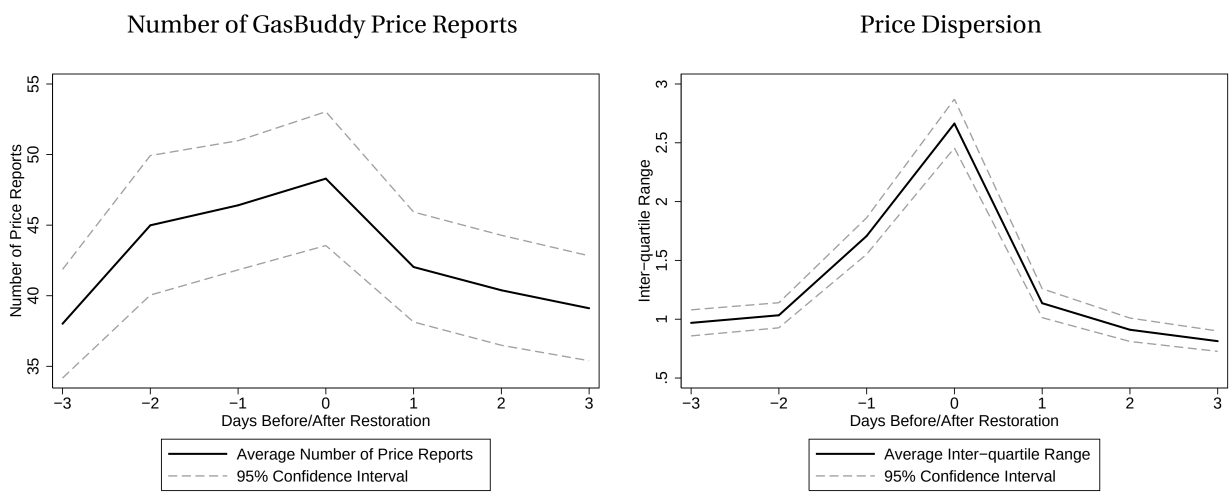


Figure 4: Retail/Wholesale Price Adjustment Ratios for Cost-Based and Sticky Markets

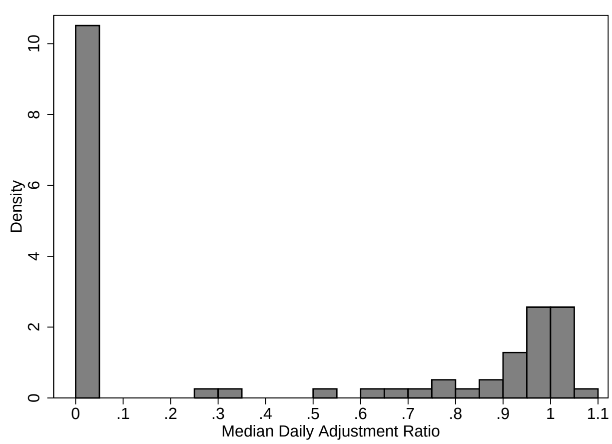
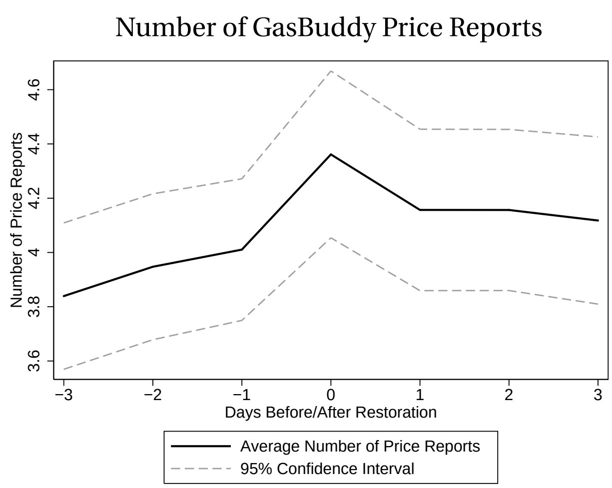


Figure 5: Price Reporting Around Restoration Price Jumps in Sticky Markets



Tables

Table 1: Price Cycle Summary Statistics by Market

Economic Region, City	Population	Station Count	Avg. Restoration Price Jump		Avg. Cycle Duration	
Hamilton-Niagara						
St Catharines	131990	33	3.56	(1.54)	11.44	(6.94)
Niagara Falls	82185	23	3.88	(1.40)	10.27	(5.81)
Welland	50335	16	3.34	(1.36)	13.21	(7.47)
Simcoe	31175	10	4.29	(1.54)	11.00	(6.47)
Kingston-Pembroke						
Kingston	117205	44	6.96	(1.88)	6.46	(1.89)
Belleville	48825	15	5.90	(2.43)	7.47	(3.85)
Trenton	42695	19	4.75	(1.83)	8.58	(5.04)
Brockville	21955	16	8.71	(3.15)	9.14	(5.12)
Napanee	15405	7	7.22	(1.75)	7.63	(4.55)
Gananoque	5285	4	5.99	(2.68)	11.60	(6.84)
London						
St Thomas	36110	14	6.19	(2.09)	11.87	(6.11)
Woodstock	35480	14	3.81	(1.37)	5.91	(3.67)
Muskoka-Kawarthas						
Orillia	30255	25	4.46	(1.88)	7.18	(5.67)
Huntsville	18280	9	5.58	(2.19)	10.21	(7.41)
Northeast						
Sudbury	157855	19	6.38	(2.26)	11.65	(6.54)
North Bay	53970	21	5.92	(2.06)	8.97	(4.39)
Sturgeon Falls	13410	5	5.53	(2.45)	10.77	(4.65)
Val Caron	4036	4	6.51	(2.09)	7.71	(4.61)
Thunder Bay	109140	41	4.93	(2.73)	5.31	(4.33)
Sault Ste Marie	74950	18	4.57	(2.69)	7.31	(6.79)
Ottawa						
Cornwall	45965	21	4.36	(1.50)	10.25	(5.56)
Renfrew	7850	9	5.02	(1.96)	14.88	(9.66)
Prescott	4180	6	7.18	(2.23)	9.00	(4.44)
Stratford-Bruce-Peninsula						
Stratford	30460	10	5.68	(2.35)	9.73	(5.50)
Owen Sound	21745	10	6.17	(2.21)	8.74	(6.25)
Port Elgin	11725	7	4.81	(1.82)	8.70	(5.22)
Meaford	10945	2	4.76	(1.98)	8.50	(5.80)
Hanover	7150	7	5.37	(2.28)	14.25	(10.66)
Windsor-Sarnia						
Windsor	216470	53	5.35	(1.32)	7.20	(3.22)
Chatham	108175	16	6.03	(1.52)	11.27	(6.21)
Wallaceburg	108175	6	5.05	(1.48)	9.00	(5.13)
Sarnia	71420	26	7.89	(2.38)	14.05	(7.27)
Essex	20030	5	4.40	(2.00)	13.09	(7.52)

Notes: Standard deviations are reported in parentheses. These statistics are based on 776 cycles identified by a cut-off rule thats defines restorations as one- or two-day periods where a market's median daily price increases by more than 1.5 cpl. The Economic Region definitions are from Statistics Canada.

Table 2: Level and Variability of Brands' and Independents' Gas Prices over the Price Cycle

Cycle Day	All Stations	Brands	Independents	t-stat for test of $\mu_{Brand} = \mu_{Ind}$	Large Independents	Small Independents	t-stat for test of $\mu_{Large} = \mu_{Small}$
Panel A: Average Price Cut from Last Restoration Price by Day of the Cycle							
1	-0.591	-0.254	-0.877	-11.442**	-0.836	-0.903	-0.912
2	-1.306	-0.952	-1.501	-6.696**	-1.418	-1.460	-0.452
3	-1.750	-1.376	-1.950	-6.132**	-1.898	-1.786	1.119
4	-2.113	-1.763	-2.312	-5.053**	-2.279	-2.105	1.513
5	-2.449	-2.112	-2.659	-4.464**	-2.654	-2.383	2.060*
6	-2.636	-2.202	-2.882	-4.820**	-2.904	-2.534	2.575**
7	-2.786	-2.329	-3.039	-4.313**	-3.060	-2.778	1.619^{+}
Panel B: Average Inter-quartile Range of Prices by Day of the Cycle							
1	1.398	1.097	1.294	2.082*	1.225	0.783	-4.333**
2	1.027	1.059	0.846	-2.801**	0.830	0.592	-3.205**
3	0.864	0.882	0.703	-2.738**	0.627	0.544	-1.261
4	0.837	0.874	0.610	-4.249**	0.579	0.568	-0.172
5	0.920	0.942	0.672	-4.091**	0.608	0.763	1.968*
6	1.021	1.168	0.723	-5.155**	0.682	0.835	1.679^{+}
7	0.947	1.253	0.677	-5.866**	0.636	0.837	1.905^{+}

Notes: The brands are Esso, Shell, Petro-Canada, and Sunoco. All other non-branded gasoline companies are classified as independents. Among the independents, firms with more than 20 stations in Ontario are classified as large independents; independents with less than 20 stations in Ontario are classified as small. See Section 3.1 in the text for cycle day definitions. **, *, + indicate statistical significance at the 1%, 5% and 10% levels.

