Gasoline Pricing in the Country and the City*

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Abstract

In many markets prices adjust quickly when costs rise yet adjust sluggishly when costs fall. Such asymmetry raises concerns of collusion, however competitive search-based explanations complicate tests of conduct. Using novel data from urban and rural gasoline markets, I attempt to identify the collusive channel. Focusing on rural markets, I document unprecedented pricing asymmetry. I test for and rule out search-based explanations, which provides indirect evidence of the collusive channel. I then provide a direct test by exploiting the 2007-08 global oil price shock. I show pricing asymmetry became negligible during this period of uncertainty when cartel stability was threatened.

JEL Codes: L11, L9, D22

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1 Introduction

Prices rise like rockets and fall like feathers. Bacon (1991) coined this phrase to describe his finding that retail gasoline prices quickly adjusted to rising wholesale costs however sluggishly adjusted to falling costs. Since his study, such *pricing asymmetry* or *asymmetric pricing* has been documented in many industries (Peltzman, 2000). Particular attention has been paid to major sectors like gasoline, banking, and agriculture – industries that have a large impact on households' budgets, and where firms have market power.[1] The prevalence of pricing asymmetry in these and other oligopolistic industries naturally raises concerns of collusive behavior. Retail gasoline has been at the forefront of these discussions as concerns about anti-competitive conduct are salient in light of mounting evidence of price fixing, coordinated practices and tacit collusion.[2]

Yet despite its relevance for anti-trust policy, there has been little progress in identifying the collusive channel for asymmetric pricing. In general, diagnosing collusion is a difficult problem (Porter, 2005). Among other issues, there are often competitive explanations for outcomes that initially appear collusive. The case of asymmetric pricing is no exception as Yang and Ye (2008), Tappata (2009), and Lewis (2011) put forth a rival leading (competitive) explanation for asymmetry pricing: asymmetry search.[3] These authors develop models where consumers face search costs, are imperfectly informed about firms' costs and current prices, and form expectations about the returns to search based on past price or cost

[1] For example, see Borenstein, Cameron, and Gilbert (1997) or Bachmeier and Griffin (2003) (gasoline), Richards, Gomez, and Lee (2014) (agriculture), Neumark and Sharpe (1992) (banking).

[2] Lewis (2011), Clark and Houde (2013, 2014), Lewis (2013), Byrne, Leslie, and Ware (2015).

[3] Borenstein, Cameron, and Gilbert (1997) originally put forth collusive and search-based channels as the leading explanations for asymmetry pricing.

realizations. While the mechanisms in their models differ, they yield the common prediction that search intensity (and hence demand elasticity) is asymmetrically higher around positive cost shocks. In equilibrium this causes firms to more quickly adjust prices in response to positive shocks than negative shocks. That is, they engage in competitive asymmetric pricing. Empirical studies have indeed found evidence of asymmetric search behavior and this channel.[4]

In this article, I attempt to identify the collusive channel using unique station-level gasoline price data from Ontario, Canada. The key novelty of the dataset is it contains a diverse cross-section of urban and rural markets. This contrasts with previous studies on asymmetric pricing that largely focus on urban markets, where the collusive and search-based channels potentially coexist. Unlike previous work, my data permit an urban-rural contrast in pricing asymmetry that helps me isolate the collusive channel.

More specifically, two key features of rural gasoline markets make them well-suited for uncovering the collusive channel. First, these markets look like the oligopolies familiar to undergraduates in economics: most have four or fewer stations that are located on a single street or near highway exits. This suggests there are negligible search frictions. Second, the scope for collusion is large. Rural stations are locally owned, can easily observe each others' prices, are subject to common cost shocks, and repeatedly interact in isolation. Given the potential for collusion and absence of search frictions, any observed pricing asymmetry in these markets can likely be attributed to collusive behavior.

To identify asymmetric pricing, I estimate error correction models that al-

[4] Lewis (2009), Lewis and Marvel (2011), and Richards, Gomez, and Lee (2014).

low for asymmetric price responses to positive and negative cost shocks. The baseline results for rural markets reveal some of the largest pricing asymmetry ever documented. After one month, 70% of a typical cost shock is passed through to retail prices whereas only 40% of an equal-magnitude negative shock is passed through. In contrast, I find positive and negative shocks are symmetrically passed through to retail prices within three days in urban markets.

Having found substantial pricing asymmetry in rural markets, I investigate its underlying channels. I first rule out search-based explanations. To do so, I develop a test for search frictions based on comparative statics from Varian (1980).[5] The model predicts a positive equilibrium relationship between price dispersion and the number of firms in a market, when the number of firms is small. My empirical setting is well-suited for revealing this relationship as I have station-level price data for many small markets. I do not find, however, any evidence of such a relationship. This undermines search-based explanations for asymmetric pricing in rural markets, leaving collusion as the underlying channel.[6]

I directly test the collusive channel by leveraging another useful feature of the data. Within the 2007-08 sample period, global crude oil prices experienced the largest run-up and crash in history (Hamilton, 2009). A key result from learning models of collusion (Slade, 1989) suggests this large, exogenous cost shock can be exploited to test for collusion. In particular, these models predict price wars and short-run cartel breakdowns as firms adjust prices, learn about new de-

[5]Previous studies (Lewis, 2009; Chandra and Tappata, 2011) have argued Varian (1980) provides a useful framework for developing tests of search frictions in gasoline markets. My test leverages theoretical predictions from Chandra and Tappata (2011).

[6]The fact that cartels operated in multiple markets both in Ontario and neighboring Quebec around the 2007-08 sample period raises concerns about collusion in my sample. Below, I discuss these cartels and the 2012 price-fixed case in which collusive behavior was uncovered.

mand/supply structural parameters, and ultimately renegotiate profit-maximizing collusive agreements in response to major shocks. Indeed, historical evidence from actual cartel breakdowns supports these predictions (Levenstein and Suslow, 2006). Following this intuition, if the global crude oil price shock caused collusive agreements to break down, and if collusion causes asymmetric pricing in rural markets, then rural pricing asymmetry should become negligible in response to the crude oil price shock, at least in the short-run.

My results show this is exactly what happened. Passthrough sped up and pricing asymmetry disappeared in rural markets during the crude oil shock period. Simply put, rural market pricing started looking like competitive urban market pricing following the shock. While I cannot identify the precise mechanism(s) stations employ to engage in asymmetric pricing, I argue in the conclusion that tacit collusion is likely given the structure of rural markets.

I also consider an inventory-and-price-adjustment based explanation for pricing asymmetry. This has not been previously considered and is motivated by my conversations with station owners. Specifically, rural station owners can potentially realize higher margins if they expedite (delay) fuel inventory refills and margin adjustments in the presence of rising (falling) wholesale costs.[7] Such a pricing strategy can also generate asymmetric pricing. While I do not have inventory data to test this channel, I can test whether stations expedite (delay) margin adjustments in the presence of rising (falling) costs. I find these strategies cannot explain pricing asymmetry in the sample's rural markets.

[7] Rural station owners purchase fuel from wholesalers and are at personal risk of purchasing fuel inventories at high costs and selling at low prices later if costs fall. By contrast, when costs are rising owners can lock in low costs by refilling inventories and selling fuel later at higher prices.

Related literature

This article is closely related to earlier studies of collusion in retail gasoline by Slade (1987, 1992) and Borenstein and Shepard (1996), and recent work by Clark and Houde (2013, 2014). Slade tests for collusion in a single market (Vancouver) and concludes retail pricing is indeed collusive. She also finds infrequent breakdowns in collusive agreements arising from infrequent demand shocks. Borenstein and Shepard similarly find evidence of collusion in U.S. markets. They show retail margins today rise (fall) with higher expected demand (costs) tomorrow, an empirical result that confirms predictions from Rotemberg and Saloner's (1986) and Haltiwanger and Harrington's (1991) models of collusion. Clark and Houde study the collapse of cartels in retail gasoline markets in Quebec, Canada following the announcement of investigation by the Canadian Competition Bureau. Among their many results, the most relevant for the current article is their finding that these cartels engaged in asymmetric pricing.

This article's tests of collusive behavior significantly departs from this previous research. The novelty of my approach is it combines recent empirical strategies for testing search theory (Chandra and Tapatta, 2011) together with a "natural experiments" approach to detecting collusive pricing based on aggregate supply/demand shocks. In the conclusion, I argue this tandem approach to identifying collusive pricing can be applied more generally to retail markets that exhibit asymmetric pricing, of which there are many (Peltzman, 2000).

I also contribute to a large literature on asymmetric pricing in retail markets. Previous articles have tested channels for pricing asymmetry; much of this work is motivated by Borenstein, Cameron, and Gilbert (1997) who identified

tacit collusion and search behavior as the leading channels. Some articles have found evidence consistent with search frictions generating asymmetric pricing (Lewis, 2009; Lewis and Marvel 2011; Richards, Gomez and Lee 2014). Others have shown asymmetric pricing tends to occur in locations where firms have market power, but do not test for collusion (Deltas, 2008; Verlinda 2008; Richards, Gomez and Lee 2014).[8] My study is the first to disentangle the collusive channel from the search-based channel.

Finally, this article's findings extend our understanding of competition and conduct in gasoline markets to rural markets. Indeed, virtually all previous studies of gasoline retailing focus on cities, likely because this is where data from marketing companies is readily available for researchers.[9] The fact that the rural markets in my sample exhibit substantial pricing asymmetry best explained by models of collusion gives rise to anti-trust concerns and motivate further investigation into rural market pricing.

This article is organized as follows. The next section describes the empirical context and data. In Section 3, I describe the asymmetric error correction model and my baseline results. Section 4 examines the underlying channels for asymmetric pricing. Section 5 summarizes and discusses policy implications.

2 Context and data

This section provides an overview of the empirical context. I first describe the data and markets the study is based on. I highlight aspects of market struc-

[8]Eckert (2002) and Lewis and Noel (2011) gasoline price cycles can also play a role in determining the degree of pricing asymmetry.

[9]See Eckert (2013) for an excellent overview of the empirical literature on gasoline retailing.

ture that influence gasoline stations' pricing, and present preliminary evidence of differential pricing behavior across urban and rural markets. I also discuss the global oil price shock of 2007-08 and its effect on retail and wholesale prices.

2.1 Data

I have daily, station-level panel data on regular unleaded gasoline prices in Ontario, Canada. These data were obtained from a web-based company called GasBuddy. Specifically, the data come from voluntary price spotters who observe stations' prices and upload them to GasBuddy's advertiser-sponsored websites.[10] By uploading prices, spotters build profiles and potentially win prizes. Both spotters and non-spotters also use GasBuddy to find low-priced fuel. Indeed, in 2006 GasBuddy was the most popular gasoline price reporting website in North America (Lewis and Marvel, 2011). Its popularity, combined with the local nature of price spotting, generates a vast amount price data across many markets.

GasBuddy provided me with the universe of these price reports for the August 1, 2007-August 12, 2008 period. In total, the panel contains 544,646 station-level price observations from 1947 stations located across 82 markets.[11] The data also include each station's brand and address.

I complement the price data with four additional sources of information: (1) daily market-level wholesale (or "rack") prices for gasoline; (2) each market's distance from its nearest refinery and wholesale gasoline distribution terminal;[12] (3)

[10]The websites include GasBuddy's national site (www.gasbuddy.com), its provincial website (www.ontariogasprices.com), and city-specific websites (e.g., www.torontogasprices.com). GasBuddy also has a web application that allows individuals to upload prices using mobile devices.

[11]Data Appendix A provides additional details on sample construction. Given the GasBuddy data are self-reported, sample representativeness is a potential issue. In Appendix A I also validate the GasBuddy data using market-level data on gasoline prices from MJ Ervin and Associates.

[12]Distribution terminals receive gasoline from refineries via pipeline or ship and are the main

annual highway counts of the traffic passing each market; and (4) demographics. Appendix A describes these variables and their sources in detail. The first column of Table 1 reports summary statistics for all variables used in the article.

As mentioned in the Introduction, the key novelty of the price data is that they span a rich cross-section of urban *and* rural markets. For instance, 20 (24%) markets in the sample have five or fewer stations, whereas 21 other markets have more than 30 stations. Figure 1 maps out the locations of the markets. Many urban markets are in the south toward Toronto, along major highways and the U.S. border. The rural markets are spread out across the province.

2.2 Market structure

Table 1 highlights a high degree of retail market concentration. The C4 ratios show that on average 75% of the stations in a market operate under one of four retail brand names. This reflects the presence of four major oil companies in Ontario who are refiners, wholesalers, and retailers of gasoline: Esso, Shell, Petro-Canada and Sunoco. Among the sample's 1947 stations, 384 (20%), 293 (15%), 338 (17%) and 227 (12%) operate under these respective retail names. Going forward, I refer to such stations as "brands" and all other station-types as "independents." Regardless of station-type, virtually every station in the province is supplied with wholesale fuel by one of the four major oil companies.

