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Essays in Empirical Industrial Organization

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Dedication

I dedicate this thesis to my dear mother who has loved me unreservedly since the first day of my life.

Acknowledgments

I am immensely grateful to my supervisors David Byrne and Joe Hirschberg for their invaluable guidance and unwavering support. I am also grateful to the department's PhD Director Kalvinder Shields for her constant encouragement and advice. I also thank Kevin Staub, May Li, Simon Loetscher, Steve Puller and participants at the 2018 Australian Conference of Economists and 2018 Asia-Pacific Industrial Organization Conference for their many useful comments. This research is supported by an Australian Government Research Training Program (RTP) Scholarship. All errors are of my own.

Declaration

All work contained in this thesis has not been previously submitted to meet requirements for a degree at this or any other higher education institution. The thesis contains only my original work except where due reference is made. Due acknowledgment has been made in the thesis to all material used. The thesis is no more than 100,000 words in length, exclusive of tables, appendices and bibliographies.

——————————————

Peng Xue

Abstract

This dissertation studies pricing behavior in the retail gasoline market. The main research questions are: How does traffic congestion affect market power of gas stations? How does traffic congestion affect equilibrium price dispersion between gas stations? Is gasoline price cycle consistent with Edgeworth Cycle in terms of how their shapes respond to aggregate demand elasticity? These questions are explored in three separate chapters respectively using unique datasets comprised of station-level gasoline price data and direction-specific road-level traffic data from metropolitan Sydney and the rest of New South Wales.

Evidence from chapter 2 suggests that traffic congestion, through its impact on spatial friction for consumers, dampens the intensity of price competition between gas stations. By exploiting a panel of 61 gasoline stations on 13 roads in Metropolitan Sydney, it is found that the margins of regular gasoline increased with travel delay in local traffic. Specifically, retail margins of regular gasoline increased by 0.32 cents per liter (4%) when travel delay in local traffic has increased unexpectedly by 1 minute per kilometer. Unique to this paper is the high-frequency nature of its data which allows me to examine how fast gasoline companies are responding to spatial frictions at the hourly resolution. Analysis based on a dynamic model suggests that this response is "instantaneous" as margins rise as early as the same hour when a shock in traffic congestion is observed.

In chapter 3, traffic congestion is found to have an impact on equilibrium price dispersion between gas stations. Motivated by empirical evidence that the majority of consumers search for cheaper fuel while they drive, I exploit variation in traffic delay to identify the effect of consumer search cost on price dispersion in the equilibrium retail gasoline market. I find

that the relationship between price dispersion of regular gasoline and search cost is indeed non-monotonic (inverse U-shaped). This finding is consistent with the consumer search model by a consumer search model presented in the chapter which predicts no dispersion at the extremes: market prices converge to marginal cost when search cost approaches zero and to the monopoly price when search cost approaches the upper bound. I find that at the sample average level of traffic delay (0.387 Min/KM) in New South Wales, pricing for regular gasoline is more consistent with competitive pricing, but becomes more monopolistic once traffic delay rises above 1.20 Min/KM.

Finally in chapter 4, I establish new empirical evidence which suggests that gasoline price cycles are consistent with Edgeworth Cycles. Using daily station-level price data for regular gasoline over 2 years, I find that a higher price than a reference-price at the start of a gasoline price cycle has an positive effect on cycle length and a negative effect on undercutting aggressiveness. Based on established empirical evidence that gasoline demand is reference-dependent and the predicted pricing response to aggregate demand elasticity under the Edgeworth Cycle equilibrium, I infer from these results that the shape of a gasoline price cycle depends on aggregate demand elasticity the same way the shape of a Edgeworth Cycle does.

Insights from this dissertation can inform public agencies who are concerned with addressing the issue of traffic congestion and regulators who are concerned with competition and pricing behavior in the retail gasoline industry.