Table 3: Firm Participation in Restorations

	Cut-off Price Change for Price Restoration		
	1.5 cents/liter	2 cents/liter	2.5 cents/liter
Esso	0.287**	0.296**	0.293**
	(0.041)	(0.039)	(0.040)
Shell	0.256**	0.270**	0.266**
	(0.057)	(0.056)	(0.056)
Petro-Canada	0.335**	0.350**	0.351**
	(0.039)	(0.039)	(0.038)
Sunoco	0.215**	0.240**	0.242**
	(0.048)	(0.047)	(0.045)
Canadian Tire	0.188**	0.196**	0.193**
	(0.051)	(0.050)	(0.049)
Ultramar	-0.069	-0.057	-0.054
	(0.071)	(0.071)	(0.070)
Pioneer	-0.144**	-0.139**	-0.135**
	(0.050)	(0.050)	(0.050)
Olco	0.034	0.064	0.071
	(0.081)	(0.072)	(0.073)
7-Eleven	0.075	0.099	0.122
	(0.104)	(0.098)	(0.097)
MacEwen	-0.095+	-0.096+	-0.098+
	(0.054)	(0.055)	(0.057)
Mac's	-0.252**	-0.213**	-0.199**
	(0.056)	(0.054)	(0.056)
R-Squared (Adj.)	0.168	0.176	0.172
Observations	9309	8719	8341

Notes: The dependent variable is an indicator that equals 1 if a station sets its price at or above its market's median price during a restoration period. Standard errors are reported in parentheses and are clustered at the city-brand level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels.

Table 4: Firm-Specific Price Undercutting Aggressiveness by Day of Cycle

	Days Since Last Restoration						
	Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
Esso	0.687**	0.249	-0.098	0.065	-0.139	-0.137	0.185
	(0.170)	(0.409)	(0.539)	(0.604)	(0.694)	(0.683)	(0.680)
Shell	0.310	-0.054	-0.340	-0.255	-0.308	-0.364	-0.276
	(0.222)	(0.364)	(0.494)	(0.537)	(0.624)	(0.639)	(0.625)
Petro-Canada	0.641**	0.052	-0.245	-0.297	-0.548	-0.454	-0.400
	(0.167)	(0.259)	(0.314)	(0.344)	(0.398)	(0.471)	(0.513)
Sunoco	0.336+	-0.042	-0.307	-0.386	-0.442	-0.467	0.014
	(0.178)	(0.366)	(0.463)	(0.541)	(0.648)	(0.727)	(0.744)
Canadian Tire	0.155	-0.074	-0.368	-0.212	-0.419	-0.447	-0.394
	(0.204)	(0.379)	(0.447)	(0.475)	(0.579)	(0.578)	(0.631)
Ultramar	-0.756**	-1.795**	-2.179**	-2.290**	-2.489**	-2.759**	-2.884**
	(0.176)	(0.418)	(0.530)	(0.566)	(0.620)	(0.704)	(1.091)
Pioneer	-0.441*	-1.102+	-1.419*	-1.447*	-1.722*	-1.654*	-1.578+
	(0.180)	(0.581)	(0.686)	(0.685)	(0.791)	(0.824)	(0.906)
Olco	-0.108	-0.437	-0.644+	-0.485	-0.864	-0.959+	-0.848
	(0.285)	(0.289)	(0.390)	(0.491)	(0.574)	(0.540)	(0.616)
7-Eleven	0.067	0.479**	0.427*	0.354	0.455	0.525	0.793
	(0.166)	(0.154)	(0.194)	(0.395)	(0.383)	(0.524)	(0.494)
MacEwen	-0.398**	-0.633	-0.601*	-0.520+	-0.821+	-0.940+	-1.069+
	(0.138)	(0.386)	(0.273)	(0.287)	(0.452)	(0.491)	(0.573)
Mac's	-1.266**	-0.696	-0.864+	-0.347	-0.346	-0.217	-0.360
	(0.270)	(0.572)	(0.445)	(0.415)	(0.520)	(0.603)	(0.726)
Constant	-1.389**	-1.436**	-1.718**	-2.143**	-2.547**	-2.770**	-3.022**
	(0.130)	(0.133)	(0.142)	(0.153)	(0.210)	(0.226)	(0.231)
R-Squared (Adj.)	0.036	0.077	0.082	0.088	0.086	0.074	0.069
Observations	23375	10059	8944	8603	8624	7640	5778

Notes: The dependent variable is the difference between a station's price and the last restoration price where restorations are identified as days where a market's one- or two-day price difference is more than 1.5 cpl. Standard errors are reported in parentheses and are clustered at the city-brand level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels.

Table 5: Determinants of price reporting over the cycle

	Baseline OLS Estimates					Instrumental Variables	Truncated Regression	Restricted Sample
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
3 days before restoration	0.013	0.010	0.000	0.015	0.014	0.012	0.016	0.024
	(0.028)	(0.028)	(0.027)	(0.039)	(0.035)	(0.034)	(0.037)	(0.042)
2 days before restoration	0.019	0.015	0.011	0.029	0.037	0.034	0.038	0.065^{+}
	(0.028)	(0.028)	(0.028)	(0.038)	(0.034)	(0.031)	(0.035)	(0.037)
1 day before restoration	0.056^{+}	0.036	0.019	0.044	0.046	0.041	0.047	0.046
	(0.028)	(0.029)	(0.028)	(0.039)	(0.034)	(0.028)	(0.036)	(0.032)
Restoration day	0.068^{*}	0.024	0.037	0.074	0.062	0.081	0.063	0.059
	(0.030)	(0.028)	(0.035)	(0.069)	(0.060)	(0.129)	(0.062)	(0.069)
1 day after restoration	0.050	0.041	0.052	0.088	0.075	0.085	0.081	0.063
	(0.034)	(0.033)	(0.041)	(0.071)	(0.062)	(0.083)	(0.064)	(0.059)
2 days after restoration	0.039	0.036	0.051	0.044	0.031	0.034	0.034	0.001
	(0.029)	(0.029)	(0.032)	(0.050)	(0.042)	(0.041)	(0.044)	(0.033)
Inter-quartile range of prices		0.021^{**}	0.022^{**}	0.023^{**}	0.023^{**}	0.023^{**}	0.026^{**}	0.020^{**}
		(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)
Price cycle day			0.003	0.003	0.001	0.001	0.002	-0.001
			(0.003)	(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
Length of last price cycle			0.002	0.002	0.003^{*}	0.003^{*}	0.003^{*}	0.001
			(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Δp_t^+				-0.003	-0.004	-0.009	-0.004	-0.005
				(0.004)	(0.004)	(0.040)	(0.004)	(0.004)
Δp_{t-1}^+				-0.004	-0.006	-0.008	-0.007	-0.008^{+}
				(0.006)	(0.005)	(0.013)	(0.006)	(0.004)
Δp_{t-2}^+				0.005	0.003	0.002	0.003	0.003
				(0.007)	(0.005)	(0.007)	(0.006)	(0.006)
⋮				⋮	⋮	⋮	⋮	⋮
Δp_t^-				0.005	0.005	0.005	0.006	-0.001
				(0.007)	(0.007)	(0.068)	(0.007)	(0.008)
Δp_{t-1}^-				0.017^{*}	0.014^{+}	0.013	0.016^{+}	0.010
				(0.007)	(0.007)	(0.008)	(0.008)	(0.007)
Δp_{t-2}^-				0.015^{*}	0.013^{+}	0.013	0.015^{+}	0.010
				(0.006)	(0.007)	(0.008)	(0.008)	(0.010)
⋮				⋮	⋮	⋮	⋮	⋮
$\ln(\text{Report}_{mt-1})$					0.108^{**}	0.109^{**}	0.127^{**}	0.092^{**}
					(0.022)	(0.020)	(0.022)	(0.021)
$\ln(\text{Report}_{mt-2})$					0.086^{**}	0.087^{**}	0.098^{**}	0.085^{**}
					(0.013)	(0.013)	(0.015)	(0.017)
$\ln(\text{Report}_{mt-3})$					0.093^{**}	0.092^{**}	0.108^{**}	0.074^{**}
					(0.022)	(0.021)	(0.023)	(0.021)
Constant	2.236^{**}	2.242^{**}	2.133^{**}	2.177^{**}	1.717^{**}	1.730^{**}	1.521^{**}	2.020^{**}
	(0.098)	(0.100)	(0.106)	(0.134)	(0.143)	(0.142)	(0.149)	(0.217)
R-Squared (Adj.)	0.708	0.712	0.728	0.727	0.751	0.751	–	0.745
Observations	2949	2949	2800	2626	2626	2626	2626	1826

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive. The estimates in columns (1) to (7) are based on samples that include market-dates with 8 are more station-level price observations. The estimates in column (8) are based on a more restrictive sample that includes market-dates with 12 or more station-level price observations.