Beyond concentration, two others aspects of market structure are important when considering pricing and conduct. First, most stations are locally owned and operated. While there has been a shift toward centrally run stations over

source of gasoline supply. They hold gasoline inventories that are eventually loaded onto trucks, trains, or ships and sent to their final destination for retail sale (MJ Ervin and Associates, 2010).

time (particularly among branded stations), as of 2010 74% of stations in Canada remained locally run (MJ Ervin, 2010). My conversations with station owners further revealed that almost all rural stations are locally owned. These facts are important for my analysis of conduct as they imply local pricing decisions.[13]

Second, gasoline inventory management differs across urban and rural stations. An extensive industry report from MJ Ervin & Associates (2010) and my conversations with station owners indicate that: (1) stations store gasoline using in-ground storage tanks and actively monitor their inventories; (2) stations can submit fuel inventory orders to wholesalers at any time; and (3) rural stations tend to submit orders much less often than urban stations. The difference in order frequency across urban and rural markets reflects the fact that rural stations have higher fuel shipping costs and deplete their inventories at much slower rates than urban stations.[14]

Differences in inventory behavior can potentially create differences in pricing behavior and cost passthrough across markets. Local station owners purchase fuel directly from wholesalers. This implies their price-cost margins are heavily influenced by the cost of fuel at times when they replenish their inventories. Thus, if stations tend to adjust their prices to reflect wholesale costs around inventory orders, and if rural stations make inventory orders less frequently, then rural markets are likely to exhibit a relatively higher degree of price rigidity.[15]

[13]Numerous articles in the academic literature have also emphasized local decision-making in retail gasoline. See, for example, Chandra and Tappata (2011) and Houde (2012).

[14]MJ Ervin & Associates (2010) estimates that stations in urban markets like Toronto pump 7-8 million liters of fuel per year, whereas rural stations pump only 1-2 million liters. Urban stations thus tend to turn over their inventories much more rapidly.

[15]In addition to causing price rigidity, inventory-based pricing can potentially generate asymmetric pricing. I address this issue in Section 4 when studying channels for pricing asymmetry.

2.3 Retail pricing regimes

Raw price plots reveal three pricing regimes in the data. As Figure 2 highlights, the regimes tend to exist across different-sized markets. The figure shows that in Ajax (90,000 people, 33 stations) retail prices move in lock-step with wholesale costs.[16] This contrasts with St. Thomas (36,000 people, 14 stations) where prices exhibit asymmetric cycles, and Atikokan (3,300 people, 2 stations) where there is substantial price rigidity. I adopt naming conventions from Noel (2007a) and refer to these regimes as *cost-based pricing*, *price cycles*, and *sticky pricing*.

Lewis and Noel (2011) emphasizes the importance of accounting for pricing regimes in studying asymmetric pricing. Accordingly, I classify markets into one of three mutually exclusive groups that are defined by the pricing regimes. I classify markets in two steps. First, I follow Lewis and Noel and classify cycling and non-cycling markets using a threshold rule: a market is cycling if the median daily price change is negative. Intuitively, cycling markets exhibit many days of price undercutting and few with price increases. In contrast, cost-based and sticky markets tend to have offsetting numbers of days with price increases and decreases. Panel A of Figure 3 shows that indeed a large mass of markets have median price changes of zero (cost-based and sticky markets) whereas a non-negligible number of markets have negative price changes (cycling markets). Based on these median price changes, I classify 22 of 82 markets as cycling.

The second step classifies the remaining 60 non-cycling markets as being either cost-based or sticky. I do so using an adjustment ratio (Clark and Houde,

[16] Daily market-level prices are computed as the average price across stations within a market.

2013) which summarizes how fast market-level retail prices respond to cost changes:

$$\text{adjratio}_i = \text{median}\left(\frac{p_{it} - p_{it-1}}{c_{it} - c_{it-1}}\right)$$

where p_{it} and c_{it} are the retail and rack price for market i on date t. Panel B of Figure 3 presents the distribution of adjustment ratios across the non-cycling markets. The distribution is bi-modal: many markets with rigid pricing exhibit adjustment ratios of zero, whereas others exhibit positive ratios indicating cost-based pricing. I therefore classify a non-cycling market as having sticky prices if its adjustment ratio is zero - otherwise it is cost-based. This classification yields 38 cost-based and 22 sticky markets.[17]

Pricing regimes and market structure

What types of markets exhibit cost-based, cycling and sticky pricing? Table 1 reports descriptive statistics by pricing regime. Market size appears to predict regimes in the sample: cost-based pricing tends to occur in cities with 94,000 people and 37 stations; cycling markets are intermediate-sized with 44,000 people and 19 stations; sticky markets are rural towns with 8,000 people and five stations. Sticky markets are also considerably more concentrated and isolated from wholesale supply (refineries, petroleum terminals) than other market types.[18]

Returning to Figure 1, cost-based markets correspond to urban markets near Toronto/Hamilton in Southern Ontario. Cycling markets tend to be intermediate-

[17] I have experimented extensively with the threshold median price change and adjustment ratios for classifying cycling/non-cycling markets and cost-based/sticky markets. All of the results throughout are robust to varying these thresholds within reasonable ranges.

[18] Appendix A.3 presents linear probability and multinomial logit models that identify variables that predict cost-based/cycling/sticky pricing. The results reaffirm this discussion of pricing regimes, market size, concentration and isolation.

sized cities along major highways both in the north and the south. Sticky markets correspond to isolated, rural locations throughout the province.[19]

2.4 2007-08 crude oil price shock

A final important feature of the context is the 2007-08 global shock to crude oil prices. This shock, which I depict in panel A of Figure 4, saw crude oil prices experience the largest and most rapid run-up and in crash history (Hamilton, 2009). Among other factors, a global demand shock driven by unexpectedly high Chinese economic growth caused the run-up (Kilian, 2009).[20] These fluctuations had a large and direct impact on wholesale and retail gasoline prices in Ontario. I highlight this for Toronto in panel B of Figure 4.

Importantly, the sample contains the run-up in crude oil prices as well as the first month of the crash. In Section 4 I exploit this large, exogenous and unexpected rise in stations' costs and uncertainty over wholesale supply to test for collusive conduct. Unfortunately, GasBuddy would not share a longer time series that would allow me to investigate the long-run effects of the shock. This does not, however, prevent me from examining short-run effects of the shock on pricing and conduct. My test for collusion is based on such short-run effects.

3 Identifying asymmetric pricing

This section studies the extent to which market-level retail prices respond asymmetrically to positive and negative cost shocks. I first describe the asym-

[19] Atkinson et. al (2014) show price cycles existed in and around Toronto prior to February 2007 and document a permanent change to cost-based pricing. They propose Hurricanes Ivan, Katrina and Rita, and a fire at the Nanticoke refinery as explanations for the change.

[20] I further discuss factors that contributed to crude oil price uncertainty in Section 4.

metric error correction model used to identify pricing asymmetry. I present baseline asymmetric pricing results for cost-based, cycling and sticky markets in which I pool data for each of these market types. I then estimate market-specific error correction models and use auxiliary regressions to study the determinants of pricing asymmetry. Importantly, the latter two-step market-level analysis forms the basis for my test of the collusive channel for pricing asymmetry in Section 4.

3.1 Asymmetric error correction model

Keeping with previous research (Borenstein et. al, 1997), I use an error correction model to identify asymmetry pricing,

$$\Delta p_{it} = \sum_{j=0}^{39} (\beta_j^+ \Delta c_{jt-1}^+ + \beta_j^- \Delta c_{jt-1}^-) + \sum_{k=1}^{15} (\gamma_k^+ \Delta p_{kt-1}^+ + \gamma_k^- \Delta p_{kt-1}^-)$$
$$+ \phi^+ z_{kt}^+ + \phi^- z_{kt}^- + \epsilon_{kt} \tag{1a}$$

$$z_{kt} = p_{it-1} - \psi c_{kt-1} - \mu_i \tag{1b}$$

where p_{it} is the before-tax average retail price in market i on date t, c_{it} is the wholesale cost,[21] $\Delta p_{it} = p_{it} - p_{it-1}$ and $\Delta c_{it} = c_{it} - c_{it-1}$. The error correction term z_{kt} is estimated from a first stage regression of p_{it} on c_{it} and market dummies that control for fixed effects μ_i. The + and − superscripts correspond to positive and negative cost/price changes and values of error correction terms. Specifically $\Delta c_{jt-1}^+ = \max\{0, \Delta c_{jt-1}\}$, $\Delta c_{jt-1}^- = \min\{0, \Delta c_{jt-1}\}$ (similarly for Δp_{jt-1}^+, Δp_{jt-1}^-, z^+, and z^-). The β_j^+ and β_j^- coefficients thus capture asymmetric

[21] Recall that I use the rack price as a proxy for wholesale cost. This is an appropriate proxy for studying retail price responses to cost shocks as rack prices are the primary time-varying component of stations' wholesale fuel costs (recall Figures 2 and 4).

price responses to current and lagged positive and negative cost shocks. The γ_j^+ and γ_j^- coefficients similarly capture asymmetric price changes to lagged positive and negative price changes. The ϕ^+ and ϕ^- coefficients allow for asymmetric responses to positive and negative error correction terms.

The objects of interest from the error correction model are the impulse responses of retail prices to cost shocks.[22] Throughout, I report results based on equal-magnitude $\Delta c = \pm 2.5$ cents per liter positive and negative cost shocks; this shock magnitude corresponds to the sample standard deviation of Δc_{it}. Asymmetric pricing exists if the impulse responses reveal faster retail price adjustment to positive shocks than negative shocks.[23]

For the first set of results, I pool data for cost-based, cycling and sticky markets and estimate error correction models and impulse responses for each market-type. Panel A of Figure 5 presents the corresponding cumulative retail price responses to positive and negative cost shocks for cost-based and sticky markets, where the price responses are reported as a percentage of the cost shock.[24] The figure highlights substantial differences in pricing asymmetry. In (urban) cost-based markets, positive and negative cost shocks are passed through symmetrically and completely within three days. In contrast, passthrough in (rural) sticky markets is incomplete and highly asymmetric. After two weeks, 70% of a positive cost shock is passed through to retail prices, whereas only 40% of a negative

[22] See Borenstein et. al (1997) for details on how to compute impulse responses. Error correction model parameter estimates are listed in Appendix A.4. Standard errors for impulse responses are computing using the bootstrap; see Appendix B for descriptions of bootstrap routines.

[23] The main results throughout are robust to using alternative shocks of $\Delta c = \pm 1$ and $\Delta c = \pm 4$. These are available upon request.

[24] To focus the analysis on the novel urban-rural contrast the sample permits, and because the issue has already been studied by Eckert (2002) and Lewis and Noel (2011), I do not discuss price responses for cycling markets in great detail.

shock is passed through. Panel B, which plots the difference between the price responses in rural markets, shows these differences become statistically significant after a week and are permanent in the long-run.

3.2 Asymmetric pricing, market structure and pricing regimes

The pooled results suggest that asymmetry is related to market structure and pricing regimes. Stations in isolated rural markets that achieve sticky pricing also engage in asymmetric pricing. As markets grow and competition becomes fierce, pricing becomes cost-based and response asymmetries disappear.

To investigate how pricing asymmetry varies with market structure and pricing regimes, I employ a two-step regression analysis. First, I estimate the model in (1a) and (1b) market-by-market.[25] Using these market-specific error correction models, I compute market-specific impulse responses to positive and negative shocks. Doing so yields a cross-section of cumulative price responses across markets for both positive and negative shocks, for each day following a shock.

In the second step, I stack the cross-sections of cumulative responses for positive and negative shocks τ days after a shock and run the following regression,

$$\begin{aligned} PriceResp_{m\tau} = {} & \delta_0^\tau 1\{NegShock\}_{m\tau} + \delta_1^\tau 1\{CycMkt\}_{m\tau} + \delta_2^\tau 1\{StickyMkt\}_{m\tau} \\ & + \gamma_1^\tau 1\{CycMkt\}_{m\tau} \times 1\{NegShock\}_{m\tau} + \gamma_2^\tau 1\{CycMkt\}_{m\tau} \times 1\{PosShock\}_{m\tau} \\ & + \gamma_3^\tau 1\{StickyMkt\}_{m\tau} \times 1\{NegShock\}_{m\tau} + \gamma_4^\tau 1\{StickyMkt\}_{m\tau} \times 1\{PosShock\}_{m\tau} \\ & + \mathbf{X}_{m\tau}\beta^\tau + \epsilon_{m\tau}. \end{aligned} \tag{2}$$

The dependent variable $PriceResp_{m\tau}$ is the cumulative price response as a per-

[25] The only difference in model specification is market fixed effects are not included in (1b) since the market-level heterogeneity is accounted for in the model parameters.

centage of the cost shock in market m, τ days after the cost shock (as presented in Figure 5). The indicator variables $1\{NegShock\}_{m\tau}$ and $1\{PosShock\}_{m\tau}$ equal one if $PriceResp_{m\tau}$ was generated by a negative or positive shock. The dummies $1\{CycMkt\}_{m\tau}$ and $1\{StickyMkt\}_{m\tau}$ equal one if market m exhibits price cycles or sticky pricing. The vector $\mathbf{X}_{m\tau}$ includes other market characteristics that could affect the rate of passthrough including size, concentration and proximity to wholesale supply. The τ superscripts on the coefficients indicate that I run separate regressions using cross-sections of cumulative price responses for each day τ after a cost shock.[26]

The main coefficients of interest in (2) are γ_3^τ and γ_4^τ. They quantify the degree of pricing asymmetry in markets with sticky pricing regimes, τ days after a cost shock. This interpretation stems from the combination of dummies for negative/positive shocks and cycling/sticky pricing and their interactions in equation (2). Together, they imply a baseline group of "positive cost shocks in cost-based markets." The γ_3^τ and γ_4^τ estimates thus quantify the asymmetry and sluggishness of price responses to positive and negative cost shocks in sticky markets relative to cost-based markets with symmetric and rapid passthrough.