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Chapter 1

Introduction

1.1 Motivation

The price of gasoline is salient: few other products have their price as closely watched by consumers and it is not difficult to see why. For starters, we are reminded of the price every time we drive past a gas station and see them displayed in large numbers. Unlike bills that are paid monthly or a few times a year, gasoline is usually bought every week. And when compared to other goods purchased with similar frequency, say milk, we pay substantially more each time we fill up. As the price of gasoline continues to rise in recent years creating upward pressure on the cost of living for consumers, the price of gasoline has appeared frequently in news headlines reporting consumer anger towards alleged price gouging behavior by gasoline companies. Rising gasoline price also appears to be more detrimental for poorer Australians as it has been reported that they spend a larger share of their income on gasoline (Hurst (2014)). It is therefore unsurprising that the retail gasoline industry is one of the most scrutinized by antitrust and regulatory authorities in many countries (Eckert (2013)). In Australia, public actions targeting this industry includes monitoring by the competition regulator, parliamentary inquiry for pricing behavior and the introduction of price transparency law in four of its six states.[1]

[1]As of March 2020, four Australian states have introduced price transparency law for gasoline and they are Western Australia, New South Wales, Queensland and Northern Territory.

The retail gasoline market is monopolistically competitive. Despite selling a largely homogeneous product, gasoline companies can differentiate themselves through a number of dimensions including station location, loyalty program, and ancillary service. Product differentiation therefore offers a possible explanation as to why a common equilibrium price is rarely observed in this market. Beyond product differentiation however, price differences may still be attributed to the exercise of market power and exploitation of consumer behavior. Understanding gasoline price variations caused by these issues is pertinent to public agencies as it can inform policies aimed at promoting competition and protecting the welfare of consumers in this market.

1.2 Research questions

Structural estimations (Slade (1987), Manuszak (2010) and Houde (2012b)) using both price and demand data confirm that gasoline companies indeed have some market power to charge a price above the competitive level. In addition, many studies have attempted to identify factors beyond static station characteristics that gasoline companies can exploit for market power. The first two chapters of this thesis contribute to this literature by being the first to document the impact local traffic congestion on the retails gasoline market.

In chapter 2, I examine the impact of traffic congestion on the intensity of competition in the retail gasoline market. In the economic literature, researchers have investigated the impact of traffic congestion on the macroeconomy including outputs (Boarnet (1997) and Fernald (1999)), growth (Sweet (2011)) and unemployment (Hymel (2009)). However, little attention has been given to understanding its impact on consumer market outcomes. This is surprising for two reasons. First, the relationship between consumer travel cost and the intensity of competition has been acknowledged in spatial competition models since Hotelling (1929). The typical intuition from these models is that consumer travel cost increases the spatial differentiation between firms giving them market power to charge a higher price above the marginal cost. Second, travel delays in traffic represents a higher level of travel cost for consumers in a number of markets that require consumers to travel in traffic first before visiting the store (e.g., supermarkets and gas stations). Of these, the travel cost for purchasing auto fuel is most likely to be affected by traffic congestion due to the fact that delivery service is usually not available for this product. Consequently, I hypothesize that through its impact on creating travel delay in traffic, traffic congestion can lower the intensity of competition in the retail gasoline market. To empirically test this hypothesis, I estimate the effect of traffic delay on gasoline margins based on a hourly panel comprised of station-level price from 61 gas stations and direction-specific traffic observations from 13 roads in Sydney during the August-October 2016 periods.

In chapter 3, I examine how traffic congestion can affect equilibrium price dispersion in the retail gasoline market. Empirically identifying the global effect of search cost on equilibrium price dispersion has been challenging for researchers due to the lack of a suitable proxy for search cost that can accommodate a potentially non-monotonic relationship. In the retail gasoline market, there is evidence suggesting that the majority of its consumers search for cheaper price while they are driving. This implies, for these consumers, they will face higher search cost when traffic delay occurs. In this paper, I exploit hourly variations in traffic delay observed on 36 direction-specific road segments in Sydney from August to October 2016 to identify the global effect of search cost on equilibrium price dispersion in the retail gasoline market.