Table 6: Determinants of price reporting by day of the cycle

	Days Relative to the Start of a Restoration						
	$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Inter-quartile range of prices	0.023	0.015	0.020*	0.034**	-0.005	0.021	0.057**
	(0.025)	(0.020)	(0.007)	(0.009)	(0.014)	(0.021)	(0.017)
Cycle Day	-0.001	-0.003	-0.003	0.001			
	(0.007)	(0.007)	(0.006)	(0.006)			
Length of last price cycle	-0.002	-0.002	-0.002	0.004	-0.002	-0.003	0.005
	(0.006)	(0.005)	(0.005)	(0.003)	(0.005)	(0.006)	(0.006)
Δp_t^+	-0.004	0.015	-0.910^{+}	0.002	-0.003	0.004	0.027
	(0.083)	(0.049)	(0.374)	(0.008)	(0.017)	(0.043)	(0.066)
Δp_{t-1}^+	-0.022	-0.045^{+}	0.032	0.731^{+}	-0.008	0.009	0.016
	(0.022)	(0.023)	(0.056)	(0.380)	(0.013)	(0.017)	(0.034)
Δp_{t-2}^+	-0.020	0.018	-0.049^{+}	0.056	0.869*	0.013	0.026^{+}
	(0.028)	(0.031)	(0.028)	(0.043)	(0.423)	(0.013)	(0.013)
⋮		⋮		⋮		⋮	
Δp_t^-	-0.018	-0.072^{+}	0.021		-0.006	-0.016	0.045^{+}
	(0.051)	(0.037)	(0.032)		(0.019)	(0.018)	(0.023)
Δp_{t-1}^-	0.024	0.056	-0.019	0.059*		-0.016	0.023
	(0.034)	(0.050)	(0.041)	(0.027)		(0.021)	(0.027)
Δp_{t-2}^-	0.010	0.021	0.068^{+}	0.037	0.023		-0.004
	(0.035)	(0.027)	(0.033)	(0.028)	(0.022)		(0.015)
⋮		⋮		⋮		⋮	
Constant	1.300*	1.540**	2.988**	0.409	1.758**	1.703**	2.364**
	(0.501)	(0.403)	(0.201)	(0.358)	(0.420)	(0.296)	(0.308)
R-Squared (Adj.)	0.706	0.728	0.751	0.803	0.786	0.722	0.727
Observations	339	399	405	429	416	382	375

Notes: The dependent variable, ln(Report$_{mt}$), is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive. Three lags of the dependent variable are also controlled for in all specifications. The columns are indexed by τ, the number of days from the start of a restoration; $\tau = 0$ are days classified as the start of the restoration. See Section 3.1 in the text for cycle day definitions. The blank cells indicate no coefficients were estimated. These arise by construction in defining price restorations since the start of price restorations (where $\tau = 0$) must involve at least a 1.5 cpl price increase. Therefore, we cannot estimate changes in consumer search intensity to contemporaneous negative price changes on day 0 of the cycle, lagged negative price changes on $\tau = 1$ days, and so on.

Table 7: Determinants of price reporting over the cycle in sticky markets

	Baseline OLS Estimates					Truncated Regression
	(1)	(2)	(3)	(4)	(5)	(6)
3 days before restoration	0.002	-0.017	0.004	0.046	0.050	0.063
	(0.035)	(0.036)	(0.039)	(0.044)	(0.040)	(0.043)
2 days before restoration	0.018	0.008	0.039	0.049	0.052	0.061
	(0.033)	(0.045)	(0.051)	(0.052)	(0.051)	(0.054)
1 day before restoration	0.024	0.001	0.023	0.028	0.031	0.037
	(0.038)	(0.043)	(0.047)	(0.055)	(0.049)	(0.053)
Restoration day	0.056	0.042	0.074	0.095^{+}	0.109^{+}	0.126^{+}
	(0.043)	(0.049)	(0.055)	(0.053)	(0.063)	(0.067)
1 day after restoration	0.015	0.015	0.025	0.041	0.033	0.038
	(0.031)	(0.034)	(0.036)	(0.044)	(0.049)	(0.051)
2 days after restoration	0.005	0.002	0.010	-0.006	-0.011	-0.015
	(0.030)	(0.031)	(0.035)	(0.044)	(0.049)	(0.052)
11-17 days since restoration		0.021	0.003	0.020	0.006	-0.001
		(0.037)	(0.040)	(0.046)	(0.034)	(0.040)
18-24 days since restoration		0.019	0.013	0.037	0.008	0.010
		(0.052)	(0.057)	(0.052)	(0.037)	(0.036)
25-31 days since restoration		0.011	-0.031	0.026	0.012	0.001
		(0.085)	(0.085)	(0.079)	(0.071)	(0.074)
>31 days since restoration		0.021	-0.012	-0.004	-0.012	-0.021
		(0.046)	(0.055)	(0.067)	(0.052)	(0.055)
Length of most recent cycle 11-17 days			0.015	0.056	0.048	0.056
			(0.043)	(0.050)	(0.040)	(0.042)
Length of most recent cycle 18-24 days			0.059	0.090	0.068	0.086
			(0.060)	(0.064)	(0.051)	(0.055)
Length of most recent cycle 25-31 days			-0.074	0.008	0.029	0.057
			(0.075)	(0.089)	(0.074)	(0.082)
Length of most recent cycle >31 days			-0.024	-0.019	0.002	0.007
			(0.045)	(0.047)	(0.030)	(0.030)
Δp_t^+				0.007	0.002	0.003
				(0.014)	(0.014)	(0.014)
Δp_{t+1}^+				-0.002	-0.007	-0.009
				(0.015)	(0.014)	(0.015)
Δp_{t+2}^+				0.013	0.012	0.013
				(0.013)	(0.011)	(0.012)
$\vdots$				$\vdots$		
Δp_t^-				-0.016	-0.014	-0.027
				(0.015)	(0.014)	(0.020)
Δp_{t-1}^-				-0.020^{+}	-0.020^{+}	-0.027^{*}
				(0.010)	(0.011)	(0.013)
Δp_{t-2}^-				-0.020	-0.014	-0.024
				(0.012)	(0.015)	(0.018)
$\vdots$				$\vdots$		
$\ln(\text{Report}_{mt-1})$					0.194^{**}	0.209^{**}
					(0.034)	(0.034)
$\ln(\text{Report}_{mt-2})$					0.110^{**}	0.116^{**}
					(0.038)	(0.040)
$\ln(\text{Report}_{mt-3})$					0.089^{**}	0.098^{**}
					(0.032)	(0.032)
R-Squared (Adj)	0.637	0.639	0.643	0.685	0.710	
Observations	3129	2985	2757	2316	2316	2316

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive. See the Section 4.4 in the text for further discussion of variable definitions.

Appendix
(Not For Publication)

A Alternative price dispersion measures and sample size

In this Appendix, we study how three different measures of price dispersion (inter-quartile range, standard deviation, and range) vary with sample size. This is a critical issue in the paper: if a positive relationship exists, it simultaneously explains the positive relationship between price reporting intensity and price dispersion found in the paper. This simultaneity would undermine our claim that this relationship reflects search behavior; it could simply reflect a systematic relationship between price dispersion and sample size since our reporting intensity measure is the sample size for a given market and date.

Our analysis is based on Monte Carlo simulations of price distributions that reflect market- and date-specific price distributions observed in the data. Unfortunately, we do not have large samples of prices at the market-day level, which means we cannot reliably estimate these price distributions non-parametrically. Given this, we present results based on a parametric normal distribution, as well as a mixture of two normals that can flexibly take on a number of shapes, including bi-modal distributions. We often see bi-modal price distributions around price restorations with stations setting both high and low prices during the transition from the bottom to the top of the cycle. We estimate the parameters of these respective distributions by maximum likelihood for dates and markets with 20 or more price observations (or 13.5% of all market-dates in the sample). We then use these parameter estimates to determine what are "typical" market-date price distributions. Our Monte Carlo samples are generated using these typical distributions.

A.1 Monte Carlo simulations

The following steps outline how we generate Monte Carlo samples and conduct our analysis:

1. For all market-dates, estimate the parameters of the normal distribution and of a mixture of two normals with station-level price data.

2. Set the seed for the pseudo-random number generator. Specify market size (`Nobs`) and the number of Monte Carlo simulations/samples (`Nsim`).

3. Specify parameters of one of two distributions of interest:

   3a. Normal distribution: mean μ and variances σ

   3b. Mixture: means (μ_1,μ_2), standard deviations (σ_1,σ_2), and mixing parameter k

4. Simulate `Nsim` datasets each with `Nobs` observations using the distribution specified in step 3.

5. Compute the three price dispersion measures (range, inter-quartile range, standard deviation) for each of the `Nsim` datasets.

6. Compute the mean and standard deviation of the price dispersion measures across the `Nsim` datasets. Denote the simulated means of these dispersion measures as `range`, `iqr`, `std`. Also compute the simulated standard deviations of these dispersion measures.

We repeat steps 1-6 for `Nobs`=2,...,100. We use `Nsim`=10,000 Monte Carlo samples. These sample sizes reflect those seen across market-dates in the sample, which range from 20 to 99 station-level observations. With the resulting 100 simulated means and standard deviations for `range`, `iqr`, `std` we investigate how these price dispersion measures vary with sample size `Nobs`.

Parameterizations

We run four sets of simulations. The first simulation is based on the normal distribution and the other simulations are based on a mixture of two normals. The details of the parameterizations for each of these simulations are as follows:

1. Normal distribution, varying standard deviation
   - $\mu = 78.24$; this is the 50th percentile of the distribution of μ estimates across market-dates.
   - $\sigma \in \{0.63, 1.08, 1.81\}$; these are the 25th, 50th, and 75th percentiles of the distribution of σ estimates across market-dates.
2. Mixture of two normal distributions, varying standard deviations
   - (μ_1, μ_2) = (77.42,79.22); these are the 50th percentiles of the distributions of μ_1 and μ_2 estimates across market-dates.
   - $(\sigma_1, \sigma_2) \in \{(0.19, 0.31), (0.31, 0.63), (0.59, 1.42)\}$; the values in these three respective pairs are the 25th, 50th, and 75th percentiles of the distributions of σ_1 and σ_2 estimates across market-dates.
   - $k = 0.6149$; this is the 50th percentile of the distribution of the mixing parameter estimates across market-dates.
3. Mixture of two normal distributions, varying means
   - $(\mu_1, \mu_2) \in \{(74.41, 75.42), (63.88, 65.84), (78.94, 81.73)\}$; the values in these three respective pairs correspond to the 25th, 50th, and 75th percentiles of the distribution of the absolute difference of the estimated means ($|\mu_1 - \mu_2|$) across market-dates. These pairs increasingly vary the size of the distance between the two estimated means.
   - (σ_1, σ_2) = (0.31,0.63); these are the 50th percentiles of the distributions of σ_1 and σ_2 estimates across market-dates.
   - $k = 0.6149$; this is the 50th percentile of the distribution of mixing parameter estimates across market-dates.
4. Mixture of two normal distributions, varying mixing parameter
   - (μ_1, μ_2) = (77.42,79.22); these are the 50th percentiles of the distributions of μ_1 and μ_2 estimates across market-dates.
   - (σ_1, σ_2) = (0.31,0.63); these are the 50th percentiles of the distributions of σ_1 and σ_2 estimates across market-dates.
   - $k \in \{0.45, 0.64, 0.82\}$; these are the 25th, 50th, and 75th percentiles of the distribution of k estimates across market-dates.