Table 2 presents the regression results for $\tau = 7$ days after the cost-shock. The column (1) estimates highlight sluggish price responses in cycling and sticky markets. The insignificant 'Negative Shock' coefficient and constant together imply 98.3% of a cost shock is passed through to retail prices in cost-based markets after seven days. This reflects the symmetric and rapid passthrough for these

[26]The dependent variable in equation (2) is a function of market-specific error correction model parameter estimates. I therefore report boostrap standard errors for the regression coefficients in (2). Appendix B describes the bootstrap procedure.

markets from Figure 5. The estimates further imply that the fraction of cost passed through to prices after seven days falls by 27.4% and 37.6% in markets with cycling and sticky pricing. That is, only 70.9% and 60.7% of the cost shock is passed through in markets with these pricing regimes.

Columns (2) and (3) expand the specification to allow for asymmetric price responses in cycling and sticky markets, and to control for other variables that affect passthrough. The results again highlight large asymmetry in sticky markets. Column (3) indicates that the fraction of cost passed through to prices after seven days falls by 33.7% for negative shocks in markets with sticky pricing. The analogous figure for positive shocks is only 16.7%. This 17 percentage point difference in passthrough rates $\tau = 7$ days after the cost shock closely corresponds to the estimated difference in passthrough rates for sticky markets from Figure 5.

There are some other results of note from columns (2) and (3). Like previous research (Eckert, 2002; and Lewis and Noel, 2011), I find asymmetric pricing in cycling markets, though the asymmetry is smaller in magnitude compared to sticky market asymmetry. Moreover, the coefficient estimates for the other market structure variables confirm the intuition that passthrough is sluggish in markets that are farther from wholesale supply. I also find markets with fewer competitors exhibit more sluggish price adjustment.

The results thus far suggest that pricing asymmetry is larger in markets where firms use simple sticky-pricing strategies. These regime effects could, however, be explained by market structure variables that simultaneously explain pricing asymmetry and rigidity. I explore this possibility in columns (4)-(7) of Table 2 by including interactions between the negative/positive cost shock dummies and

market characteristics. If a characteristic (e.g., market size, concentration or isolation) explains pricing asymmetry and rigidity, then the inclusion of these regressors should render the sticky pricing regime effects small and insignificant.

Looking across columns (4)-(7) we see this does not happen. Indeed, the regime effects $\hat{\gamma}_3^\tau$ and $\hat{\gamma}_4^\tau$ are statistically significant and the null hypothesis that $\gamma_3^\tau - \gamma_4^\tau = 0$ is rejected at the 5% level in each specification across columns (2)-(7). I see this as an important result: controlling for the effect of market size, concentration and isolation on pricing asymmetry and rigidity, I find stations who coordinate on sticky pricing are also able to engage in asymmetric pricing.[27]

3.3 Pricing asymmetry and sticky pricing regimes

The sticky pricing regime effects just discussed are based on cumulative price responses to negative and positive cost shocks $\tau = 7$ days after the shocks. To investigate how pricing asymmetry evolves in markets where firms engage in sticky pricing, I plot the γ_3^τ and γ_4^τ estimates for $\tau = 1, \ldots, 12$ in panel A of Figure 6. Panel B plots the differences in the coefficient estimates and their standard errors.[28]

The results from Figure 6 corroborate the pooled results from Figure 5. Their interpretation differs, however, since the sticky pricing regime effects in Figure 6 control for other market characteristics that affect passthrough. The figure shows price responses to positive and negative shocks diverge and become significantly different five days after a cost shock. After ten days there is a permanent, 40

[27] The result that more concentrated markets (in terms of HHI) have faster passthrough for positive cost shocks is driven by the fact that cost-based markets tend to have more concentrated station ownership and hence larger HHI's than cycling markets; see Table 1.

[28] All figures are based on the column (3) specification from Table 2. For the sake of clarity in panel A of Figure 6, I do not present confidence intervals for the sticky pricing regime effect estimates. See Appendix B for details on how the confidence intervals in panel B are constructed.

percentage point difference in passthrough rates for positive and negative cost shocks in markets where stations engage in sticky pricing. If anything, the evolution of these regime effects raise further concern that rural stations who engage in sticky pricing are keeping prices excessively high when costs fall.

4 Testing channels for asymmetric pricing

Why do we observe asymmetric pricing? While the results from Section 3 identify a link between sticky pricing behavior and pricing asymmetry, they do not isolate channels. This section takes up this task, focusing on the sample's unique collection of rural sticky markets where asymmetry is largest.

From the Introduction recall that the literature has emphasized collusive and competitive search-based explanations. Some articles have found evidence of the search-based channel; virtually none have isolated the collusive channel. In what follows, I present anecdotal evidence and empirical tests that argue the large pricing asymmetry in sticky markets is collusive. My argument proceeds in three steps. I first rule out search frictions in sticky markets. This provides indirect evidence of the collusive channel since it is the remaining explanation for asymmetry pricing. I then develop a direct test for collusion that exploits the 2007-08 global crude oil price shock. The results also point to collusive behavior. Finally, I examine a new channel related to inventory-based pricing. My test suggests this channel cannot explain pricing asymmetry in sticky markets.

4.1 Search

Anecdotal evidence

There is little scope for search-based theories (e.g., Yang and Ye, 2008; Tappata, 2009; Lewis, 2011) to explain asymmetric pricing is sticky markets. Recall from Table 1 that these markets have only five stations on average. There is little spatial dispersion across these stations as most are located on the same street, or at highway exists. Indeed, the average standard distance[29] among stations in sticky markets is 1.7 kilometers (e.g., a typical station is 1.7 kilometers from the center of a market). In contrast, standard distances in cycling and cost-based markets are 3.3 and 10.1 kilometers on average. Consumers thus face minimal search costs in comparing stations' prices in rural sticky markets.

I can further assess the relevance of search frictions for retail pricing by examining price dispersion across stations at a point in time (*spatial* price dispersion; Varian, 1980) and within stations over time.[30] Like the classic Varian (1980) model of sales, the cited search theories do not have pure strategy Nash Equilibria. Instead, equilibrium pricing is characterized by mixed strategies where firms randomize over prices. An empirical implication of this behavior is spatial and inter-temporal price dispersion. That is, if search frictions exist then we should see both forms of price dispersion.

Figure 7 shows this prediction is not borne out in the data for sticky markets.

[29] Standard distance is a spatial statistic similar to standard deviation that summarizes dispersion of stations around the center of a market

[30] Within-station price variation is related *temporal* price dispersion. This exists if firms' position in market-level price distributions change over time. My data is not sufficiently rich to permit a formal analysis of temporal price dispersion in rural markets.

Panel A presents the distribution of the daily market-level price range across stations in cost-based, cycling and sticky markets. Panel B presents the distribution of daily within-station price changes.[31] The differences in price dispersion and rigidity across these market types is stark. Compared to cost-based and cycling markets, stations in sticky markets set identical prices on most days and keep their price constant over time. This conflicts with predictions from search theory, thereby undermining search-based explanations for pricing in sticky markets.

Empirical test

Comparative statics based on a variant of Varian's (1980) model from Chandra and Tappata (2011) suggest a further test for search frictions. They show equilibrium price dispersion increases at a decreasing rate with the number of competitors in a market (see Figure 2B of their article). Intuitively, firms' incentives to randomize over prices where they sometimes offer low prices (e.g., have sales) to discriminate among informed and uninformed consumers is high when there are few firms.[32] Thus, additional firms can have large effects on equilibrium price dispersion when the number of firms is small. As the number of firms grows large, their ability to attract informed consumers through sales diminishes since there are many firms offering sales. Firms tend to set less disperse prices, and equilibrium price dispersion mainly reflects the number of firms.[33]

[31] To construct these figures I use the daily station-level price data from GasBuddy. From Table 1 there are 544,646 station-date observation. The sample is restricted such that are at least two price observations from two different stations for a given market-date.

[32] In the context of gasoline, informed consumers are people who actively shop for low-priced fuel. Uninformed consumers can be thought of as naive "fill-up-the-tank-when-empty" types.

[33] Figure 2B from Chandra and Tappata (2011) also highlights a non-monotonic relationship between average prices and the number of firms. This reflects firms' disincentive to have sales with many competitors; they instead set higher prices more often to exploit uninformed consumers.

The above discussion suggests that the following regression can be used to test for the presence of search frictions,

$$PriceRange_{it} = \alpha_0 + \alpha_1 N_i + \alpha_2 N_i^2 + \mathbf{X}_{it}\beta + \epsilon_{it}, \tag{3}$$

where $PriceRange_{it}$ is the range of prices in market i on date t, N_i is the number of competitors in market i, $\mathbf{X}_{it}$ are other variables that affect price dispersion[34] and ϵ_{it} is the econometric error. For inference, I report asymptotic standard errors that are clustered at the market-level. If search frictions influence firms' pricing decisions as predicted by theory, then we should expect $\alpha_1 > 0$ and $\alpha_2 < 0$. Further, given that the marginal impact of additional stations is *largest* when N_i is small, the magnitude of α_1 (α_2) should be particularly large (small) when regression equation (3) is estimated using data from sticky markets.

The empirical results in Table 3 reveal no such relationship in the data; the number of competitors has a statistically and economically insignificant relationship with spatial price dispersion.[35] Through the lens of a search model, this finding implies that additional competitors in sticky markets fail to randomize their prices in a way that is consistent with equilibrium behavior in a model with demand-side search frictions. The lack of spatial price dispersion in sticky markets from Figure 7 exists regardless of the number of stations in a market.

[34] These include daily rack prices for market i, the market structure and demographic variables from Table 1, and gasoline retailer dummy variables. The latter dummy for retailer j equals one if one or more stations in market i operates under retailer j's name.

[35] Table 3 also highlights an insignificant relationship between the level of marginal cost and price dispersion. This is also contradicts the prediction of a negative equilibrium relationship between price dispersion and marginal cost from the search model of Chandra and Tappata (2011).

4.2 Collusion

The large degree of pricing asymmetry in sticky markets from Section 3, together with the evidence against search frictions in these markets from Section 4.1, provide indirect evidence of the collusive channel. Both anecdotal evidence and a novel direct test of the collusive channel reinforces this interpretation.

Anecdotal evidence

Cartels actually existed in Ontario and neighboring Quebec around the sample's 2007-08 time period. In 2012, the Canadian Competition Bureau announced that retailers in Kingston and Brockville, Ontario pleaded guilty to engaging in price fixing in 2007. In Quebec, the Bureau uncovered a 128-station, 64-firm cartel operating across four markets in 2005-06.[36] In both cases, the retail markets exhibited price cycles.[37] There is thus direct evidence of collusion in the sample context from larger markets where collusion would have been more difficult to sustain compared to rural sticky markets.

The structure of sticky markets and their degree of price rigidity further raises concerns of collusion. These markets have few, geographically proximate stations which: (1) experience persistent cost shocks with a common component (e.g., crude oil price); (2) sell a homogeneous product; (3) face inelastic demand; and (4) post prices on large signs. These features of market structure create incentives for cartels and facilitate monitoring and punishment strategies that help

[36] See http://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/03447.html (Ontario) and http://www.competitionbureau.gc.ca/eic/site/cb-bc.nsf/eng/03079.html (Quebec) for details.

[37] My sample partly includes the May to November 2007 period where price fixing was found in Kingston and Brockville. Both markets exhibit stable price cycles between August and November 2007. Clark and Houde (2013, 2014) document price cycles in the Quebec-based cartel.

ensure their stability. Athey and Bagwell (2008) indeed show that price rigidity can emerge from an optimal collusive agreement in dynamic Bertrand pricing environments that closely resemble sticky markets.[38] This provides a theoretical basis for concerns that sticky pricing behavior in rural markets is collusive.[39]

Empirical test

Moving beyond anecdotes, I can directly test the collusive channel for pricing asymmetry by exploiting the global crude oil price shock of 2007-08. Recall from Section 2 that this unprecedented shock caused a rapid rise and fall in retail and wholesale prices in Ontario. It also created substantial uncertainty for retailers regarding wholesale costs. Hamilton (2009) documents various sources of uncertainty including: (1) surging and highly speculative Chinese oil demand; (2) Saudi Arabia breaking from its historical practice of supplying crude reserves to markets with excess oil demand; and (3) the emergence of speculative investors who fueled the shock and created a permanent rise in crude price volatility.

[38]Athey and Bagwell (2008) assume publicly observed prices and private, persistent cost shocks. The observability of prices clearly applies to rural gasoline markets. Stations also have private information regarding their costs: each individually contract with gasoline suppliers and hence can realize different privately-observed per-unit wholesale costs that slightly differs from rack prices day-to-day.

[39]Alternative explanations of price rigidity include menu costs. Previous studies on menu costs in retail gasoline markets strongly reject their presence (Davis and Hamilton, 2004; Douglas and Hererra, 2010). This is perhaps not surprising given: (1) it is costless to change prices on a gasoline stations' signs; and (2) station managers are updated each day by wholesalers on current fuel costs. The latter fact, which was revealed to me through conversations with station owners, undermines theories of rational inattention (Reis, 2006) that provide a micro-foundation for menu costs. These latter models assume it is costly for firms to learn about their costs/mark-ups.