Chapter 4 examines dynamic price variations observed in the retail gasoline market. Asymmetrical price cycles are observed in retail gasoline markets around the world including the United States, Canada ,Germany and Australia. An ongoing research question in the literature revolves around whether it reflects competition or collusion. In this paper, I contribute towards answering this question by comparing observed pricing behavior of gasoline companies to the competitive pricing behavior implied by the Edgeworth Cycle model. I use daily station-level price data from January, 2017 to June, 2019 in New South Wales to test if aggregate demand elasticity affects the shape of gasoline price cycles in the same way as its impact on the shape of Edgeworth Cycle based on the predictions by Noel (2008) that more (price) elastic aggregate demand should increase the cycle length as it decreases undercutting aggressiveness within each Edgeworth Cycle.

1.3 Findings and Policy Implications

Chapter 2 finds that, consistent with equilibrium relationship implied by the seminal "circular-city" model, the margins of regular gasoline increased with travel delay in local traffic. Based on a subsample more associated with congestion and commuter traffic, margins of regular gasoline increased by 0.32 cents per liter (4%) when travel delay in local traffic increases by 1 minute per kilometer. The same effect is not found for mid-grade and premium gasoline suggesting that spatial differentiation may be less relevant for pricing higher-end products. Analysis by station brands reveals that the average effect of traffic congestion is driven by the response of three largest gasoline chains who are also dominant firms in the supermarket industry. This result suggests that response to traffic congestion may reflect pricing sophistication of gasoline companies. Results based on the dynamic effect of traffic congestion suggest that some gasoline companies may be closely monitoring traffic condition as the margins respond instantaneously to contemporaneous shocks in traffic congestion.

The main finding from this analysis may be informative for policy makers when developing solutions for traffic congestion. Solutions for traffic congestion are often financially burdensome (e.g., infrastructure upgrade such as road expansions) or socially unpopular (e.g., congestion charges), policy makers should therefore consider all associated benefits to justify their financial and social costs. This paper suggests that in addition to the benefits conventionally associated with less traffic congestion such as reduced pollution and savings in travel time, motorists may also benefit from stronger competition in the retail gasoline market.

Chapter 3 finds that the effect of traffic congestion on price dispersion in the retail gasoline market is non-monotonic and inverse U-shaped. My results are consistent with the predicted relationship between search cost and equilibrium price dispersion based on a consumer search model presented in the paper. Based on the price of regular gasoline, traffic congestion at the estimated turning-point is around 1.40 Min/KM or 42% of the legal speed limit. For other gasoline types, I find this relationship to be weaker for mid-grade gasoline and absent for premium gasoline. A possible explanation for these results is that gasoline firms expect the wealthier consumers to search less or do not search for cheaper alternatives in traffic so that changes in traffic congestion have little to no impact on their pricing decisions.

My results can be appreciated by antitrust agencies who monitor the level of price competition in the gasoline market. Following the interpretation of the turning-point by Chandra and Tappata (2011), it can be inferred from my result that regular gasoline is more consistent with being competitively priced for about 94% of the time as the travel delay at the estimated turning-point for regular gasoline represents the 94th percentile of my sample.

Chapter 4 finds that when gasoline price is higher than an expected price based on past prices, gasoline price cycles are longer and the average price cut is smaller. Extrapolating from empirical evidence for the reference-dependent nature of gasoline demand, relative high gasoline price can be interpreted as a proxy for relatively more elastic demand. Based on this extrapolation, I infer that undercutting is less aggressive when demand is more price elastic. This interpretation of my results implies that pricing response to demand elasticity observed in my data is consistent with the predicted pricing response to demand elasticity under an Edgeworth Cycle equilibrium. As the first attempt to empirically identify these pricing behaviors, the findings in this paper therefore represent a new piece of evidence that supports the Edgeworth Cycle explanation for gasoline price cycles.