Results

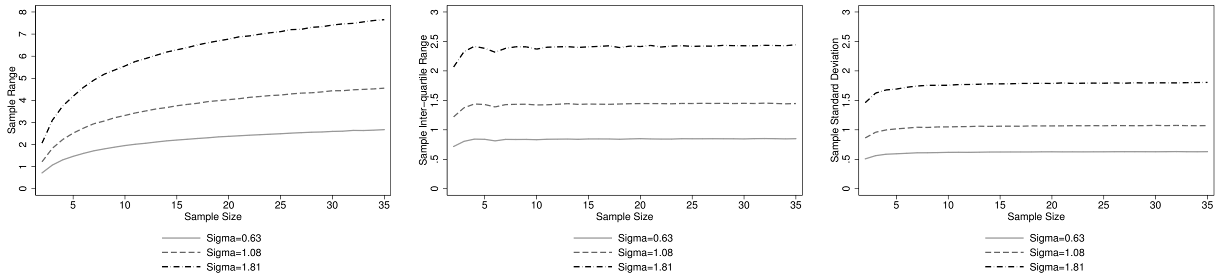
The four panels in Figure A.1 present plots of the simulated means for the range (`range`), inter-quartile range (`iqr`), and standard deviation (`std`) against sample size (`Nobs`) for simulations one through four.[55] Across all four sets of simulations, the main takeaway is the same: the range increases at a decreasing rate as sample size increases, while the inter-quartile range and standard deviation increases with sample size only for relatively small samples. For `Nobs` > 7, the simulated means of the inter-quartile range and standard deviation level off and are unrelated to sample size.

[55] To provide a sense of how disperse the simulated dispersion measures, we also plot the simulated means plus or minus one simulated standard deviation of each dispersion measure across the Monte Carlo samples.

Figure A.1: Price Dispersion vs. Sample Size

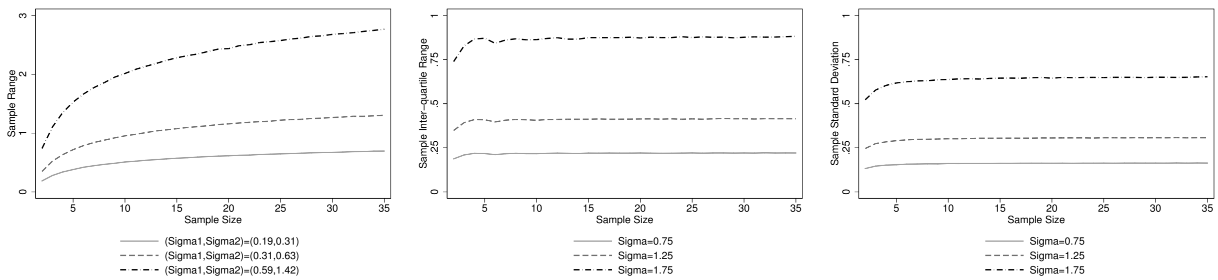
Monte-carlo simulations 1: normal distribution, varying standard deviation

Range | Inter-quartile Range | Standard Deviation



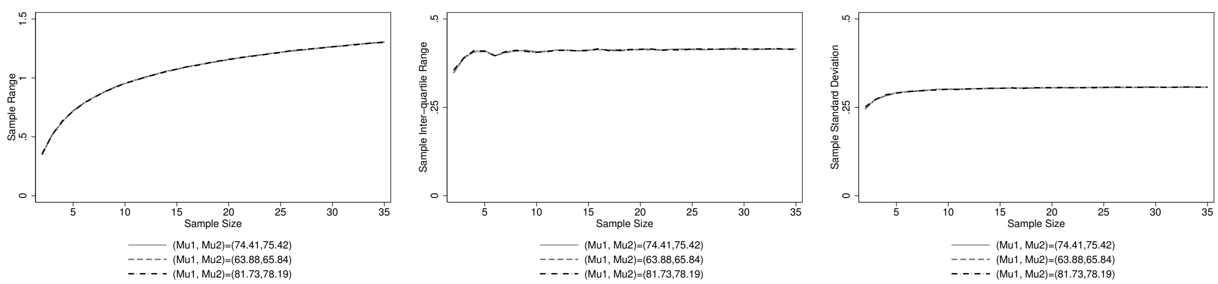
Monte-carlo simulations 2: mixture of two normals, varying standard deviations

Range | Inter-quartile Range | Standard Deviation



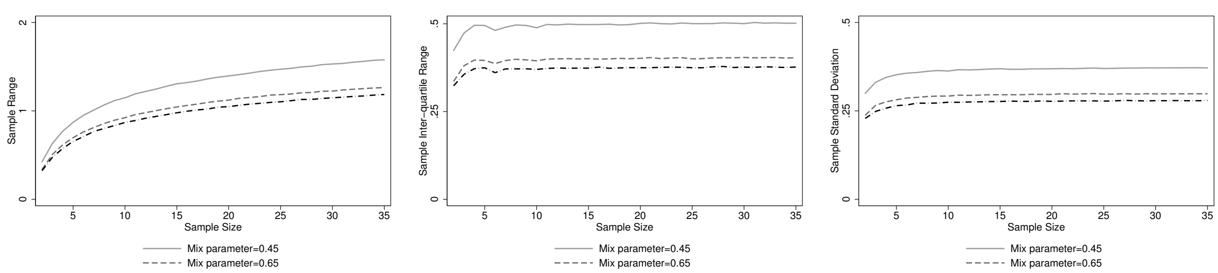
Monte-carlo simulations 3: mixture of two normals, varying means

Range | Inter-quartile Range | Standard Deviation



Monte-carlo simulations 4: mixture of two normals, varying mixing parameter

Range | Inter-quartile Range | Standard Deviation



A.2 Empirical results with alternative dispersion measures and sample restrictions

The simulation results motivate two econometric modeling choices in the paper: (1) avoid using the range as a price dispersion measure; and (2) restrict our analysis of the relationship between price reporting and price dispersion to market-dates with 8 or more station-level price observations. In this section, we illustrate how using different dispersion measures (inter-quartile range, standard deviation, range) and sample restrictions affects our empirical results.

Table A.1 reports results based on the inter-quartile range dispersion measure. For reference, the first three columns reproduce the estimates from Table 5 of the paper under the column (2), (3), and (5) specifications. The remaining columns vary the minimum number of station-level observations required to be in the estimation sample from $N_{mt} = 2$ up to $N_{mt} = 16$. Looking at the coefficient estimates on the inter-quartile range variable across the columns, we see how less restrictive samples result in larger coefficient estimates, particularly for the $N_{mt} \geq 2$ and $N_{mt} \geq 4$ samples. This upward bias reflects the positive relationship between the inter-quartile range and sample size for small samples from the Monte Carlo simulations.

Importantly, the coefficient estimate settles down around the $N_{mt} \geq 6$ sample. The slightly smaller estimates for the $N_{mt} \geq 14$ and $N_{mt} \geq 16$ samples suggest there may be some bias remaining in the coefficient estimate. None of the sample restrictions affect the conclusion that a statistically significant positive relationship exists between reporting intensity and price dispersion, however.

Tables A.2 and A.3 report analogous estimates where price dispersion is instead measured using the standard deviation and range of station-level prices. For both of these alternative dispersion measures, we see similar small-sample biases, particularly for the $N_{mt} \geq 2$ through $N_{mt} \geq 6$ samples. Unlike the inter-quartile range and standard deviation results, the estimates based on the price range continue to fall even for larger sample cut-offs. Thus, the small-sample is persistent in more restrictive samples based on this dispersion measure, an empirical result that was also foreshadowed by the Monte Carlo simulations.