Rotemberg (2011) proposes a demand-side micro-foundation for price rigidity that assumes consumers are angered by price increases. Beyond price effects, demand is lower for firms with higher prices because they are deemed "unfair" by consumers. All else equal, this reduces firms' incentives to adjust prices upward, thus creating price rigidity. While I do not rule out this channel, it is worth noting that to the extent price increases create anger, this channel for price rigidity mitigates pricing asymmetry. That is, the large asymmetric price responses in sticky markets exist *despite* any consumer anger effects.

Theory suggests that this exogenous variation in stations' cost uncertainty can be used to test for collusion. Learning models of collusion (Slade, 1989) predict short-run cartel breakdowns in the presence of major demand or cost shocks.[40] The prediction rests on the assumption that colluding firms become imperfectly informed about structural demand and cost parameters when major shocks occur. Following a permanent shock to cost/demand parameters, the joint profit-maximizing pricing strategies of cartels change. In adjusting prices in response to the shock, firms can thus trigger a short-run price war. The variation in prices generated by the price war ultimately helps firms to learn about new structural parameters, and, in the long-run, renegotiate collusive agreements.

Applying these theoretical insights to my empirical setting, if uncertainty over structural changes to crude oil markets in 2007-08 caused a short-run breakdown in collusive agreements among rural stations, and if collusion causes asymmetric pricing, then pricing asymmetry in sticky markets should become less pronounced at the onset of the crude oil shock. To explore this hypothesis, I re-estimate the sticky pricing regime effects γ_3^τ and γ_4^τ from equation (2) using a February 1, 2008 - August 17, 2008 subsample, which corresponds to the crude oil shock period.[41] By comparing the baseline regime effects in Figure 6 to those based on the crude oil shock subsample, I can see whether pricing asymmetry became muted around the shock in sticky markets.

Figure 8 presents sticky pricing regime effects and their differences for the

[40] See Levenstein and Suslow (2006) for an overview of these models and examples of cartel breakdowns arising from demand/cost shocks.

[41] I have experimented with the definition of the shock period, rolling back the starting date for all dates back to October 1, 2007. The results suggest that February 1, 2008 is the relevant date for which a break in asymmetric price responses starts to emerge.

crude oil shock period. The estimates reveal an upward shift in the sticky pricing regime effects for negative shocks. For instance, the baseline results in panel A of Figure 6 show that the passthrough rate for negative shocks after $\tau = 10$ days is 32 percentage points smaller in markets with sticky regimes relative to those with cost-based pricing. In Figure 8 this figure falls by 50% to 16 percentage points during the crude oil shock period. By contrast, the sticky pricing regime effects for positive shocks after 10 days are similarly close to zero in Figures 6 and 8.

This contrast in the difference in sticky pricing regime effects for positive and negative shocks indicate a fall in pricing asymmetry due to faster passthrough of negative cost shocks. Panel B of Figure 8 indeed shows that sticky pricing regime effects for negative and positive shocks no longer diverge, and that their difference becomes statistically insignificant for all periods following the shock (unlike the baseline estimates in Figure 6).

Overall, these findings are consistent with rural stations abandoning collusive asymmetric pricing strategies in the face of cost uncertainty caused by the global oil price shock. Rather than keeping prices high in the face of falling costs, rural stations engaged pricing strategies that resulted in faster and symmetric passthrough. In other words, gasoline pricing in the country looked like pricing in the city during the shock, a result that is consistent with cartel breakdown.

4.3 Inventories

Inventory-based pricing is another potential channel for pricing asymmetry. This channel is motivated by my conversations with stations owners; to my knowledge it has not been previously considered. I was informed that station

owners sometimes try to time wholesale inventory orders and related price/margin adjustments in anticipation of future cost changes. If an owner anticipates fuel costs are going to rise, there is pressure to refill inventories and adjust prices/margins. By doing so, they can lock in a lower costs today, and earn higher margins on the fuel in their storage tanks by matching their competitors' retail prices in the future. This is profitable if costs do rise and at least one rival refills their inventories and adjust their prices upward at a later date. Hence, when costs are rising, retailers have an incentive to refill inventories and adjust prices quickly.[42]

In contrast, when costs are falling there is an incentive to delay inventories orders and price adjustments. If an order is made too early, an owner risks purchasing fuel at a higher wholesale cost and having their margins fall in the future if a competitor delays refilling inventories, realizes lower costs, and subsequently cuts their prices. Hence, all else being equal, retailers have an incentive to delay inventory refills and price adjustments when costs are falling. Together, these price-and-inventory-adjustment strategies yield asymmetric pricing.[43]

Developing testable hypotheses based on a game-theoretic model of pricing and inventory adjustment is beyond the scope of this article.[44] Moreover, in-

[42]Notice the industry fact that stations are locally owned plays an important role in shaping these incentives. As sole proprietors, rural station owners bear all the risk and reward in terms of profits from their decisions about when to refill inventories and adjust prices/margins.

[43]One station owner further suggested that dynamic demand behavior can reinforce asymmetric pricing. If consumers are forward looking and anticipate rising wholesale costs and retail prices, then there will be more demand for fuel immediately. This increases stock-out risk for stations, and hence raises their incentive to replenish their inventories immediately and adjust prices when costs are rising. In contrast, if consumers anticipate falling gasoline costs and prices, then current demand for fuel falls and future demand rises. This implies immediate stock-out risk is lower, and future stock-out risk is higher, which gives stations an incentive to delay inventory and price adjustments. I have found empirical evidence that consumers are indeed forward-looking in retail gasoline markets (Byrne, Leslie and Ware, 2015; Byrne and de Roos, 2015).

[44]To my knowledge, such a model has not been developed. This may be because of the complexity of dynamic state-space games which can be numerically intensive and are not guaranteed

ventory data for gasoline stations is proprietary and unavailable to researchers; this prohibits me from directly testing how prices, inventories, and costs jointly evolve.[45] However, the above discussion suggests a relatively simple, albeit crude, test of whether market prices adjust in advance of future cost changes, possibly as a result of station owners hastening and delaying inventory and price adjustments in anticipation of rising and falling costs. Denoting the dummy variables $d_{it}^{+} = 1$ if $\Delta p_{it} > 0$, $d_{it}^{-} = 1$ if $\Delta p_{it} < 0$, and $d_{it} = 1$ if $\Delta p_{it} > 0$ or $\Delta p_{it} < 0$, and zero otherwise, I estimate the following linear-in-probability model to see if future cost changes affect the likelihood of a market-level price change today:

$$d_{it} = \sum_{j=0}^{K_1} \delta_k \Delta c_{t+k} + \sum_{j=0}^{K_2} \gamma_k p_{t-k} + \sum_{j=0}^{K_3} \beta_k c_{t-k} + \mu_i + \tau_t + \epsilon_{it} \tag{4}$$

where p_{it} is the average price across all stations in market i on date t, c_{it} is the wholesale cost, and μ_i and τ_t are market and date fixed effects.[46] I run analogous regressions for positive and negative price changes (e.g., where the dependent

to deliver unique equilibrium predictions. See Slade (1999) for further discussion on these issues in the context of a strategic model with dynamic demand (current demand depends on lagged prices because of potential "goodwill" effects), and where there is equilibrium price rigidity with firms employing (s,S) pricing rules.

[45]Aguirregabiria (1999) is perhaps the most relevant theoretical and empirical reference price and inventory adjustment. He develops an industry model with monopolistically competitive firms that make pricing and inventory decisions and face ordering and menu costs. To evaluate the importance of these latter costs quantitatively, he structurally estimates the model using unique data on inventories and prices from a supermarket chain. Unfortunately, his approach likely does not apply to the current setting. Unlike the cities he studies with multiple retailers, the rural markets in this study with few firms likely implies a strategic oligopoly model is required; abstracting away from this aspect of market structure with a monopolistically competitive assumption is likely too strong. Moreover,the lack of inventory data or any other information on inventory ordering prevents me from taking a structural approach to directly studying the role of inventory decisions on strategic pricing behavior. This is left for future work.

[46]It is well-known that incorporating fixed effects in dynamic panel models can be problematic when the explanatory variables are not strictly exogenous. This is a caveat to the specifications with market fixed effects below (which are reported as a robustness check).

variable is d_{it}^{+} or d_{it}^{-}) to see if there are asymmetries in upward and downward price adjustment in anticipation of future cost changes.[47]

The coefficients of interest are δ_k for $k = 1 \ldots K_1$. If station owners systematically refill their inventories and adjust their prices in anticipation of future cost increases, then we should expect $\delta_k > 0$ in regressions that predict d_{it}. If inventories tend to be refilled (not refilled) during periods of rising (falling) costs, then we should see $\delta_k > 0$ ($\delta_k < 0$) in the regressions that predict d_{it}^{+} (d_{it}^{-}). In practice I let $K_1 = 10$ and $K_2 = K_3 = 14$. This assumes stations owners use up to two weeks' of past prices and costs to forecast cost changes up to ten days into the future.

It is worth emphasizing that these tests are necessarily conducted at the market level since the asymmetric pricing results above are based on market-level prices. Inventory-related price adjustments in anticipation of future costs confound the claim that asymmetric pricing arises from collusion if we see a corresponding increase/decrease in the likelihood of market-level price adjustment in advance of future positive/negative cost changes. For the interested reader, I present the corresponding station-level estimates in Appendix A.4.

Table 4 presents the results. They do not provide a strong case for the inventories-based channel for asymmetric pricing: market-level prices do not adjust quickly upward (sluggishly downward) in anticipation of future cost increases (decreases). At best, there is weak evidence that prices adjust upward today in anticipation of future cost increases two days into the future, but not for other future periods with positive cost changes. The station-level results in Appendix A.4 similarly

[47] While I am taking an atheoretic empirical approach, the specification in (4) is informed by the dynamic models of retail price adjustment of Slade (1999) and Aguirregabiria (1999). In these models, current and lagged prices and/or costs enter as state variables.

does not suggest station owners are successful at anticipating near-term changes when wholesale costs in making inventory and pricing decisions. This may simply reflect the difficulty of predicting highly volatile crude oil prices.

5 Summary and discussion

This article has argued that asymmetric pricing can arise from collusive conduct. Using novel data on gasoline prices from urban and rural markets, I uncover substantial pricing asymmetry in rural areas and disentangle collusive and search-based explanations for these patterns. I test for and rule out search frictions which, in effect, provides indirect evidence of collusion. This indirect test is reinforced by a direct test that exploits the 2007-08 global oil price shock. I show asymmetry falls with the shock, a result that is consistent with theories and evidence of cartel breakdowns in the presence of major economic shocks.

In terms of policy, the results motivate investigations and monitoring of gasoline pricing in highly concentrated markets. Indeed, the finding that rural stations maintain high prices despite falling costs - whereas urban stations pass on discounts immediately - make concerns of price gouging salient.[48] While I am unable to identify the collusive mechanism that generates these patterns, tacit collusion is a distinct possibility. Rural stations have few rivals and near-perfect ability to monitor each other, and are thus can arrive at a common understanding in which they: (1) slowly reduce prices when costs fall in order to realize above-average margins; and (2) quickly increase prices when costs rise to maintain margins. The results presented here suggest that immunity programs may

[48] Price gouging in retail gasoline persists as an area for public policy debate. For instance, see Congressional Research Office (2011).

be relatively more useful than wire-taps for cartel detection in smaller markets.[49]

The article's policy relevance likely extends beyond retail gasoline. Given asymmetric pricing exists across many industries (Peltzman, 2000), and given the emergence of new datasets containing high-frequency disaggregated price data spanning many markets,[50] my tandem approach to testing search frictions and changes in pricing asymmetry following major shocks can be employed more broadly to identify markets where the collusive channel operates.

[49]This contrasts with cartel detection in cycling markets where wire-taps have been successful employed; see Wang (2008) and Clark and Houde (2014). In these markets, stations have engaged in explicit communication via telephone to coordinate on price jumps and price undercutting.

[50]Scanner datasets on prices, which has spurred a huge literature on price rigidity in macroeconomics (Nakamura and Steinsson, 2008), and recent work on markups and misallocation in trade (Hottman, 2015), could be used to undertake such tests across a range of industries.

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Tables

Table 1: Summary Statistics

	Full Sample		Cost-Based Pricing		Price Cycling		Sticky Pricing	
Market structure variables								
Number of stations	23.73	(2828)	37.55	(35.32)	18.68	(11.50)	4.91	(3.38)
Share of independent stations	0.479	(0.232)	0.385	(0.211)	0.553	(0.131)	0.565	(0.286)
HHI	0.241	(0.226)	0.19	(0.142)	0.141	(0.04)	0.43	(0.328)
C1 ratio	0.313	(0.213)	0.268	(0.139)	0.217	(0.068)	0.484	(0.306)
C4 ratio	0.750	(0.167)	0.730	(0.125)	0.622	(0.119)	0.912	(0.142)
Distance to nearest refinery	220.38	(207.98)	130.28	(77.37)	223.65	(180.70)	372.73	(290.91)
Distance to nearest petroleum terminal	79.62	(93.87)	38.10	(34.46)	74.07	(91.30)	153.15	(121.44)
Daily highway traffic past market	30000	(59378)	54207	(80627)	13201	(10757)	4990.45	(4345.39)
Demographic variables								
Population	39227	(541773)	93833	(753878)	44330	(54126)	8380	(10669)
Population per station	5086	(6548)	7441	(8780)	3002	(1763)	3102	(2783)
Urban density	69.93	(93.88)	111.39	(117.96)	51.48	(46.23)	16.76	(30.26)
Median household income	27703	(3875)	29912	(3854)	25538	(2168)	26051	(3234)
% of pop. that drives to work	0.765	(0.085)	0.757	(0.107)	0.769	(0.047)	0.776	(0.071)
% of pop. with post-secondary schooling	0.520	(0.049)	0.551	(0.045)	0.501	(0.029)	0.486	(0.04)
Number of markets	82		38		22		22	
Number of stations	1947		1428		411		108	
Number of station-date observations	544646		430774		82345		31527	
Number of market-date observations	28029		13363		7622		7044	

Notes: Sample means and sample standard deviations (in parentheses) reported. Sample medians are reported for population. In computing the market-level HHI and C1/C4 ratios, I calculate the market share of a given retailer in a given market as the fraction of stations in the market that operate under the retailer's name. See data Appendix A for detailed descriptions of data sources and variable construction. See the text for how cost-based/cycling/sticky markets are classified.