While my findings cannot rule out that collusion may still be responsible for cycling gasoline prices, my results do address the public concern to the extend that there is evidence of competitive pricing behavior based on the observed prices. In addition, the empirical relationship identified in this paper could be of interest to public agencies (e.g., Australian Consumer& Competition Commission and the Federal Trade Commission) who wish to help consumers to make better purchase decisions. For example, such agencies may provide forecasts for the length of gasoline price cycles so that consumers can time their purchase closer to the trough of the cycle. In practice, this paper suggests that a forecaster should consider including a measure of price elasticity of demand as a predictor for cycle length in addition to the length of past cycles and other predictors.

Chapter 2

Traffic Congestion and Market Competition: Evidence from the Retail Gasoline Market

2.1 Introduction

Traffic congestion needs little introduction - it is ubiquitous in our modern world and it frustrates travelers because it forces them to spend more time in traffic. In the economic literature, researchers have established its impact on macroeconomic outcomes including outputs (Boarnet (1997) and Fernald (1999)), growth (Sweet (2011)) and unemployment (Hymel (2009)). However, little attention has been given to understanding its impact on consumer market outcomes. This is surprising for two reasons. First, the relationship between consumer travel cost and the intensity of competition have been acknowledged in spatial competition models since Hotelling (1929). The typical intuition from these models is that consumer travel cost increases the spatial differentiation between firms giving them market power to charge higher price above their marginal cost. Second, traffic congestion can increase the consumer travel cost in markets where driving to the store is the norm . Of these, the travel cost for purchasing gasoline is perhaps the most affected by traffic due since consumers usually drive their vehicle to the gas station for refills. Consequently, I hypothesize that, through its impact on travel cost for consumers, traffic congestion is expected to lower the intensity of competition in the retail gasoline market.

My empirical strategy for testing this hypothesis exploits a hourly panel based on data observed in Sydney during a 3-month period from August to October 2016. The dataset contains contemporaneous observations of retail margins at the station level and corresponding local traffic condition based the side of the road where the gas station is located. Importantly, the high-frequency nature of the data allows me to exploit hourly variations in traffic conditions and control for unobserved effects across space and time with fixed effects. I find that an additional 1 minute per kilometer travel delay in local traffic significantly increased retail margins of regular gasoline by 0.32 cents per liter which represents 4% of the sample mean. One way to interpret this result is that traffic congestion has a competition-dampening effect in the market of regular gasoline. However, this effect is insignificant for mid-grade and premium gasoline. I also find that margin response by three brands of gasoline stations are responsible for the overall effect of traffic congestion. Finally, I estimate a dynamic model that includes lead and lag values of traffic congestion in addition to its contemporaneous observations. Based on the results from this model, I find no evidence to suggest that margins respond to future traffic delays which suggests that the variations I exploit is close to random. On the other hand, traffic congestion is found to have a persistent effect for up to an hour. These results are consistent with the interpretation that gasoline companies are responding to temporary changes in traffic condition on an hourly basis.

This paper is the first to document and quantify a consumer market outcome of traffic congestion using observational data. It is related to three branches of literature. The first branch focuses on the social and economic consequences of traffic congestion including wasted time (Li, Purevjav, and Yang (2017)), health (Currie and Walker (2011)), crime (Beland and Brent (2018)), economic output (Fernald (1999)) and unemployment (Hymel (2009)). This paper contributes towards this literature by identifying the impact of traffic congestion in the context of a consumer market.

This paper is also a first to demonstrate the speed with which gasoline companies are capable of exploiting sudden and temporary changes in market condition such as traffic congestion. Related literature includes papers that examine intraday pricing strategy within the gasoline industry. (e.g., Neukirch and Wein (2016) and Haucap, Heimeshoff, and Siekmann (2016)).