Table A.1: Determinants of price reporting over the cycle

Price dispersion measure: inter-quartile range of prices

	OLS estimates with alternative dispersion measure ($N_{mt} \geq 8$)			Robustness checks with varying sample restriction for minimum number of station-level price observations in market m and date t (N_{mt})						
				$N_{mt} \geq 2$	$N_{mt} \geq 4$	$N_{mt} \geq 6$	$N_{mt} \geq 10$	$N_{mt} \geq 12$	$N_{mt} \geq 14$	$N_{mt} \geq 16$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
3 days before restoration	0.010	0.000	0.014	-0.015	0.017	0.008	0.008	0.024	0.045	0.025
	(0.028)	(0.027)	(0.035)	(0.031)	(0.029)	(0.030)	(0.036)	(0.042)	(0.043)	(0.042)
2 days before restoration	0.015	0.011	0.037	0.039	0.054^{+}	0.047	0.026	0.065^{+}	0.068^{+}	0.038
	(0.028)	(0.028)	(0.034)	(0.029)	(0.029)	(0.030)	(0.036)	(0.037)	(0.036)	(0.027)
1 day before restoration	0.036	0.019	0.046	0.039	0.036	0.032	0.032	0.046	0.061	0.019
	(0.029)	(0.028)	(0.034)	(0.036)	(0.031)	(0.030)	(0.030)	(0.032)	(0.042)	(0.035)
Restoration day	0.024	0.037	0.062	0.013	0.040	0.022	0.068	0.059	0.079	-0.000
	(0.028)	(0.035)	(0.060)	(0.050)	(0.040)	(0.043)	(0.063)	(0.069)	(0.075)	(0.081)
1 day after restoration	0.041	0.052	0.075	-0.002	0.055	0.052	0.076	0.063	0.070	0.006
	(0.033)	(0.041)	(0.062)	(0.043)	(0.042)	(0.045)	(0.062)	(0.059)	(0.066)	(0.063)
2 days after restoration	0.036	0.051	0.031	-0.006	0.022	0.019	0.007	0.001	0.021	-0.009
	(0.029)	(0.032)	(0.042)	(0.032)	(0.030)	(0.032)	(0.036)	(0.033)	(0.042)	(0.053)
Dispersion	0.021^{**}	0.022^{**}	0.023^{**}	0.029^{**}	0.027^{**}	0.024^{**}	0.020^{**}	0.020^{**}	0.016^{**}	0.019^{**}
	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Cycle Day		0.003	0.001	0.002	0.002	0.001	0.001	-0.001	-0.000	-0.001
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Length of last price cycle		0.002	0.003^{*}	0.001	0.002	0.004^{**}	0.002	0.001	0.001	0.001
		(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δp_t^+			-0.004	0.006	0.004	0.005	-0.006	-0.005	-0.007	0.000
			(0.004)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Δp_{t-1}^+			-0.006	0.002	-0.006	-0.005	-0.008^{*}	-0.008^{+}	-0.004	0.001
			(0.005)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)
Δp_{t-2}^+			0.003	0.004	0.001	0.002	0.005	0.003	-0.001	-0.005
			(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
⋮				⋮		⋮		⋮		⋮
Δp_t^-			0.005	0.012	0.007	0.001	-0.003	-0.001	-0.001	-0.005
			(0.007)	(0.012)	(0.012)	(0.009)	(0.007)	(0.008)	(0.010)	(0.008)
Δp_{t-1}^-			0.014^{+}	0.006	0.008	0.007	0.016^{+}	0.010	0.000	-0.000
			(0.007)	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)	(0.011)	(0.011)
Δp_{t-2}^-			0.013^{+}	0.007	0.009	0.008	0.011	0.010	0.008	0.010
			(0.007)	(0.011)	(0.008)	(0.009)	(0.011)	(0.010)	(0.007)	(0.009)
⋮				⋮		⋮		⋮		⋮
ln(Report$_{mt-1}$)			0.108^{**}	0.176^{**}	0.142^{**}	0.131^{**}	0.087^{**}	0.092^{**}	0.099^{**}	0.098^{**}
			(0.022)	(0.028)	(0.028)	(0.023)	(0.023)	(0.021)	(0.019)	(0.014)
ln(Report$_{mt-2}$)			0.086^{**}	0.111^{**}	0.113^{**}	0.103^{**}	0.081^{**}	0.085^{**}	0.074^{**}	0.065^{**}
			(0.013)	(0.014)	(0.012)	(0.015)	(0.014)	(0.017)	(0.016)	(0.013)
ln(Report$_{mt-3}$)			0.093^{**}	0.108^{**}	0.099^{**}	0.094^{**}	0.074^{**}	0.074^{**}	0.072^{**}	0.069^{**}
			(0.022)	(0.025)	(0.021)	(0.021)	(0.023)	(0.021)	(0.017)	(0.016)
R-Squared (Adj.)	0.712	0.728	0.751	0.710	0.735	0.744	0.756	0.745	0.769	0.760
Observations	2949	2800	2626	3634	3489	3126	2212	1826	1497	1236

Notes: The dependent variable, ln(Report$_{mt}$), is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive.

Table A.2: Determinants of price reporting over the cycle

Price dispersion measure: standard deviation of prices

	OLS estimates with alternative dispersion measure ($N_{mt} \geq 8$)			Robustness checks with varying sample restriction for minimum number of station-level price observations in market m and date t (N_{mt})						
				$N_{mt} \geq 2$	$N_{mt} \geq 4$	$N_{mt} \geq 6$	$N_{mt} \geq 10$	$N_{mt} \geq 12$	$N_{mt} \geq 14$	$N_{mt} \geq 16$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
3 days before restoration	0.010	0.002	0.017	-0.013	0.019	0.011	0.009	0.026	0.047	0.027
	(0.029)	(0.028)	(0.034)	(0.031)	(0.029)	(0.031)	(0.037)	(0.042)	(0.043)	(0.042)
2 days before restoration	0.012	0.010	0.038	0.039	0.054^{+}	0.048	0.027	0.067^{+}	0.070^{+}	0.039
	(0.028)	(0.028)	(0.033)	(0.028)	(0.028)	(0.029)	(0.035)	(0.036)	(0.035)	(0.026)
1 day before restoration	0.027	0.015	0.041	0.025	0.028	0.024	0.027	0.044	0.061	0.015
	(0.032)	(0.031)	(0.035)	(0.036)	(0.031)	(0.031)	(0.031)	(0.032)	(0.043)	(0.037)
Restoration day	0.026	0.041	0.069	0.012	0.048	0.024	0.075	0.069	0.090	0.007
	(0.029)	(0.037)	(0.060)	(0.052)	(0.042)	(0.044)	(0.065)	(0.070)	(0.077)	(0.084)
1 day after restoration	0.041	0.050	0.074	-0.003	0.055	0.049	0.075	0.063	0.071	0.008
	(0.034)	(0.042)	(0.062)	(0.044)	(0.042)	(0.045)	(0.062)	(0.059)	(0.066)	(0.065)
2 days after restoration	0.038	0.052	0.034	-0.004	0.025	0.021	0.010	0.003	0.025	-0.005
	(0.029)	(0.031)	(0.042)	(0.032)	(0.030)	(0.031)	(0.035)	(0.032)	(0.042)	(0.052)
Dispersion	0.036^{**}	0.034^{**}	0.037^{**}	0.059^{**}	0.046^{**}	0.045^{**}	0.033^{**}	0.030^{**}	0.024^{**}	0.032^{**}
	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)	(0.007)	(0.008)	(0.006)	(0.008)	(0.009)
Cycle Day		0.003	0.001	0.002	0.002	0.001	0.001	-0.001	-0.000	-0.001
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Length of last price cycle		0.002	0.002^{+}	0.001	0.002	0.004^{**}	0.002	0.001	0.001	0.001
		(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δp^{+}_{t}			-0.004	0.005	0.003	0.004	-0.006	-0.005	-0.007^{+}	0.000
			(0.004)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Δp^{+}_{t-1}			-0.006	0.003	-0.005	-0.004	-0.008^{*}	-0.007^{+}	-0.003	0.001
			(0.005)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)
Δp^{+}_{t-2}			0.003	0.005	0.002	0.003	0.005	0.004	-0.001	-0.005
			(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
⋮			⋮		⋮		⋮		⋮	
Δp^{-}_{t}			0.006	0.016	0.009	0.002	-0.002	-0.001	-0.002	-0.004
			(0.007)	(0.012)	(0.012)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Δp^{-}_{t-1}			0.014^{+}	0.009	0.010	0.008	0.016^{*}	0.010	0.000	-0.000
			(0.007)	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)	(0.011)	(0.012)
Δp^{-}_{t-2}			0.014^{+}	0.009	0.010	0.009	0.012	0.010	0.009	0.013
			(0.007)	(0.011)	(0.007)	(0.009)	(0.011)	(0.009)	(0.007)	(0.009)
⋮			⋮		⋮		⋮		⋮	
ln(Report$_{mt-1}$)			0.109^{**}	0.176^{**}	0.143^{**}	0.131^{**}	0.087^{**}	0.091^{**}	0.097^{**}	0.095^{**}
			(0.022)	(0.028)	(0.028)	(0.023)	(0.023)	(0.021)	(0.019)	(0.015)
ln(Report$_{mt-2}$)			0.087^{**}	0.112^{**}	0.114^{**}	0.104^{**}	0.082^{**}	0.085^{**}	0.075^{**}	0.068^{**}
			(0.013)	(0.014)	(0.012)	(0.014)	(0.014)	(0.017)	(0.016)	(0.013)
ln(Report$_{mt-3}$)			0.093^{**}	0.107^{**}	0.099^{**}	0.094^{**}	0.075^{**}	0.075^{**}	0.073^{**}	0.070^{**}
			(0.022)	(0.026)	(0.021)	(0.021)	(0.023)	(0.021)	(0.018)	(0.017)
R-Squared (Adj.)	0.711	0.726	0.749	0.711	0.734	0.743	0.754	0.743	0.766	0.757
Observations	2949	2800	2626	3634	3489	3126	2212	1826	1497	1236

Notes: The dependent variable, ln(Report$_{mt}$), is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive.