Table 2: Pricing Regimes, Market Structure and Pricing Asymmetry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Negative shock	-0.006	0.058	0.056	0.092	0.098^{+}	0.014	0.100
	(0.041)	(0.047)	(0.041)	(0.077)	(0.056)	(0.043)	(0.072)
Cycling market	-0.274**						
	(0.051)						
Sticky market	-0.376**						
	(0.053)						
Determinants of pricing asymmetry							
Cycling market ×		-0.305**	-0.206**	-0.215**	-0.211**	-0.226**	-0.218**
Negative shock		(0.058)	(0.066)	(0.069)	(0.066)	(0.067)	(0.069)
Cycling market ×		-0.244**	-0.144^{+}	-0.135	-0.138	-0.124	-0.132
Positive shock		(0.084)	(0.084)	(0.086)	(0.084)	(0.083)	(0.085)
Sticky market ×		-0.461**	-0.337**	-0.353**	-0.311**	-0.396**	-0.356**
Negative shock		(0.062)	(0.082)	(0.086)	(0.087)	(0.089)	(0.085)
Sticky market ×		-0.290**	-0.167^{+}	-0.152	-0.194^{+}	-0.103	-0.149
Positive shock		(0.085)	(0.096)	(0.101)	(0.103)	(0.106)	(0.100)
Number of stations ×				0.007			
Negative shock				(0.007)			
Number of stations ×				0.017^{+}			
Positive shock				(0.009)			
HHI ×					0.194		
Negative shock					(0.155)		
HHI ×					0.415*		
Positive shock					(0.181)		
Distance to nearest terminal ×						-0.038	
Negative shock						(0.029)	
Distance to nearest terminal ×						-0.148**	
Positive shock						(0.035)	
Urban density ×							0.034
Negative shock							(0.036)
Urban density ×							0.073^{+}
Positive shock							(0.042)
Determinants of price rigidity							
Number of stations			0.012*		0.012*	0.012*	0.012*
			(0.005)		(0.005)	(0.006)	(0.005)
HHI			0.303*	0.303*		0.300**	0.303*
			(0.124)	(0.124)		(0.110)	(0.123)
Share of independent stations			-0.099	-0.099	-0.100	-0.093	-0.100
			(0.121)	(0.122)	(0.118)	(0.117)	(0.121)
Distance to nearest terminal			-0.092**	-0.092**	-0.092**		-0.092**
			(0.021)	(0.021)	(0.021)		(0.021)
Daily highway traffic past market			0.013	0.013	0.013	0.013	0.013
			(0.020)	(0.019)	(0.020)	(0.020)	(0.018)
Population per station			-0.055	-0.055	-0.055	-0.055	-0.054
			(0.041)	(0.041)	(0.042)	(0.039)	(0.041)
Urban density			0.054	0.054	0.054	0.054	
			(0.036)	(0.036)	(0.036)	(0.034)	
Constant	0.983**	0.952**	0.896**	0.878**	0.875**	0.915**	0.875**
	(0.033)	(0.037)	(0.077)	(0.085)	(0.083)	(0.075)	(0.084)
R-Squared	0.276	0.280	0.367	0.365	0.368	0.385	0.366
Observations	164	164	164	164	164	164	164

Notes: Dependent variable is fraction of 2.5 cost shock passed through seven days after the shock. Number of stations is in terms of 10 stations. Distance to nearest refinery is in terms of 100 kilometers. Urban density is in terms of 100 people per square kilometer. Population per station is in terms of 1000 people. Daily highway traffic is in terms of 100,00 vehicles. Bootstrap standard errors reported in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 3: Spatial Price Dispersion and Competition

	(1)	(2)	(3)	(4)	(5)
Number of stations	-0.098	0.391	0.406	0.958	0.603
	(0.070)	(0.359)	(0.357)	(1.624)	(0.430)
(Number of stations)^2		-0.030	-0.031	-0.018	
		(0.020)	(0.020)	(0.065)	
Rack price			0.011	0.003	0.003
			(0.009)	(0.008)	(0.008)
Market structure controls				Y	Y
Demographic controls				Y	Y
Gasoline retailer dummies				Y	Y
R-Squared	0.019	0.039	0.043	0.410	0.410
Observations	5098	5098	5098	5098	5098

Notes: Dependent variable is daily market-level price range. Market structure and demographic controls are listed in Table 1. The dummy variable for retailer j in market i equals one if one or more stations in market i operate under retailer j's name. Asymptotic standard errors clustered at the market-level reported in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$

Table 4: Predicting Current Price Changes with Future Cost Shocks

	Any Price Change			Positive Price Change			Negative Price Change		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δc_{t+1}	-0.003	-0.002	-0.002	-0.008*	0.002	0.001	0.005	-0.003	-0.003
	(0.005)	(0.007)	(0.007)	(0.003)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Δc_{t+2}	0.006	0.006	0.007	0.004	0.011**	0.011**	0.001	-0.005	-0.004
	(0.004)	(0.005)	(0.006)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Δc_{t+3}	0.010+	0.012*	0.014*	0.003	0.005	0.005	0.006	0.007*	0.009*
	(0.006)	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.004)
Δc_{t+4}	-0.009*	-0.000	0.002	-0.008+	0.000	0.000	-0.001	-0.000	0.001
	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Δc_{t+5}	-0.013*	-0.011+	-0.007	-0.009*	-0.009*	-0.008+	-0.003	-0.002	0.001
	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.006)	(0.006)
Δc_{t+6}	-0.007	-0.005	-0.002	-0.007	-0.005	-0.003	-0.000	-0.000	0.001
	(0.005)	(0.005)	(0.006)	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)
Δc_{t+7}	0.002	0.002	0.005	0.002	0.002	0.004	-0.000	-0.000	0.001
	(0.005)	(0.006)	(0.007)	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
Δc_{t+8}	0.000	0.005	0.009+	-0.008*	0.001	0.004	0.009+	0.003	0.005
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Δc_{t+9}	0.011*	0.009*	0.013**	0.006	0.003	0.005	0.005	0.006+	0.007*
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Δc_{t+10}	0.008	0.005	0.007+	0.009*	0.004	0.005	-0.002	0.001	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Lagged Prices	N	Y	Y	N	Y	Y	N	Y	Y
Lagged Costs	N	Y	Y	N	Y	Y	N	Y	Y
Days Since Last Price Change	N	Y	Y	N	Y	Y	N	Y	Y
Quadratic Time Trend	N	N	Y	N	N	Y	N	N	Y
Market Fixed Effects	N	N	Y	N	N	Y	N	N	Y
R-Squared	0.002	0.156	0.329	0.002	0.397	0.451	-0.000	0.255	0.329
Observations	4593	3074	3074	4593	3074	3074	4593	3074	3074

Notes: Clustered standard errors at the market level are reported in parentheses. **, *, + indicate statistical significance at the 1% 5%, and 10% levels. Lagged prices and costs are included up to 14 days.

Figures

Figure 1: Retail Gasoline Markets and Wholesale Distribution Network in Ontario
Statistics Canada Economic Regions Shaded

Figure 2: Retail Gasoline Pricing Regimes

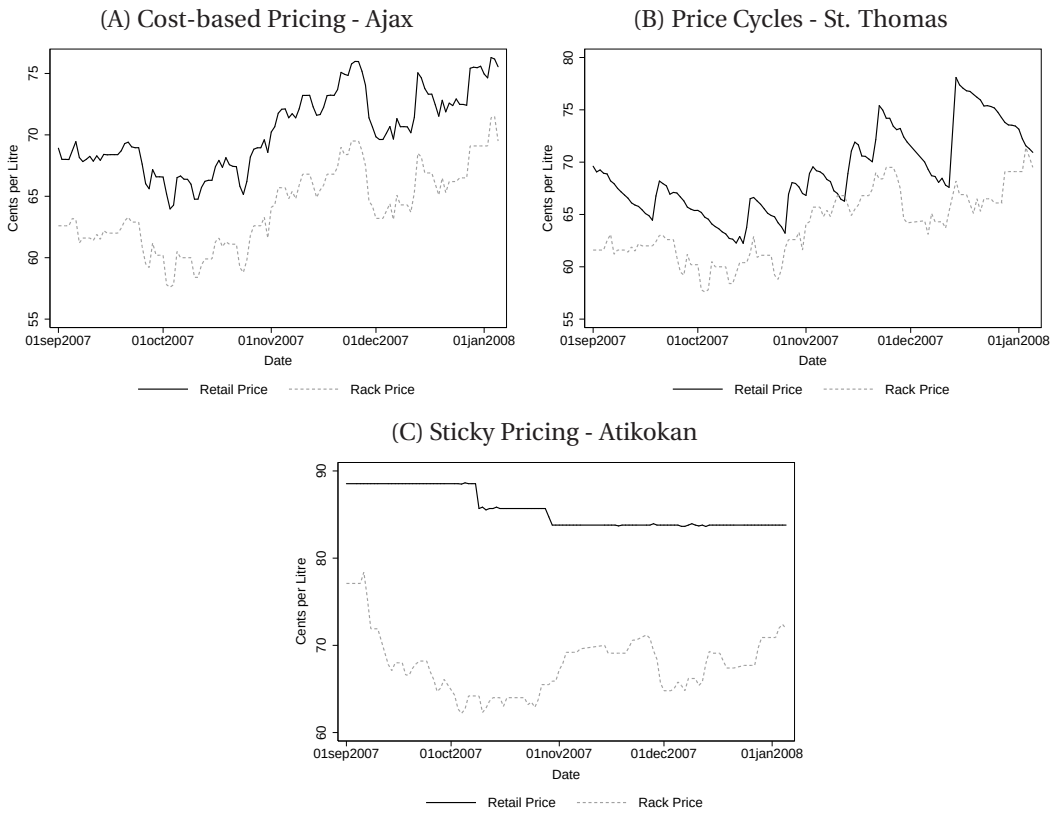


Figure 3: Distributions Used in Classifying Pricing Regimes

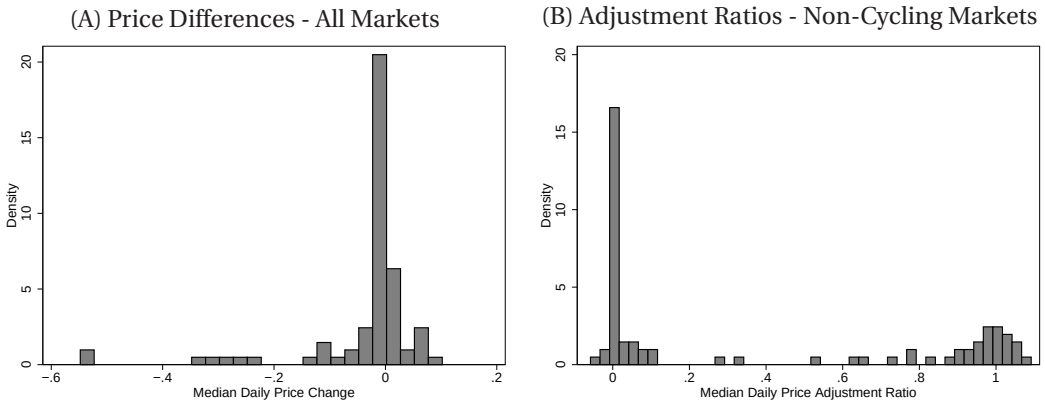
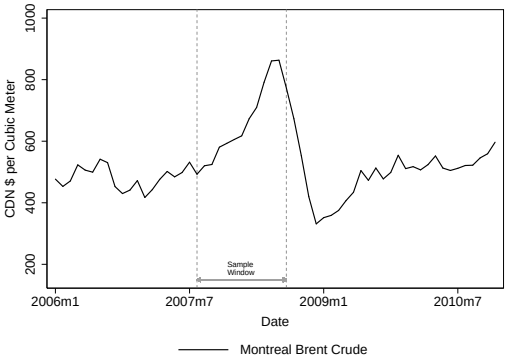


Figure 4: 2007-08 Global Crude Oil Price Shock

(A) Global Crude Oil Prices



(B) Retail and Wholesale Prices -Toronto

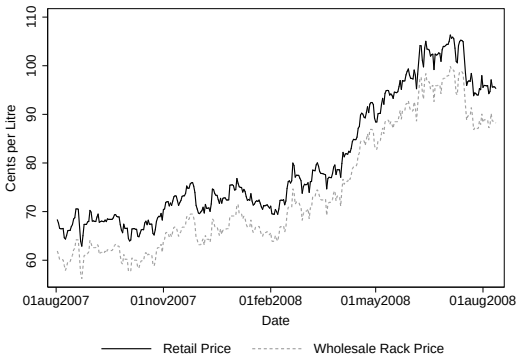
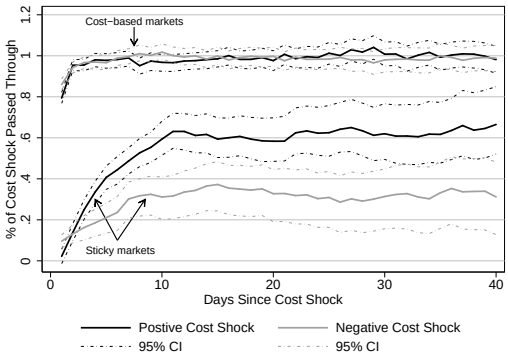