The paper also sheds new light on spatial differentiation in the gasoline market. Directed related to this paper is Houde (2012a) who use commuting routes to define the location of consumers where gas stations compete spatially. Other papers in this literature include Van Meerbeeck (2003) who finds that stations near a highway commands a price premium and Pennerstorfer and Weiss (2013) who find that gasoline stations derive market power from spatial clustering of stations of the same brand. Compared to existing literature, this paper highlights the role of temporal distance between competing stations in the gasoline market.

The paper is organized as follows. In section 2, I reproduce the circular model in Salop (1979) to illustrate how traffic congestion is related to spatial price competition in the retail gasoline market. Section 3 describes the industry and the data used for my empirical analysis. Section 4 describes the empirical strategy. Section 5 presents the results. Section 6 provides a discussion on two alternative pricing strategies that can potentially explain my results. Finally, section 7 concludes.

2.2 How does traffic congestion affect competition?

In this section, I present a simple model that illustrates how traffic congestion may affect market outcomes in the retail gasoline market. I follow the seminal analysis of Salop (1979) on spatial competition and assume that individual firms and consumers are located along a unit-circle. Each consumer has an inelastic demand for one unit of a homogeneous product. Firms play a two-stage game: in stage one, the firms choose where to locate in the circular-city, and in stage two, firms choose a profit maximizing price. To appreciate the theoretical pricing decisions made by gasoline stations in this model, it is sufficient to focus on only the pricing stage of this game and take firm locations as given. For simplicity, assume that there are N competing firms spaced evenly on the unit-circle so that the distance between any two firms is $\frac{1}{N}$.

To visit a station, consumers must pay a linear travel cost t. I further assume that conditional on the travel cost, consumers value all stations equally. That is, for a consumer with valuation of buying a unit of gasoline v, located at x, who purchases from firm i that charges price p_i, receives an indirect utility equals to $v - p_i - tx$ and if she buys from firm $i+1$ then her utility $v - p_{i+1} - t\left(\frac{1}{N} - x\right)$.

A consumer is indifferent from purchasing from firm i or $i+1$ is she is located at $\tilde{x}_{i,i+1} = \frac{p_{i+1} - p_i + \frac{t}{n}}{2t}$. The indifference consumer between firm $i-1$ and firm i is similarly $\tilde{x}_{i-1,i} = \frac{p_{i-1} - p_i + \frac{t}{n}}{2t}$. The total demand for firm i is

$$d_i = \frac{p_{i-1} + p_{i+1} - 2p_i + \frac{2t}{N}}{2t}$$

.

Therefore, firm i chooses a p_i so that it maximizes its profit function

$$\pi_i = (p_i - c)\left(\frac{p_{i-1} + p_{i+1} - 2p_i + \frac{2t}{N}}{2t}\right) - F_i$$

where π_i is the firm's profit, F_i represents the fixed cost and c is the constant marginal cost for each firm. The symmetric equilibrium price[1] is

$$p^* = c + \frac{t}{N}. \tag{2.1}$$

Rearranging equation 2.1, the expression for retail margin in equilibrium is shown in equation 2.2 to equal to consumer travel cost, t, and the number of competitors, N, in the market.

$$\underbrace{p^* - c}_{\text{Margin}} = \frac{t}{N} \tag{2.2}$$

Equation 2.2 implies that, given a fixed N, equilibrium margin is increasing in consumer

[1]In equilibrium, $p_1 = \ldots = p_N = p^*$. There is no collusion or coordination in this model so the equilibrium price is the competitive equilibrium price.

travel cost t. Assuming that the majority of consumers travel in traffic first to purchase gasoline and they have positive valuation of their time, then the travel cost t in this market is expected to be increasing in the intensity of traffic congestion on the road where station i is located.

In the following empirical sections, I test the hypothesis that traffic congestion has negative impact on the intensity of competition in a market with spatially differentiated firms by estimating the causal effect of traffic delay on the retail margins of gas stations in Sydney, Australia.