Table A.3: Determinants of price reporting over the cycle

Price dispersion measure: range of prices

	OLS estimates with alternative dispersion measure ($N_{mt} \geq 8$)			Robustness checks with varying sample restriction for minimum number of station-level price observations in market m and date t (N_{mt})						
				$N_{mt} \geq 2$	$N_{mt} \geq 4$	$N_{mt} \geq 6$	$N_{mt} \geq 10$	$N_{mt} \geq 12$	$N_{mt} \geq 14$	$N_{mt} \geq 16$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
3 days before restoration	0.008	0.002	0.021	-0.006	0.023	0.016	0.013	0.029	0.051	0.031
	(0.029)	(0.028)	(0.035)	(0.031)	(0.029)	(0.031)	(0.038)	(0.044)	(0.044)	(0.043)
2 days before restoration	0.006	0.005	0.039	0.040	0.055^{+}	0.048^{+}	0.029	0.069^{+}	0.072^{+}	0.041
	(0.027)	(0.028)	(0.032)	(0.027)	(0.027)	(0.028)	(0.035)	(0.036)	(0.035)	(0.026)
1 day before restoration	0.013	0.003	0.036	0.010	0.015	0.016	0.025	0.045	0.063	0.019
	(0.033)	(0.032)	(0.035)	(0.035)	(0.032)	(0.031)	(0.031)	(0.032)	(0.044)	(0.037)
Restoration day	0.013	0.029	0.067	-0.001	0.036	0.019	0.077	0.075	0.095	0.016
	(0.028)	(0.037)	(0.059)	(0.053)	(0.043)	(0.044)	(0.064)	(0.069)	(0.077)	(0.085)
1 day after restoration	0.036	0.044	0.071	-0.006	0.050	0.045	0.073	0.062	0.070	0.009
	(0.034)	(0.042)	(0.062)	(0.046)	(0.043)	(0.045)	(0.063)	(0.059)	(0.067)	(0.067)
2 days after restoration	0.039	0.053^{+}	0.035	-0.001	0.025	0.022	0.011	0.006	0.027	-0.004
	(0.028)	(0.031)	(0.041)	(0.032)	(0.030)	(0.031)	(0.035)	(0.032)	(0.041)	(0.051)
Dispersion	0.020^{**}	0.019^{**}	0.020^{**}	0.039^{**}	0.030^{**}	0.026^{**}	0.016^{**}	0.014^{**}	0.011^{**}	0.014^{**}
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Cycle Day		0.002	0.001	0.002	0.002	0.001	0.001	-0.001	-0.000	-0.001
		(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Length of last price cycle		0.002	0.002^{+}	0.000	0.002	0.004^{*}	0.002	0.000	0.000	0.001
		(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Δp_t^+			-0.004	0.004	0.003	0.004	-0.006	-0.005	-0.007^{+}	0.000
			(0.004)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Δp_{t-1}^+			-0.004	0.006	-0.003	-0.002	-0.007^{+}	-0.006	-0.002	0.002
			(0.005)	(0.007)	(0.007)	(0.006)	(0.004)	(0.004)	(0.004)	(0.005)
Δp_{t-2}^+			0.005	0.008	0.004	0.004	0.007	0.005	-0.000	-0.004
			(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.005)
⋮										
Δp_t^-			0.009	0.023^{+}	0.014	0.007	0.001	0.002	0.000	-0.003
			(0.006)	(0.011)	(0.011)	(0.009)	(0.007)	(0.008)	(0.009)	(0.007)
Δp_{t-1}^-			0.017^{*}	0.015^{+}	0.015^{*}	0.012^{+}	0.019^{*}	0.013^{+}	0.003	0.002
			(0.007)	(0.009)	(0.007)	(0.006)	(0.007)	(0.007)	(0.011)	(0.012)
Δp_{t-2}^-			0.017^{*}	0.014	0.014^{+}	0.012	0.015	0.013	0.011^{+}	0.017^{*}
			(0.007)	(0.011)	(0.007)	(0.008)	(0.010)	(0.008)	(0.006)	(0.008)
⋮										
$\ln(\text{Report}_{mt-1})$			0.108^{**}	0.171^{**}	0.140^{**}	0.129^{**}	0.087^{**}	0.091^{**}	0.095^{**}	0.091^{**}
			(0.022)	(0.028)	(0.028)	(0.024)	(0.024)	(0.021)	(0.019)	(0.017)
$\ln(\text{Report}_{mt-2})$			0.087^{**}	0.109^{**}	0.112^{**}	0.103^{**}	0.081^{**}	0.085^{**}	0.076^{**}	0.071^{**}
			(0.013)	(0.014)	(0.012)	(0.014)	(0.014)	(0.017)	(0.016)	(0.012)
$\ln(\text{Report}_{mt-3})$			0.090^{**}	0.101^{**}	0.095^{**}	0.090^{**}	0.074^{**}	0.074^{**}	0.073^{**}	0.070^{**}
			(0.022)	(0.025)	(0.020)	(0.021)	(0.023)	(0.021)	(0.017)	(0.017)
R-Squared (Adj.)	0.717	0.731	0.754	0.722	0.742	0.750	0.758	0.745	0.768	0.759
Observations	2949	2800	2626	3634	3489	3126	2212	1826	1497	1236

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive.

B Alternative dependent variables and model specifications

In this Appendix, we investigate the impact that using alternative dependent variables and econometric models have on our empirical results. Recall that the dependent variable used in the various price reporting regressions was $\ln(\text{Report}_{mt})$, where Report_{mt} is the number of station-level price reports GasBuddy's websites receive in market m on date t. We consider two alternative dependent variables: reporting counts in levels (Report_{mt}) and reporting counts scaled by the average number of reports market m receives on a given day $\text{Report}_{mt} \big/ \overline{\text{Report}}_m$ where $\overline{\text{Report}}_m = \sum_{t=1}^{T} R_{mt}/N_m$. By scaling Report_{mt} by the average number of reports received in a market, the latter dependent variable helps account for market-level unobserved heterogeneity in reporting intensity, for example due to the number of heavy commuters in a market or because of particularly keen GasBuddy users. We also consider limited dependent variables (Poisson and Ordered Probit) that account for Report_{mt} being a discrete count variable bounded from below by zero.[56]

Table B.1 contains four panels that list analogous OLS-1, OLS-3, and OLS-5 results to those from Table 5 of the paper based on the three dependent variables and the Poisson model. Comparing the estimates across the four panels, we find the paper's main empirical conclusions are unchanged under the alternative dependent variables and econometric models. Specifically, we continue to find price reporting intensity is statistically significantly higher on the day of and day before restoration events, when price dispersion is higher, and when price cuts lagged by one day become smaller. The economic magnitudes of the estimates are also similar across the specifications. For instance, the benchmark results based on $\ln(\text{Report}_{mt})$ indicate that price reporting intensity rises by 5.9% on the day before and day of a restoration; the results based on Report_{mt} in levels implies there are 1.49 and 1.30 more reports on average, marginal effects that are 6.2% and 5.4% of the average number of daily price reports of 24. As another example, the OLS-3 estimates imply that a typical 3 cpl increase in the inter-quartile range of prices during a restoration day increases reporting rates by $1.9\% \times 3 = 5.7\%$ when $\ln(\text{Report}_{mt})$ is the dependent variable. In the analogous levels regression, this marginal effect is $3 \times 0.464 = 1.39$, or 5.8% of the sample average number of daily price reports.

As a check on the results on reporting intensity by day of the cycle in Table 6, in Tables B.2 and B.3 we reproduce the results from the table, except we replace the dependent variable with Report_{mt} and $\text{Report}_{mt} \big/ \overline{\text{Report}}_m$. Again, we see that using these alternative dependent variables has little impact on the main conclusions in the paper. Price reporting responds to higher price dispersion on various days of the cycle, particularly on those just before and during restoration periods. Reporting is also significantly higher on $\tau = 0$ restoration days when there have been lagged larger price increases (at both one and two day lags) and lagged smaller price cuts (at one lag).

As a final robustness check, we report analogous results for price reporting in sticky markets based on different dependent variables and econometric models that correspond to the results in columns OLS-3 and OLS-5 of Table 7 of the paper. We also report Ordered Probit results for these markets because they have much fewer daily price reports on average (4), with more than 90% of all market-dates having 10 or less station-level price observations.[57] The results highlight the robustness of the main empirical result of interest, namely that price reporting intensity is statistically significantly higher on restoration days in rural sticky markets (where there are minimal search-based reporting incentives).

[56] We have also estimated Negative Binomial models as well and find they yield very similar results as the Poisson model.

[57] The maximum number of station-level price observations for a given market-date is 24; the results are identical if we restrict the sample to market-dates in sticky markets with 10 or less station-level price observations.