Figure 5: Cumulative Price Responses to Positive and Negative Cost Shocks

(A) Impulse Response Functions (IRFs) for Cost-Based and Sticky Markets



(B) Difference in IRFs for Positive and Negative Cost Shocks in Sticky Markets

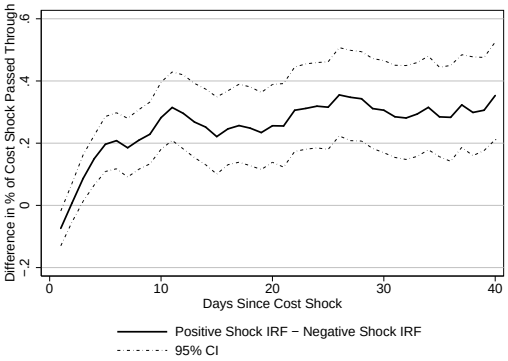
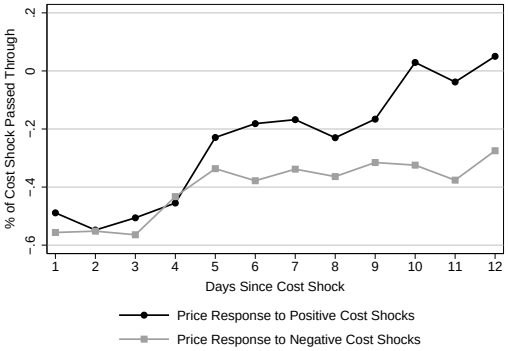


Figure 6: Sticky Pricing and Pricing Asymmetry - Baseline Estimates

(A) Sticky Pricing Regime Effects for Positive and Negative Cost Shocks



(B) Difference in Sticky Pricing Regime Effects for Positive and Negative Cost Shocks

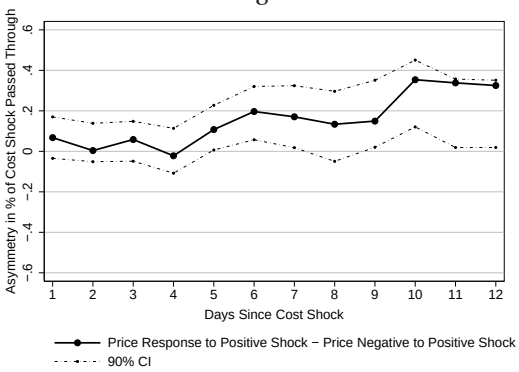
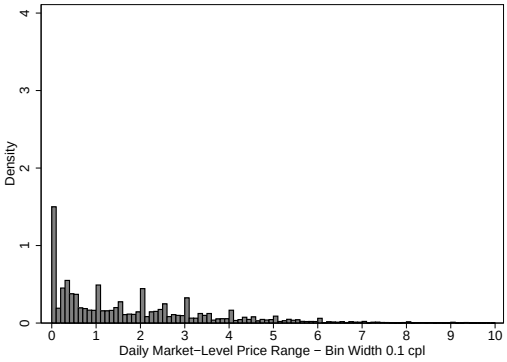


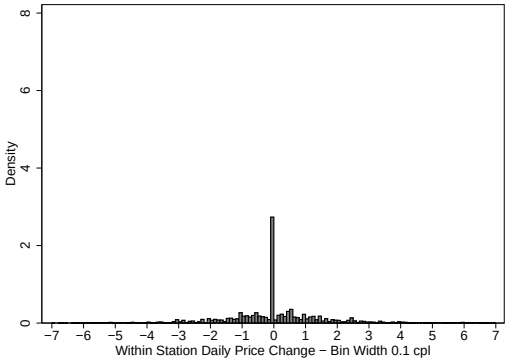
Figure 7: Spatial Price Dispersion and Price Rigidity in Gasoline Pricing

(A) Cost-based markets

Daily Price Dispersion Across Stations

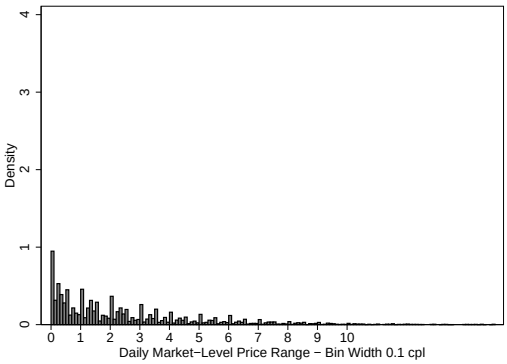


Daily Within Station Price Changes

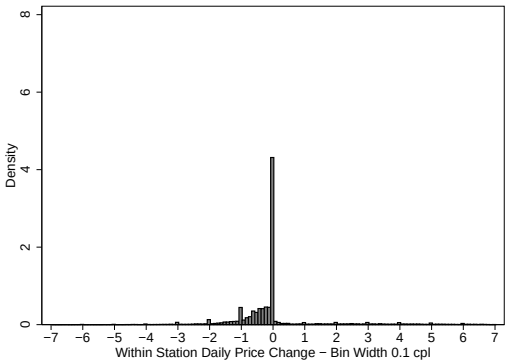


(B) Cycling Markets

Daily Price Dispersion Across Stations

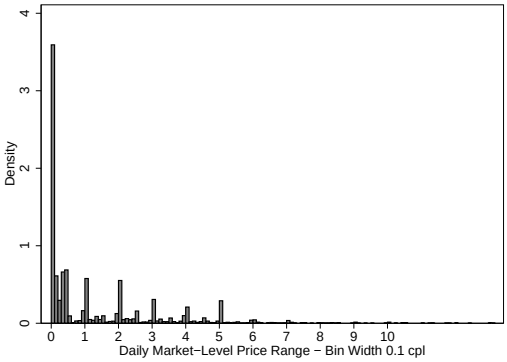


Daily Within Station Price Changes



(C) Sticky markets

Daily Price Dispersion Across Stations



Daily Within Station Price Changes

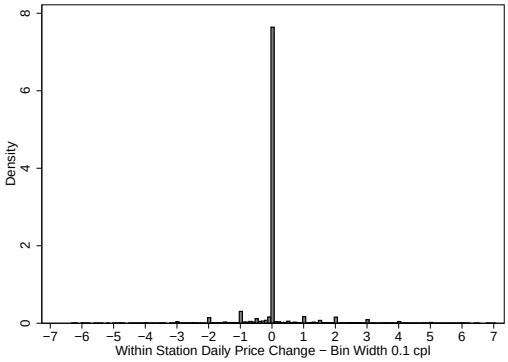
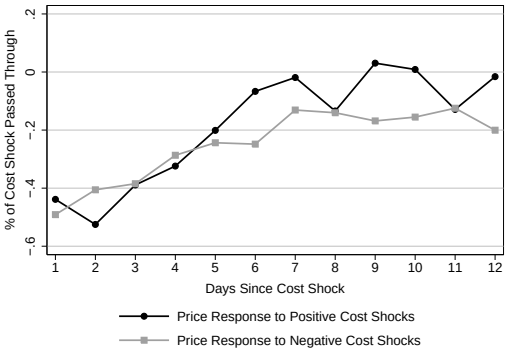
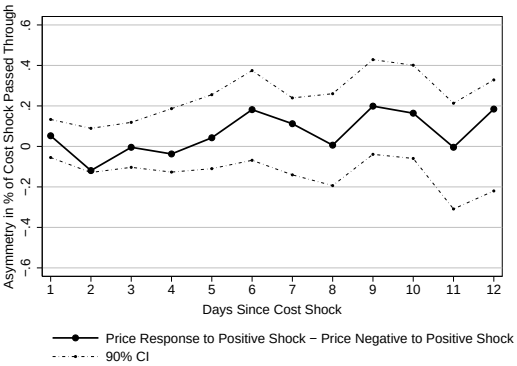


Figure 8: Sticky Pricing and Pricing Asymmetry - Crude Oil Shock Period

(A) Sticky Pricing Regime Effects for Positive and Negative Cost Shocks



(B) Difference in Sticky Pricing Regime Effects for Positive and Negative Cost Shocks



Supplemental Appendix
(not for publication)

A Data Appendix

A.1 Details on data sources

Retail and wholesale prices

The retail price data come GasBuddy, an on-line gasoline price reporting platform. Using the national site (www.gasbuddy.com), provincial site (www.ontariogasprices.com) and city-specific sites (www.torontogasprices.com, www.ottawagasprices.com), price spotters in local markets upload station-level prices to GasBuddy via the web using mobile devices and computers.

My proxy for daily marginal costs, rack prices, comes from MJ Ervin and Associates. Specifically, MJ Ervin collects station-level wholesale price data from a sample of non-branded gasoline companies from many local markets in Canada and computes the daily rack price for a given market as the average wholesale price across stations. In the article, I use rack prices from ten locations in Ontario (Maitland, Ottawa, Toronto, Hamilton, London, Sarnia, Nanticoke, Sault Ste. Marie, Thunder Bay) and one in Manitoba (Winnipeg). For a given market in the GasBuddy sample, I define its daily rack price as that reported from its nearest rack price location. Distances between retail markets and rack price locations are computed using coordinates of the centroids of retail markets and rack price locations.

Market structure variables

The GasBuddy price dataset also lists each station's retailer name and address. Using the individual station names and addresses, I compute various market structure variables from Table 1: number of stations in a market, share of independent stations, HHI, C1 and C4 ratio. With the station addresses, I can also compute each market's standard distance across stations. Standard distance is a spatial statistic that is analogous to standard deviation in that it measures the geographic spread across stations in a given market. Recall from Section 4.1 that I use this statistic to characterize the degree of spatial dispersion across stations in cost-based, cycling and sticky markets.

MJ Ervin provides another source of information in its 2007 report entitled *Canada's Downstream Logistical Infrastructure: Refining, Pipelines, Terminals, Bulk Plants and Cardlocks*. This document provides the locations for the individual parts of the wholesale gasoline distribution network in Ontario including refineries, pipelines, and distribution terminals. I obtain coordinates for the locations (centroids) for each part of the distribution network, and compute the distance between each retail market in the GasBuddy sample and the distance to its nearest refinery and petroleum terminal (both distances are reported in Table 1). These infrastructure data are also used in constructing Figure 1.

The final market structure variable in Table 1 is daily highway traffic past a market. This is available from the Ontario Ministry of Transportation (www.raqsb.mto.gov.on.ca).

Demographic variables

Accurate measures of each market's population and urban density are collected using Statistics Canada's 2006 GeoSuite package. I further match the GasBuddy locations to their corresponding 2006 Canadian Census Subdivision, and obtain data on median household income, the fraction of population that drives to work, and the fraction of population with post-secondary education.

A.2 Validating GasBuddy data with MJ Ervin price data

The asymmetric pricing analysis, which is the main part of the article, is based on daily average city-level prices constructed using the universe of daily station-level price observations from GasBuddy for 2007-2008. Using weekly regular unleaded gasoline price data from MJ Ervin, I can check the validity of these price series. The data are available at http://www.kentmarketingservices.com/dnn/PetroleumPriceData.aspx. As outlined on the website, the MJ Ervin price series is based on price reports obtained to phoning individual gas stations across the province every Tuesday at 10:00am. Both major branded oil companies and independents are included in constructing the MJ Ervin price series.

Panels (A)-(L) of Figure A.1 plot the average daily GasBuddy prices and the MJ Ervin prices for each Tuesday in the sample period. The figures show that the two price series closely track each others' movements and levels. Table A.1 reports average price differences between the two series by city and quarter. More than 75% of the average monthly price differences are less than 0.5 cpl and more than 50% are less than 0.1 cpl. The larger price differences in the 1-1.5 cpl range are sporadically found within cycling cities (Kingston, Windsor, Sudbury, Thunder Bay, North Bay) and could reflect price restorations occurring on a Tuesday. For example, if a price restoration occurs on a Tuesday after 10:00am, and the GasBuddy price reports are mainly provided after 10:00am, then the GasBuddy average price would be higher than the MJ Ervin average price. These differences are not substantial however, and as the time-series plots show, the price series track each other well in both the cycling and non-cycling markets.

I present results from tests of cointegration between the GasBuddy and MJ Ervin price series in Table A.2. The first two columns report Z test statistics from Augmented Dickey-Fuller tests for unit roots in the respective price series. The tests are based on specifications for the ADF test that include a trend and two (weekly) lags. Not surprisingly, all price series are found to be integrated of order one. Given this, it is appropriate to test for cointegration between the two non-stationary series. we use the Engle-Granger (1987) two-step procedure to do so, again including a trend and two lags in the second-step ADF test. With the exception of Sault Ste. Marie, the tests indicate that the GasBuddy and MJ Ervin price series are cointegrated in each city, despite the relatively small sample size of 49-52 weeks for a given city.