2.3 Industry and data

2.3.1 The retail gasoline market in Sydney, Australia

The gasoline industry in Sydney has two levels: wholesale and retail. The wholesale suppliers own and operate oil terminals where imported refined fuel[2] from domestic and international sources are stored and distributed to retail operators. This paper focuses on the retail gasoline market in metropolitan Sydney which, in October 2016, comprised of approximately 680 gas stations. The retail gasoline industry in Sydney is characterized by a moderate level of market concentration with the four largest brands (Woolworths, British Petroleum (BP), 7-Eleven and Coles Express) accounting for approximately 55% of the stations. Independent chains constitutes 24% of the market share while independent and one-store stations make up the last 21% of the market. In 2016, the market structure in Sydney is similar the overall market structure of retail gasoline market in Australia with over 50% of the stations nationwide operating under Coles Express, Woolworths, BP and 7-Eleven brands (ACCC (2018)).

Gasoline price in Sydney is not regulated by the government[3] and determined entirely by market forces (ACCC (2017)). Wholesale prices, also known as Terminal Gate Prices (TGP), for each geographic market area are updated once daily and published by the wholesale

[2]There is no local production of crude oil and its last operating refinery was converted to a storage terminal for refined gasoline in 2014.

[3]Fuel prices are monitored by Australian Competition & Consumer Commission (ACCC)

distributors on their respective website. For retail prices, station operators set their own prices and can update the price at any time.

In Sydney, the majority of stations sell a variety of gasoline based on their octane content that may include, regular (U91), mid-grade (P95), premium (P98), and 10% ethanol-blend (e10). The main result of this paper is based on regular gasoline which represents approximately 60% of the total amount of gasoline sold in Australia and 32% in Sydney (APS (2016)). To explore if the effect differs by gasoline type, I also explore the effect of traffic congestion on mid-grade and premium gasoline.

2.3.2 Data sources and variable construction

2.3.2.1 Price data

This paper combines two main categories of data from multiple sources. The two data categories are: price data and traffic data. The history of retail prices for station i (P_{it}^{Retail}) of gasoline in Sydney are collected and published by the state government through FuelCheck - a price transparency website. Wholesale prices ($P_{bd}^{Wholesale}$) are purchased from Fueltrac - a consultancy specializing in Australian gasoline industry data. Wholesale prices are matched to the retail prices by brand (b) and date (d). Following the literature[4], I construct station-level retail margins as the difference between the retail and wholesale gasoline prices:

$$Margin_{it} = P_{it}^{Retail} - P_{bd}^{Wholesale} \tag{2.3}$$

2.3.2.2 Traffic data

Traffic data is the second category of data. It is sourced from the Roads Report published by the Roads & Maritime Services (RMS)[5]. The Roads Report provides a record of intraday observations of traffic speed and density at the trip-level in New South Wales. A trip is defined in the Roads Report as a direction-specific section of a major road whose start and end points are also defined in the Roads Report. In total, over 50 trips in Metropolitan

[4]See Borenstein and Shepard (1996), Lewis (2012), Luco (2016) and Byrne and Roos (2016)

[5]RMS is the transport authority of New South Wales where Sydney is the capital city

Sydney are covered by the Roads Report. Unfortunately, the data provided by Roads Report has a number of shortcomings. First, for many of its trips, their observations are incomplete with either missing observations in traffic speed for a significant portion of a day or missing the corresponding observations in traffic density. Second, the Roads Report does not describe their data collection method or provide explanations as to why some trips have more complete observations than others. For the purpose of this study, I assume that the completeness of observations for each trip in the Roads Report is randomly assigned by RMS and select the trips to be sampled based on the completeness of their traffic data and the presence of a matched gas station. Specifically, a trip can only be included in the sample if its traffic speed is observed for every hour of the day from 1 August to 31 October 2016 and if a gas station can be spatially matched to it. A gas station is spatially matched to a trip if it is located immediately adjacent to left of that trip as shown in the inset of figure 2.1.