Table B.1: Determinants of price reporting over the cycle

Alternative dependent variables and model specification

	Dependent Variable: $\ln(\text{Report}_{mt})$			Dependent Variable: Report_{mt}			Dependent Variable: $\text{Report}_{mt}/\overline{\text{Report}}_{m}$			Poisson Model for Report_{mt}		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
3 days before restoration	0.013	0.000	0.014	0.431	0.294	0.052	0.010	-0.003	0.012	0.021	0.015	0.014
	(0.028)	(0.027)	(0.035)	(0.543)	(0.522)	(0.654)	(0.025)	(0.025)	(0.030)	(0.028)	(0.027)	(0.032)
2 days before restoration	0.019	0.011	0.037	0.709	0.645	0.517	0.015	0.008	0.034	0.033	0.033	0.037
	(0.028)	(0.028)	(0.034)	(0.485)	(0.548)	(0.599)	(0.026)	(0.029)	(0.035)	(0.025)	(0.025)	(0.028)
1 day before restoration	0.056^{+}	0.019	0.046	1.400^{*}	0.803	0.539	0.052^{+}	0.016	0.043	0.069^{*}	0.038	0.039
	(0.028)	(0.028)	(0.034)	(0.548)	(0.593)	(0.669)	(0.029)	(0.031)	(0.035)	(0.031)	(0.029)	(0.031)
Restoration day	0.068^{*}	0.037	0.062	1.568^{*}	0.986	0.992	0.070^{*}	0.030	0.051	0.078^{*}	0.058	0.065
	(0.030)	(0.035)	(0.060)	(0.692)	(0.764)	(1.193)	(0.031)	(0.035)	(0.054)	(0.038)	(0.038)	(0.064)
1 day after restoration	0.050	0.052	0.075	1.082^{+}	1.220	1.129	0.045	0.040	0.063	0.055	0.062	0.064
	(0.034)	(0.041)	(0.062)	(0.603)	(0.748)	(1.104)	(0.031)	(0.038)	(0.055)	(0.033)	(0.040)	(0.062)
2 days after restoration	0.039	0.051	0.031	0.683	0.873	0.071	0.040	0.047	0.022	0.035	0.046	0.015
	(0.029)	(0.032)	(0.042)	(0.595)	(0.628)	(0.874)	(0.025)	(0.028)	(0.038)	(0.036)	(0.038)	(0.043)
Inter-quartile range of prices		0.022^{**}	0.023^{**}		0.467^{**}	0.474^{**}		0.023^{**}	0.025^{**}		0.022^{**}	0.021^{**}
		(0.003)	(0.004)		(0.111)	(0.097)		(0.004)	(0.004)		(0.004)	(0.005)
Cycle Day		0.003	0.001		0.052	0.008		0.002	0.001		0.003	0.003
		(0.003)	(0.002)		(0.055)	(0.048)		(0.003)	(0.002)		(0.003)	(0.003)
Length of last price cycle		0.002	0.003^{*}		0.031	0.040^{*}		0.003	0.002^{*}		0.001	0.002
		(0.002)	(0.001)		(0.029)	(0.017)		(0.002)	(0.001)		(0.002)	(0.001)
Δp^{+}_{t}			-0.004			-0.141^{+}			-0.003			-0.002
			(0.004)			(0.074)			(0.004)			(0.003)
Δp^{+}_{t-1}			-0.006			-0.185^{*}			-0.007			-0.005
			(0.005)			(0.090)			(0.005)			(0.004)
Δp^{+}_{t-2}			0.003			-0.017			0.004			0.004
			(0.005)			(0.111)			(0.006)			(0.005)
Δp^{+}_{t-3}			0.002			-0.066			0.001			0.003
			(0.007)			(0.142)			(0.006)			(0.006)
Δp^{+}_{t-4}			-0.003			-0.102			-0.005			-0.002
			(0.005)			(0.081)			(0.004)			(0.004)
Δp^{+}_{t-5}			0.003			0.061			0.005			0.005
			(0.005)			(0.078)			(0.005)			(0.003)
Δp^{+}_{t-6}			0.001			0.162			0.003			0.009^{**}
			(0.003)			(0.113)			(0.004)			(0.003)
Δp^{+}_{t-7}			0.004			0.128			0.005			0.007^{+}
			(0.005)			(0.096)			(0.005)			(0.004)
Δp^{-}_{t}			0.005			-0.038			0.005			0.000
			(0.007)			(0.120)			(0.007)			(0.006)
Δp^{-}_{t-1}			0.014^{+}			0.251^{*}			0.020^{*}			0.017^{*}
			(0.007)			(0.120)			(0.007)			(0.007)
Δp^{-}_{t-2}			0.013^{+}			0.274^{*}			0.016^{+}			0.013^{*}
			(0.007)			(0.127)			(0.008)			(0.006)
Δp^{-}_{t-3}			0.002			-0.012			0.003			-0.000
			(0.009)			(0.170)			(0.009)			(0.009)
Δp^{-}_{t-4}			0.001			-0.028			0.005			0.004
			(0.007)			(0.121)			(0.007)			(0.006)
Δp^{-}_{t-5}			-0.004			-0.129			-0.002			-0.002
			(0.009)			(0.199)			(0.010)			(0.008)
Δp^{-}_{t-6}			0.004			-0.012			0.005			0.004
			(0.007)			(0.119)			(0.007)			(0.006)
Δp^{-}_{t-7}			-0.001			0.052			0.001			0.002
			(0.009)			(0.171)			(0.008)			(0.007)
$\text{Dependent Variable}_{mt-1}$			0.108^{**}			0.265^{**}			0.153^{**}			0.007^{**}
			(0.022)			(0.048)			(0.024)			(0.001)
$\text{Dependent Variable}_{mt-2}$			0.086^{**}			0.129^{**}			0.111^{**}			0.003^{*}
			(0.013)			(0.017)			(0.023)			(0.001)
$\text{Dependent Variable}_{mt-3}$			0.093^{**}			0.178^{**}			0.107^{**}			0.005^{**}
			(0.022)			(0.017)			(0.025)			(0.001)
R-Squared (Adj.)	0.708	0.728	0.751	0.759	0.776	0.824	0.275	0.298	0.340			
Log-likelihood										-8996	-8411	-7755
Observations	2949	2800	2626	2949	2800	2626	2949	2800	2626	2949	2800	2626

Notes: Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive.

Table B.2: Determinants of price reporting by day of the cycle

Alternative dependent variable: Report_{mt}

	Days Relative to the Start of a Restoration						
	$\tau = -3$	$\tau = -2$	$\tau = -1$	$\tau = 0$	$\tau = 1$	$\tau = 2$	$\tau = 3$
Inter-quartile range of prices	0.168	-0.006	0.355*	0.700**	0.012	0.931	1.020**
	(0.458)	(0.473)	(0.142)	(0.200)	(0.380)	(0.641)	(0.255)
Cycle Day	-0.069	-0.114	0.020	0.074			
	(0.114)	(0.123)	(0.125)	(0.115)			
Length of last price cycle	-0.110	-0.126	-0.018	0.067	-0.070	0.004	0.111
	(0.114)	(0.138)	(0.105)	(0.073)	(0.105)	(0.101)	(0.109)
Δp_t^+	0.551	0.750	-7.200	-0.025	-0.035	-0.053	-3.870
	(1.518)	(0.882)	(5.468)	(0.140)	(0.253)	(0.848)	(4.742)
Δp_{t-1}^+	-0.731	-0.859^{+}	0.691	8.913	-0.209	0.152	0.209
	(0.779)	(0.440)	(0.728)	(5.295)	(0.234)	(0.343)	(1.172)
Δp_{t-2}^+	-0.546	-0.033	-0.715	1.572^{+}	17.287^{+}	0.079	0.214
	(0.498)	(0.483)	(0.722)	(0.814)	(9.428)	(0.265)	(0.231)
$\vdots$				$\vdots$	$\vdots$	$\vdots$	$\vdots$
Δp_t^-	-0.808	-1.179	0.306		-0.939	-0.361	0.788
	(0.917)	(0.760)	(0.555)		(0.633)	(0.492)	(0.518)
Δp_{t-1}^-	0.584	1.412	0.209	1.374**		-0.630	0.508
	(0.719)	(0.935)	(0.939)	(0.470)		(0.468)	(0.312)
Δp_{t-2}^-	0.800	0.168	0.917^{+}	0.711	0.434		0.255
	(0.624)	(0.592)	(0.533)	(0.450)	(0.422)		(0.350)
$\vdots$				$\vdots$	$\vdots$	$\vdots$	$\vdots$
R-Squared (Adj.)	0.789	0.803	0.811	0.863	0.843	0.770	0.775
Observations	339	399	405	429	416	382	354

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects. The vector of controls also includes market-date-level weather-related controls including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive. Three lags of the dependent variable are also controlled for in all specifications. The columns are indexed by τ, the number of days from the start of a restoration; $\tau = 0$ are days classified as the start of the restoration. See Section 3.1 in the text for cycle day definitions. The blank cells indicate no coefficients were estimated. These arise by construction in defining price restorations since the start of price restorations (where $\tau = 0$) must involve at least a 1.5 cpl price increase. Therefore, we cannot estimate changes in consumer search intensity to contemporaneous negative price changes on day 0 of the cycle, lagged negative price changes on $\tau = 1$ days, and so on.

Table B.3: Determinants of price reporting by day of the cycle

Alternative dependent variable: $\text{Report}_{mt} \big/ \overline{\text{Report}}_m$

	Days Relative to the Start of a Restoration						
	$\tau=-3$	$\tau=-2$	$\tau=-1$	$\tau=0$	$\tau=1$	$\tau=2$	$\tau=3$
Inter-quartile range of prices	0.020	0.015	0.020*	0.039**	-0.007	0.023	0.049*
	(0.020)	(0.024)	(0.008)	(0.008)	(0.018)	(0.023)	(0.018)
Cycle Day	-0.003	-0.005	-0.002	0.001			
	(0.006)	(0.006)	(0.006)	(0.006)			
Length of last price cycle	-0.002	-0.001	-0.001	0.005	-0.002	-0.005	0.003
	(0.005)	(0.006)	(0.005)	(0.003)	(0.005)	(0.006)	(0.005)
Δp_t^+	0.000	0.012	-0.762*	0.000	-0.003	0.001	0.021
	(0.068)	(0.048)	(0.341)	(0.008)	(0.017)	(0.048)	(0.064)
Δp_{t-1}^+	-0.022	-0.055*	0.028	0.909^{+}	-0.004	0.012	-0.017
	(0.018)	(0.022)	(0.055)	(0.495)	(0.012)	(0.014)	(0.030)
Δp_{t-2}^+	-0.023	0.008	-0.048	0.072^{+}	1.274^{+}	0.015	0.021
	(0.024)	(0.030)	(0.029)	(0.042)	(0.629)	(0.014)	(0.016)
$\vdots$				$\vdots$	$\vdots$	$\vdots$	$\vdots$
Δp_t^-	-0.008	-0.076*	0.020		-0.007	-0.008	0.020
	(0.048)	(0.036)	(0.031)		(0.022)	(0.020)	(0.026)
Δp_{t-1}^-	0.011	0.056	0.001	0.074*		-0.005	0.030
	(0.030)	(0.047)	(0.043)	(0.028)		(0.024)	(0.023)
Δp_{t-2}^-	0.004	0.017	0.071*	0.038	0.038^{+}		0.001
	(0.027)	(0.030)	(0.034)	(0.027)	(0.021)		(0.016)
$\vdots$				$\vdots$	$\vdots$	$\vdots$	$\vdots$
R-Squared (Adj.)	0.340	0.234	0.265	0.398	0.364	0.255	0.485
Observations	339	399	405	429	416	382	375

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive. Three lags of the dependent variable are also controlled for in all specifications. The columns are indexed by τ, the number of days from the start of a restoration; $\tau = 0$ are days classified as the start of the restoration. See Section 3.1 in the text for cycle day definitions. The blank cells indicate no coefficients were estimated. These arise by construction in defining price restorations since the start of price restorations (where $\tau = 0$) must involve at least a 1.5 cpl price increase. Therefore, we cannot estimate changes in consumer search intensity to contemporaneous negative price changes on day 0 of the cycle, lagged negative price changes on $\tau = 1$ days, and so on.