Figure A.1: Weekly Time Series Plots of GasBuddy and MJ Ervin Price Series

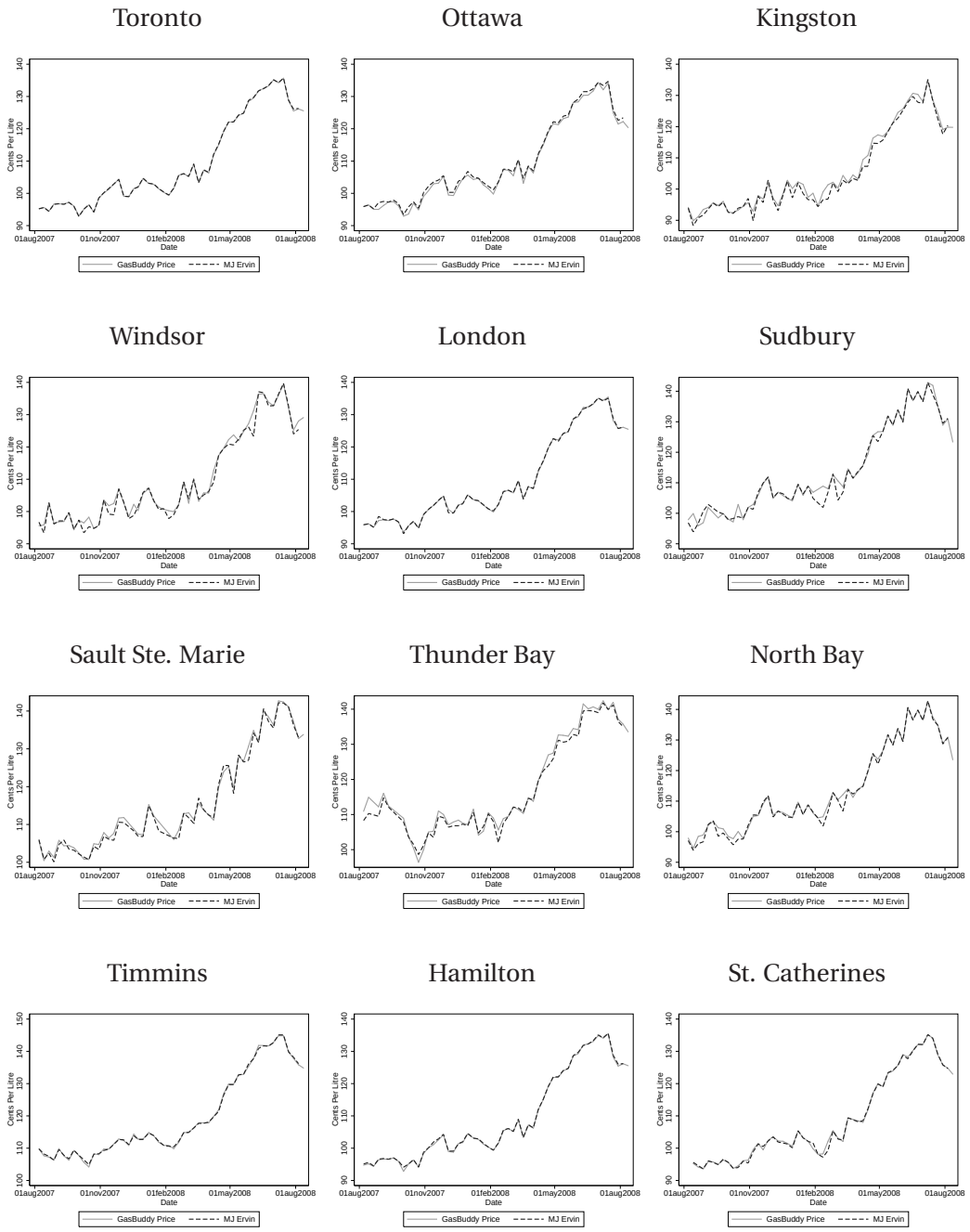


Table A.1: Average Differences Between GasBuddy and MJ Ervin Weekly Prices

	Toronto	Ottawa	Kingston	Windsor	London	Sudbury	Sault St. Marie	Thunder Bay	North Bay	Timmins	Hamilton	St. Catherines
2007Q3	0.04	-0.58	0.66	0.10	-0.19	-0.06	0.28	2.30	1.21	-0.17	-0.18	-0.15
	(0.05)	(0.75)	(0.64)	(1.02)	(0.46)	(3.07)	(0.94)	(1.63)	(1.17)	(0.25)	(0.16)	(0.23)
2007Q4	-0.05	-0.86	0.52	1.02	0.08	0.13	0.68	0.36	0.33	-0.05	-0.27	0.23
	(0.12)	(0.60)	(1.33)	(1.67)	(0.33)	(1.28)	(0.63)	(1.17)	(0.95)	(0.37)	(0.37)	(0.45)
2008Q1	-0.08	-0.58	1.48	0.21	-0.06	1.59	0.55	0.39	0.85	-0.03	-0.08	0.17
	(0.07)	(0.52)	(1.35)	(0.95)	(0.15)	(2.63)	(1.18)	(1.26)	(1.83)	(0.23)	(0.12)	(1.06)
2008Q2	-0.11	-0.63	1.40	1.21	-0.02	0.08	0.26	1.31	0.09	0.13	-0.11	0.03
	(0.12)	(0.31)	(1.10)	(2.45)	(0.24)	(1.03)	(1.33)	(0.91)	(0.51)	(0.38)	(0.15)	(0.28)
2008Q3	-0.17	-0.87	0.50	0.43	-0.07	0.42	0.38	0.63	0.18	-0.21	-0.28	-0.01
	(0.21)	(0.47)	(0.94)	(1.26)	(0.38)	(1.30)	(0.47)	(0.31)	(0.28)	(0.18)	(0.23)	(0.10)

Notes: Sample standard deviations reported in parentheses.

Table A.2: GasBuddy and MJ Ervin Series Stationarity and Cointegration Tests

City	GasBuddy Price ADF $Z(t)$ Statistic	MJ Ervin Price ADF $Z(t)$ Statistic	Engle-Granger Test $Z(t)$ Statistic
Toronto	-2.074	-2.072	-4.356*
Ottawa	-2.223	-2.162	-5.664*
Kingston	-2.030	-1.936	-3.868**
Windsor	-2.299	-2.293	-4.377*
London	-2.131	-2.051	-4.168*
Sudbury	-1.119	-1.046	-3.516**
Sault Ste Marie	-1.891	-2.036	-2.551
Thunder Bay	-1.639	-1.669	-3.929**
North Bay	-1.771	-1.875	-3.312+
Timmins	-1.886	-1.932	-3.243+
Hamilton	-2.089	-2.150	-5.233*
St Catharines	-1.538	-1.624	-6.361*

Notes: **, *, + indicate statistical significance at the 1% 5%, and 10% levels. Inference based on MacKinnon (1990, 2010) p-values.

A.3 Market characteristics and pricing regimes

In Section 2.3 I discussed summary statistics from Table 1 for market structure and demographic variables for cost-based, cycling and sticky markets. In that discussion, I emphasized the role of market size, concentration and isolation from wholesale supply in predicting whether a market has one of these pricing regimes. I this appendix, I more formally identify the independent effects of these factors in predicting pricing regimes using two linear in probability models. The first pools data from cost-based pricing and cycling markets and regresses an indicator variable for price cycles on market characteristics. This regression identifies variables that affect the transition from cost-based pricing to cycling prices among the sample's larger markets. The second regression pools data from cycling markets and sticky markets and regresses an indicator variable for sticky pricing on market characteristics to identify variables that affect the transition from cycling to sticky pricing among smaller markets.

Table A.3 presents the results. The panel A estimates show that among larger markets, price cycles are more likely as markets shrink, become less concentrated and have larger shares of independent stations. These correlations become insignificant when demographics are controlled for however, largely because of sample size and the fact that population and urban density co-move with these market structure variables. when demographics are controlled for. Panel B shows that among the relatively smaller markets, sticky pricing emerges in markets with fewer stations, higher concentration and that are further from distribution terminals.

I also estimate multinomial logit models using the entire sample of markets to predict whether a market has cost-based pricing, price cycles or sticky pricing. The results, which are reported in Table A.4, reaffirm the discussion from Section 2.3 and the linear probably model estimates in Table A.3.

Table A.3: Market Characteristics and Pricing Regimes

Dependent variable	(A) Cost-based Pricing → Price Cycles Price Cycles Dummy			(B) Price Cycles → Sticky Pricing Sticky Pricing Dummy		
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Stations	-0.025^{+}	-0.022	-0.033	-0.222**	-0.238**	-0.276*
	(0.014)	(0.014)	(0.023)	(0.070)	(0.086)	(0.130)
HHI	-1.235**	-1.211**	-0.267	0.655**	0.414^{+}	0.529
	(0.255)	(0.265)	(0.395)	(0.241)	(0.228)	(0.367)
Share of Independent Stations	0.896**	0.791*	-0.280	-0.319	-0.352	-0.436^{+}
	(0.315)	(0.338)	(0.404)	(0.260)	(0.248)	(0.245)
Population per Station	-0.041	0.006	-0.040	-0.142	0.197	0.426
	(0.035)	(0.042)	(0.221)	(0.191)	(0.250)	(0.331)
Distance to Nearest Petroleum Terminal		0.098	0.106^{+}		0.133**	0.154*
		(0.067)	(0.056)		(0.040)	(0.063)
Highway Traffic		-0.079	-0.009		-0.080	-0.038
		(0.053)	(0.045)		(0.658)	(0.744)
Constant	0.279^{+}	0.267^{+}	4.214**	0.797**	0.655**	1.811
	(0.158)	(0.157)	(1.323)	(0.169)	(0.169)	(1.242)
Demographic Controls	N	N	Y	N	N	Y
R-Squared	0.224	0.220	0.417	0.438	0.485	0.446
Observations	60	60	60	44	44	44

Notes: The regressions under "Cost-based Pricing → Price Cycles" contain observations from markets with price cycles and cost-based pricing. The regressions under "Price Cycles → Sticky Pricing" contain observations from markets with price cycles and sticky pricing. Number of stations is in terms of 10 gasoline stations. HHI and Share of Independent Stations are computed using firm-specific market shares in terms of the number of stations in a given local market; see the text for further discussion. Population per station is in terms of 10,000 people. Distance to petroleum terminal is in terms of 100 kilometres. Highway traffic is the average daily highway traffic that passes a market in terms of 100,000 vehicles. Demographic controls are listed in Table 1. Robust standard errors are reported in parentheses. $^{**}p < 0.01$, $^{*}p < 0.05$, $^{+}p < 0.1$.

Table A.4: Multinomial Logit Model for Predicting Pricing Regime

	(1)		(2)	
Outcome: Price Cycles				
Number of Stations	-0.353^{+}	(0.197)	-0.820	(0.563)
HHI	-16.462*	(8.164)	-23.258^{+}	(14.551)
Share of Independent Stations	1.414	(2.214)	-9.267*	(4.504)
Population per Station	-1.607	(2.145)	-6.060	(3.840)
Distance to Nearest Petroleum Terminal	0.449	(0.405)	-4.494^{+}	(2.616)
Highway Traffic	-1.811^{+}	(1.038)	-1.811	(0.945)
Constant	3.013	(2.367)	27.337*	(12.929)
Outcome: Sticky Pricing				
Number of Stations	-2.236*	(0.889)	-4.500^{+}	(2.394)
HHI	4.311	(2.981)	6.096	(4.253)
Share of Independent Stations	-0.098	(2.253)	-13.953**	(5.343)
Population per Station	-2.431	(2.613)	2.977	(4.306)
Distance to Nearest Petroleum Terminal	1.463*	(0.748)	2.974^{+}	(1.809)
Highway Traffic	-6.822^{+}	(3.635)	-1.114	(2.501)
Constant	1.160	(1.365)	50.992**	(14.429)
Demographic controls	N		Y	
Number of observations	82		82	
Pseudo R-squared	0.4858		0.6916	
Log-Likelihood	-44.794		-26.870	

Notes: The base outcome is cost-based markets. In total, there are 38 cost-based markets, 22 price cycling markets and 22 sticky markets. Number of stations is in terms of 10 gasoline stations. HHI and Share of Independent Stations are computed using firm-specific market shares in terms of the number of stations in a given local market; see the text for further discussion. Population per station is in terms of 10,000 people. Distance to petroleum terminal is in terms of 100 kilometres. Highway traffic is the average daily highway traffic that passes a market in terms of 100,000 vehicles. Demographic controls are listed in Table 1. Robust standard errors are reported in parentheses. ** $p < 0.01$, * $p < 0.05$, $^{+}$ $p < 0.1$.