This matching ensures that I only examine the impact of local traffic congestion on a gas station's pricing decision. Among all trips covered in the Roads Report, 22 trips located within the metropolitan area of Sydney satisfy this condition. A total of 61[6] gas stations are matched to these trips and table 2.1 presents the sampled trips and the number of stations matched to each trip. It shows that there is an even split of gas stations in terms of traffic direction. A map of gas stations located on the sampled trip is presented in figure 2.1.

Following Anderson (2014), I quantify traffic congestion in terms of travel time delay in traffic defined by the following equation:

$$TrafficDelay_{jt} = \frac{FreeflowSpeed_{jt}}{ActualSpeed_{jt}} - 1 \tag{2.4}$$

where $FreeflowSpeed_{jt}$ corresponds to the unobstructed free-flow traffic speed under the legal speed limit for trip j at time t and $ActualSpeed_{jt}$ is the observed hourly traffic speed for a trip. Equation 2.4 calculates the additional travel time under observed traffic speed compared to the travel time under the legal speed limit in minutes per kilometer

[6] This represents approximately 10% of all the stations in metropolitan Sydney.

(Min/KM).

2.3.3 Overview of data

Because opening hours can differ from station to station, I treat margins as unobserved if the station is closed at time t. Consequently, the final data set is an unbalanced panel with over 147,000 hourly observations. Figure 2.2 illustrates the evolution of average retail prices, average whole sale prices over the sample period. The retail price follows a pattern of asymmetric price cycles that has been well documented in the literature. The wholesale price has a upward trend over the sample period. In comparison to the retail price, wholesale prices are less volatile and do not exhibit any obvious cyclical patterns. Consequently, a potential endogeneity concern is that dynamic pattern in traffic may be spuriously correlated with gasoline price cycle. My empirical model controls for the effect of gasoline price cycles with date fixed effects.

Figure 2.3 presents intraday hour-to-hour variation in traffic congestion by traffic direction and day type based on the sampled trips over the sample period. The solid line represents average traffic congestion for the hour and the dashed lines are plus and minus one standard deviations. Inbound traffic corresponds to the trip traveling towards downtown Sydney as defined in the Roads Report. Figure 2.3 suggests that traffic congestion can vary significantly within a day. On business days, the worst congestion typically occurs between 8am to 9am for inbound traffic and between 5pm to 6pm for outbound traffic. For both directions, within-day traffic congestion exhibits a double-humped pattern which can be explained by the morning and afternoon rush hour traffic of commuters. In comparison, traffic congestion on weekends and public holidays has less variation with peak congestion occurring in early afternoon.

Table 2.2 reports the summary statistics of the final data set. The first panel shows that the average retail margin for regular unleaded gasoline in the sample is about 8.5 cents per liter. This sample average is slightly lower than the average retail margin for regular gasoline estimated by ACCC for Sydney which is 9.9 cents per liter (ACCC (2017)). The second panel shows that the average hourly speed of the sampled roads are 48.0 kilometers-per-hour (kmh) and the associated average traffic congestion is about 0.36 Min/KM.

2.3.4 Descriptive evidence

To preface regression results, I present figure 2.4 as a descriptive evidence for the impact of traffic congestion on retail margins of gasoline. Figure 2.4 is a binned scatter plot of margins on congestion. Each dot in the scatter plot corresponds to the average margin and average congestion for an equal-sized bin based on congestion observations. The graph suggests that retail gasoline margin is positively correlated with traffic congestion. Because traffic congestion increases the travel time of gasoline consumers, the relationship shown in the scatter plot is consistent with the prediction of the "circular-city" model. However, traffic congestion is not random. It is likely to be correlated with demand and the number of stations in a local market which can all play a role in explaining observed margin. In the next section, I use regression to isolate the impact of traffic congestion on margins.