Table B.4: Determinants of price reporting over the cycle in sticky markets

Alternative dependent variables and model specification

	Dependent Variable: $\ln(\text{Report}_{mt})$		Dependent Variable: Report_{mt}		Dependent Variable: $\text{Report}_{mt}/\overline{\text{Report}}_m$		Poisson Model for Report_{mt}		Ordered Probit Model for Report_{mt}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
3 days before restoration	0.004	0.050	-0.105	0.108	-0.009	0.029	-0.022	0.035	0.008	0.134
	(0.039)	(0.040)	(0.176)	(0.220)	(0.041)	(0.041)	(0.034)	(0.042)	(0.089)	(0.102)
2 days before restoration	0.039	0.052	0.047	0.228	0.012	0.022	0.014	0.054	0.080	0.141
	(0.051)	(0.051)	(0.195)	(0.228)	(0.045)	(0.048)	(0.039)	(0.040)	(0.113)	(0.122)
1 day before restoration	0.023	0.031	-0.042	0.136	0.011	0.020	-0.009	0.031	0.051	0.093
	(0.047)	(0.049)	(0.254)	(0.317)	(0.046)	(0.056)	(0.051)	(0.056)	(0.113)	(0.135)
Restoration day	0.074	0.109^{+}	0.408	0.563	0.083	0.123	0.086^{+}	0.111	0.200	0.321^{+}
	(0.055)	(0.063)	(0.273)	(0.423)	(0.058)	(0.077)	(0.051)	(0.070)	(0.128)	(0.169)
1 day after restoration	0.025	0.033	0.148	0.252	0.012	0.033	0.027	0.047	0.057	0.108
	(0.036)	(0.049)	(0.136)	(0.224)	(0.028)	(0.043)	(0.026)	(0.042)	(0.079)	(0.115)
2 days after restoration	0.010	-0.011	0.001	-0.094	-0.001	-0.023	-0.002	-0.018	0.019	-0.042
	(0.035)	(0.049)	(0.151)	(0.229)	(0.033)	(0.048)	(0.031)	(0.041)	(0.079)	(0.124)
11-17 days since restoration	0.003	0.006	0.132	0.111	0.020	0.021	0.037	0.030	0.024	0.025
	(0.040)	(0.034)	(0.201)	(0.182)	(0.043)	(0.042)	(0.041)	(0.039)	(0.091)	(0.102)
18-24 days since restoration	0.013	0.008	0.255	0.147	0.026	0.004	0.039	0.016	0.041	0.033
	(0.057)	(0.037)	(0.322)	(0.254)	(0.054)	(0.044)	(0.055)	(0.039)	(0.126)	(0.100)
25-31 days since restoration	-0.031	0.012	0.246	0.363	0.018	0.062	0.021	0.047	-0.042	0.052
	(0.085)	(0.071)	(0.436)	(0.425)	(0.078)	(0.070)	(0.072)	(0.058)	(0.184)	(0.169)
31 days since restoration	-0.012	-0.012	-0.059	-0.111	0.007	0.000	-0.012	-0.003	-0.031	-0.042
	(0.055)	(0.052)	(0.235)	(0.250)	(0.053)	(0.051)	(0.054)	(0.051)	(0.124)	(0.133)
Length of most recent cycle 11-17 days	0.015	0.048	0.034	0.116	0.006	0.028	0.017	0.031	0.034	0.119
	(0.043)	(0.040)	(0.233)	(0.223)	(0.045)	(0.040)	(0.046)	(0.042)	(0.101)	(0.107)
Length of most recent cycle 18-24 days	0.059	0.068	0.207	0.198	0.055	0.074	0.055	0.050	0.159	0.206
	(0.060)	(0.051)	(0.267)	(0.221)	(0.055)	(0.047)	(0.050)	(0.043)	(0.130)	(0.129)
Length of most recent cycle 25-31 days	-0.074	0.029	-0.601	-0.270	-0.067	0.003	-0.130^{+}	-0.047	-0.176	0.066
	(0.075)	(0.074)	(0.370)	(0.353)	(0.063)	(0.067)	(0.070)	(0.066)	(0.165)	(0.200)
Length of most recent cycle >31 days	-0.024	0.002	-0.187	-0.134	-0.008	-0.006	-0.024	-0.023	-0.049	-0.008
	(0.045)	(0.030)	(0.253)	(0.189)	(0.044)	(0.034)	(0.051)	(0.034)	(0.106)	(0.079)
Δp_t^+		0.002		0.063		0.005		0.016		0.013
		(0.014)		(0.075)		(0.015)		(0.014)		(0.035)
Δp_{t+1}^+		-0.007		-0.053		-0.012		-0.010		-0.030
		(0.014)		(0.065)		(0.012)		(0.012)		(0.035)
Δp_{t+2}^+		0.012		0.077		0.014		0.015^{+}		0.032
		(0.011)		(0.051)		(0.012)		(0.008)		(0.028)
Δp_{t+3}^+		-0.002		-0.022		-0.002		-0.006		-0.014
		(0.011)		(0.054)		(0.011)		(0.010)		(0.029)
Δp_{t+4}^+		0.001		-0.005		0.013		0.003		0.010
		(0.019)		(0.066)		(0.022)		(0.015)		(0.051)
Δp_{t+5}^+		-0.006		-0.010		0.002		-0.001		-0.013
		(0.013)		(0.053)		(0.010)		(0.012)		(0.037)
Δp_{t+6}^+		0.006		0.008		0.010		0.005		0.018
		(0.011)		(0.054)		(0.012)		(0.012)		(0.031)
Δp_{t+7}^+		0.015		0.047		0.008		0.014^{+}		0.045^{+}
		(0.010)		(0.040)		(0.007)		(0.008)		(0.023)
Δp_t^-		-0.014		-0.071		-0.031^{*}		-0.025		-0.056
		(0.014)		(0.057)		(0.014)		(0.016)		(0.044)
Δp_{t-1}^-		-0.020^{+}		-0.044		-0.017		-0.012		-0.045
		(0.011)		(0.056)		(0.011)		(0.013)		(0.030)
Δp_{t-2}^-		-0.014		-0.085		-0.009		-0.030^{*}		-0.054
		(0.015)		(0.087)		(0.016)		(0.014)		(0.037)
Δp_{t-3}^-		-0.006		0.045		0.005		0.011		-0.008
		(0.013)		(0.056)		(0.016)		(0.013)		(0.036)
Δp_{t-4}^-		0.011		-0.019		0.004		-0.007		0.009
		(0.026)		(0.110)		(0.022)		(0.024)		(0.065)
Δp_{t-5}^-		-0.021^{+}		-0.126^{+}		-0.026^{+}		-0.024^{+}		-0.066^{*}
		(0.012)		(0.074)		(0.014)		(0.013)		(0.032)
Δp_{t-6}^-		0.019		0.086		0.014		0.027^{*}		0.063^{+}
		(0.014)		(0.068)		(0.013)		(0.012)		(0.037)
Δp_{t-7}^-		-0.040^{*}		-0.085		-0.026		-0.014		-0.087^{*}
		(0.017)		(0.064)		(0.017)		(0.014)		(0.043)
Dependent Variable_{mt-1}		0.194^{**}		0.187^{**}		0.176^{**}		0.024^{**}		0.084^{**}
		(0.034)		(0.029)		(0.030)		(0.005)		(0.013)
Dependent Variable_{mt-2}		0.110^{**}		0.124^{**}		0.099^{**}		0.017^{**}		0.050^{**}
		(0.038)		(0.032)		(0.031)		(0.004)		(0.014)
Dependent Variable_{mt-3}		0.089^{**}		0.129^{**}		0.091^{**}		0.018^{**}		0.051^{**}
		(0.032)		(0.027)		(0.028)		(0.003)		(0.012)
R-Squared (Adj)	0.643	0.710	0.573	0.640	0.046	0.143				
Log-likelihood							-5323	-4378	-4895	-3956
Observations	2757	2316	2757	2316	2757	2316	2757	2316	2757	2316

Notes: The dependent variable, $\ln(\text{Report}_{mt})$, is the natural logarithm of the number of GasBuddy price reports a market receives on a given date. Standard errors are reported in parentheses and are clustered at the market level. **, *, + indicate statistical significance at the 1%, 5% and 10% levels. All specifications control for week-of-the-year, national holidays, and market-specific day-of-the-week fixed effects, as well as weather-related variables including maximum and minimum temperature, total rainfall, total snowfall, and rain and snow day dummies that respectively equal one if total rainfall and total snowfall are positive.