A.4 Supplemental estimation results

Table A.5: Parameter Estimates for the Pooled Error Correction Model

	Cost-based markets					Sticky markets			
	(+) coefficients		(-) coefficients			(+) coefficients		(-) coefficients	
β_0	0.86	(0.013)	0.794	(0.013)	β_0	0.096	(0.017)	0.022	(0.018)
β_1	0.348	(0.030)	0.484	(0.033)	β_1	0.076	(0.018)	0.08	(0.017)
β_2	0.22	(0.027)	0.235	(0.030)	β_2	0.066	(0.016)	0.095	(0.017)
β_3	0.092	(0.028)	0.198	(0.028)	β_3	0.051	(0.016)	0.089	(0.017)
β_4	0.096	(0.024)	0.062	(0.029)	β_4	0.045	(0.015)	0.082	(0.016)
β_5	0.117	(0.025)	0.074	(0.028)	β_5	0.041	(0.016)	0.05	(0.017)
β_6	0.080	(0.024)	0.069	(0.031)	β_6	0.075	(0.016)	0.05	(0.016)
β_7	0.034	(0.023)	0.011	(0.030)	β_7	0.024	(0.015)	0.045	(0.018)
β_8	0.059	(0.025)	-0.067	(0.030)	β_8	0.015	(0.015)	0.027	(0.017)
β_9	0.021	(0.023)	-0.016	(0.029)	β_9	-0.005	(0.014)	0.042	(0.016)
β_{10}	0.007	(0.023)	0.020	(0.027)	β_{10}	0.010	(0.013)	0.041	(0.015)
β_{11}	0.017	(0.023)	0.027	(0.027)	β_{11}	0.022	(0.015)	0.010	(0.017)
β_{12}	0.069	(0.025)	-0.010	(0.026)	β_{12}	0.009	(0.015)	-0.010	(0.016)
β_{13}	0.006	(0.023)	0.003	(0.028)	β_{13}	0.022	(0.014)	0.012	(0.016)
β_{14}	0.001	(0.023)	0.029	(0.027)	β_{14}	0.008	(0.015)	-0.019	(0.016)
β_{15}	-0.048	(0.021)	0.029	(0.028)	β_{15}	-0.018	(0.013)	0.005	(0.018)
$\vdots$									
γ_1	-0.309	(0.029)	-0.408	(0.033)	γ_1	-0.024	(0.020)	-0.100	(0.032)
γ_2	-0.198	(0.026)	-0.212	(0.031)	γ_2	-0.062	(0.018)	-0.079	(0.029)
γ_3	-0.076	(0.025)	-0.174	(0.028)	γ_3	-0.057	(0.016)	-0.045	(0.027)
γ_4	-0.102	(0.024)	-0.032	(0.030)	γ_4	-0.041	(0.017)	-0.003	(0.029)
γ_5	-0.100	(0.024)	-0.075	(0.028)	γ_5	-0.049	(0.018)	0.028	(0.026)
γ_6	-0.064	(0.024)	-0.054	(0.032)	γ_6	-0.006	(0.018)	0.012	(0.027)
γ_7	-0.006	(0.023)	-0.044	(0.030)	γ_7	-0.006	(0.018)	0.049	(0.026)
γ_8	-0.068	(0.024)	0.112	(0.030)	γ_8	0.006	(0.016)	-0.027	(0.027)
γ_9	0.003	(0.023)	-0.004	(0.030)	γ_9	-0.011	(0.015)	0.024	(0.026)
γ_{10}	-0.018	(0.023)	-0.025	(0.027)	γ_{10}	-0.007	(0.018)	-0.058	(0.028)
γ_{11}	-0.028	(0.022)	-0.023	(0.029)	γ_{11}	0.009	(0.017)	-0.008	(0.029)
γ_{12}	-0.075	(0.024)	0.020	(0.027)	γ_{12}	0.006	(0.016)	-0.029	(0.028)
γ_{13}	-0.017	(0.023)	0.001	(0.028)	γ_{13}	0.011	(0.017)	-0.002	(0.027)
γ_{14}	0.015	(0.023)	-0.027	(0.028)	γ_{14}	0.014	(0.018)	0.027	(0.030)
γ_{15}	0.035	(0.021)	-0.010	(0.028)	γ_{15}	0.026	(0.019)	-0.008	(0.028)
	Error Correction Term					Error Correction Term			
θ^+	-0.001		(0.002)		θ^+	-0.001		(0.002)	
θ^-	-0.025		(0.006)		θ^-	-0.025		(0.006)	
ψ	1.269		(0.002)		ϕ	1.185		(0.003)	

Notes: Asymptotic sample errors are reported in parentheses.

Table A.6: Predicting Current Price Changes with Future Cost Shocks at the Station-Level

	Any Price Change			Positive Price Change			Negative Price Change		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δc_{t+1}	-0.003	-0.003	0.000	-0.005*	0.000	0.001	0.002	-0.004^{+}	-0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+2}	0.001	-0.005	-0.002	-0.001	0.001	0.002	0.002	-0.007**	-0.005*
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+3}	0.009**	0.009**	0.012**	-0.000	0.006**	0.006**	0.009**	0.004^{+}	0.006*
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+4}	-0.011**	-0.002	0.000	-0.005*	0.003	0.004^{+}	-0.006**	-0.006*	-0.004^{+}
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+5}	-0.015**	-0.011**	-0.009**	-0.008**	-0.003^{+}	-0.003	-0.007**	-0.007**	-0.006**
	(0.003)	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+6}	-0.010**	-0.006*	-0.005	-0.005*	-0.005**	-0.004*	-0.005*	-0.001	-0.000
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+7}	-0.002	0.005	0.006^{+}	0.001	0.003	0.004	-0.003	0.002	0.003
	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Δc_{t+8}	0.006*	0.018**	0.018**	-0.003*	0.008**	0.009**	0.010**	0.009**	0.010**
	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Δc_{t+9}	0.021**	0.026**	0.027**	0.008**	0.011**	0.011**	0.013**	0.015**	0.015**
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Δc_{t+10}	0.017**	0.013**	0.013**	0.012**	0.008**	0.008**	0.005**	0.005*	0.005**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Lagged Prices	N	Y	Y	N	Y	Y	N	Y	Y
Lagged Costs	N	Y	Y	N	Y	Y	N	Y	Y
Days Since Last Price Change	N	Y	Y	N	Y	Y	N	Y	Y
Quadratic Time Trend	N	N	Y	N	N	Y	N	N	Y
Market Fixed Effects	N	N	Y	N	N	Y	N	N	Y
Station Fixed Effects	N	N	Y	N	N	Y	N	N	Y
R-Squared	0.012	0.106	0.188	0.005	0.540	0.566	0.008	0.219	0.293
Observations	10950	6790	6790	10950	6790	6790	10950	6790	6790

Notes: Clustered standard errors at the station level are reported in parentheses. **, *, + indicate statistical significance at the 1% 5%, and 10% levels. Lagged prices and costs are included up to 14 days.

B Bootstrap procedures

In this appendix I discuss the bootstrap procedures used to conduct inference in various parts of Sections 3 and 4. Specifically, I describe how I compute the confidence intervals in Figure 5, standard errors in Table 2 and confidence intervals in Figures 6 and 8. The main references for this discussion are Davison and Hinkley (1997) and Davidson and MacKinnon (2004), and discussion from Lewis and Noel (2011).

Confidence intervals in Figure 5

Let θ be the parameters in equation (1a) and $\widehat{\Sigma}_\theta$ be the estimated covariance matrix of $\hat{\theta}$. The bootstrap routine is as follows:

1. Draw $b = 1, \ldots, 10000$ parameter vectors from $\widehat{\Sigma}_{\theta_i}$: $\theta^1, \ldots, \theta^{10000}$

2. For each θ^b, compute cumulative impulse responses to positive/negative cost shocks for $\tau = 1, \ldots, 40$ days after the cost shock. Denote the bth set of simulated cumulative impulse responses as a fraction of the original cost shock (e.g., as reported in Figure 5) by $\sigma_1^{b,+}, \ldots, \sigma_\tau^{b,+}$ for positive shocks and $\sigma_1^{b,-}, \ldots, \sigma_\tau^{b,-}$ for negative shocks.

3. For each period τ, find the 97.5 and 2.5 percentiles of $\sigma_\tau^{1,+}, \ldots, \sigma_\tau^{10000,+}$ (denoted $\sigma_{\tau,97.5}^+$ and $\sigma_{\tau,2.5}^+$) and of $\sigma_\tau^{1,-}, \ldots, \sigma_\tau^{10000,-}$ (denoted $\sigma_{\tau,97.5}^-$ and $\sigma_{\tau,2.5}^-$). The pairs $(\sigma_{\tau,97.5}^+, \sigma_{\tau,2.5}^+)$ and $(\sigma_{\tau,97.5}^+, \sigma_{\tau,2.5}^+)$ are the upper and lower limits of the 95% bootstrap percentile confidence intervals for impulse responses to positive and negative cost shocks for $\tau = 1, \ldots, 40$. These are the confidence intervals in Figure 5.

As the article discusses, I pool data for cost-based and sticky markets and separately estimate equation (1a) for these market types. In computing the confidence intervals for the impulse response functions for these market types, I run the bootstrap procedure in steps 1-3 separately for the cost-based and sticky pooled error correction models.

Standard errors in Table 2

Recall from Section 3.2 that I estimate market specific error correction models for $i = 1, \ldots, N$ markets (where $N = 82$) before running the auxiliary regression in (2). Let θ_i be the parameters in equation (1a) and $\widehat{\Sigma}_{\theta_i}$ be the estimated covariance matrix of $\hat{\theta}_i$ for market i. The bootstrap routine is as follows:

1. Draw $b = 1, \ldots, 10000$ parameter vectors from $\widehat{\Sigma}_\theta$: $\theta_i^1, \ldots, \theta_i^{10000}$ for each of the $i = 1, \ldots, N$ markets.

2. For each θ_i^b, compute cumulative impulse responses to positive/negative cost shocks for $\tau = 1, \ldots, 40$ days after the cost shock. Denote the bth set of simulated cumulative impulse responses as a fraction of the original cost shock (e.g., as reported in Figure 5) for market i by $\sigma_{i,1}^{b,+}, \ldots, \sigma_{i,\tau}^{b,+}$ for positive shocks and $\sigma_{i,1}^{b,-}, \ldots, \sigma_{i,\tau}^{b,-}$ for negative shocks.

3. For day τ after a cost shock, denote the stacked cross-section of impulse responses to negative and cost shocks across all markets for simulation b by $\mathscr{D}_\tau^b$ where,

$$\mathscr{D}_\tau^b = \{\sigma_{1,\tau}^{b,+}, \ldots, \sigma_{N,\tau}^{b,+}, \sigma_{1,\tau}^{b,+}, \ldots, \sigma_{N,\tau}^{b,+}\}$$

4. Using $\mathscr{D}_\tau^b$, estimate the regression coefficients in equation (2). Run these regressions for each $b = 1, \ldots, 10000$ and $\tau = 1, \ldots, 40$. Let $\eta_\tau^b = [\delta_0^\tau, \delta_1^\tau, \delta_2^\tau, \gamma_1^\tau, \gamma_2^\tau, \gamma_3^\tau, \gamma_4^\tau, \beta^\tau]'$ collect the regression coefficients in (2) for a given b and τ. Thus, $\{\eta_\tau^1, \ldots, \eta_\tau^{10000}\}$ is the bootstrap distribution of regression coefficients from equation (2) for $\tau = 7$ days after the cost shock.

5. Compute the bootstrap standard error for the kth element of $\hat{\eta}_\tau$, $\hat{\eta}_{\tau,k}$, as

$$\text{se}_B(\hat{\eta}_{\tau,k}) = \left(\frac{1}{B-1} \sum_{b=1}^{B} \eta_{\tau,k}^b - \bar{\eta}_{\tau,k} \right)^{1/2}$$

   where $B = 10000$ is the number of simulated impulse responses, $\bar{\eta}_{\tau,k} = (1/B)\sum_{b=1}^{B} \eta_{\tau,k}^b$, and $\hat{\eta}_{\tau,k}$ is the estimate of $\eta_{\tau,k}$ reported in Table 2 in the article.

Inference on whether $\hat{\eta}_{\tau,k}$ is statistically significantly different different from zero with level α of significance is based on bootstrap percentile confidence intervals, specifically the $\alpha/2$ and $1-\alpha/2$ percentile of the bootstrap distribution of $\{\eta_{\tau,k}^1, \ldots, \eta_{\tau,k}^{10000}\}$ (where recall the table reports regressions absed on impulse responses for $\tau = 7$ after a cost shock).

Confidence intervals in Figures 6 and 8

The confidence intervals for the difference in sticky pricing regime effects, $\Delta\hat{\gamma}^\tau \equiv \hat{\gamma}_3^\tau - \hat{\gamma}_4^\tau$ in panel B of Figure 6 are the 5% and 95% quantiles of the bootstrap distribution of $\Delta\hat{\gamma}^\tau$ for day τ, $\{\Delta\gamma^{\tau,1}, \ldots, \Delta\gamma^{\tau,10000}\} = \{(\gamma_3^{\tau,1} - \gamma_4^{\tau,1}), \ldots, (\gamma_3^{\tau,10000} - \gamma_4^{\tau,10000})\}$, where $\{\gamma_3^{\tau,1}, \ldots, \gamma_3^{\tau,10000}\}$ and $\{\gamma_4^{\tau,1}, \ldots, \gamma_4^{\tau,10000}\}$ are generated according steps 1-4 above.

The confidence intervals in panel B of Figure 8 are computed analogously to those in Figure 6 except that that 4-step procedure for computing the bootstrap distributions of $\hat{\gamma}_3^\tau$ and $\hat{\gamma}_4^\tau$ (and their differences) use estimates of $\widehat{\Sigma}_{\theta_i}$, $i = 1, \ldots, N$, that are based on the February 1, 2008 - August 12, 2008 subsample. I denote these bootstrap distributions by $\{\gamma_3^{\tau,1s}, \ldots, \gamma_3^{\tau,10000,s}\}$ and $\{\gamma_4^{\tau,1s}, \ldots, \gamma_4^{\tau,10000,s}\}$.