2.4 Methodology

To estimate the effect of traffic congestion on competition intensity of retail gasoline, I rely on unexpected variations in traffic delay to identify the impact of traffic congestion on retail margins of gasoline. I do this by estimating the following regression model:

$$\begin{aligned} Margin_{ijt} &= \beta_0 + \beta_1 TrafficDelay_{jt} + \beta_2 E\left[TrafficDelay\right] \\ &+ \beta_3 N_{it} + \beta_4 Rain_{it} + \beta_5 TrafficDensity_{jt} \\ &+ \beta_i \times \beta_m + \beta_b + \beta_d + \beta_h + \epsilon_{it} \end{aligned} \tag{2.5}$$

where $Margin_{ijt}$ is the outcome of interest as defined in equation 2.3. My main analysis focuses on the margins for regular gasoline, but I also investigate the impact on other types of gasoline including mid-grade and premium gasoline. $TrafficDelay_{jt}$ is the variable of interest as defined in equation 2.4. My coefficient of interest, β_1, measures the impact on margins from a 1 Min/KM travel delay in traffic. $E\left[TrafficDelay\right]$ is a measure of expected traffic delay for route j. It consists of a vector of five lagged values of $TrafficDelay_{jt}$ by 24 , 48, 72, 168 and 336 hours. Lagged values of traffic delay by 24, 48 and 72 hours represent traffic delay in the same hour of the day as t from the past 3 days. Lagged values of traffic delay by 168 and 336 hours represent traffic delay in the same hour of the day in the same day of the week as t of the past two weeks. Lagged values of traffic delay in the past 3 days are included to control for recent but temporally persistent changes in traffic condition such as road works. Values of traffic delay from the past two weeks are to control for more persistent traffic patterns such as the ebb and flow of commuter traffic. More formally, the control for expected traffic delay is defined below:

$$E\left[TrafficDelay\right] \equiv \begin{bmatrix} TrafficDelay_{j(t-24)} \\ TrafficDelay_{j(t-48)} \\ TrafficDelay_{j(t-72)} \\ TrafficDelay_{j(t-168)} \\ TrafficDelay_{j(t-336)} \end{bmatrix}$$

. N_{it} is the number of stations that are open for business within a radius of 5 km of station i at time t. $Rain_{it}$ represents contemporaneous rainfall intensity for station i at time t.[7] $Rain_{it}$ controls for possible expectations in traffic delay formed based on weather conditions and potential variations in demand elasticity for gasoline due to weather.

A potential threat to identification for interpreting β_1 as causal comes from the impact of gasoline price on the demand for travel. Burger and Kaffine (2009) show that traffic congestion eases with higher gasoline price which is explained by the negative relationship between the demand for travel and the fuel cost of travel . Failing to control for this simultaneity problem may attenuate the estimated effect of traffic congestion on retail gasoline margin. To address this endogeneity concern, I include contemporaneous observations of

[7]The rainfall data is purchased from the Australian Bureau of Meteorology. The observation of rainfall for each gasoline station is based on rainfall recorded in the closest weather station. The distance between the gasoline station and the weather stations is determined based on the crow-fly distance. A total of 7 weather stations are matched to the 61 gasoline stations in the sample.

traffic density ($TrafficDensity_{jt}$) as a control which measures the the number of vehicles that passes through trip j within time t.

I include an interaction term between station fixed effects (β_i) and month-of-year fixed effects (β_m) to flexibly control for station-specific unobserved effects in the medium to long run which including demographic changes among consumers such as population, income and unemployment that are specific to station i. Brand fixed effects (β_b) are included to account for the effect of brand changes for each station. I include date fixed effects (β_d) to control for daily unobserved common shocks such as the effect of price cycle and the day-of-week effect. Lastly, I include hour-of-day fixed effects (β_h) to control for unobserved effect of each hour in a day. I cluster the standard errors at the station i and at the time t level (two-way clustering) to account for serial and spatial correlations in the estimation errors.

2.5 Results

2.5.1 Main results

Table 2.3 presents the impact of traffic congestion on retail margins of gasoline. Column 1 uses all traffic and retail margin observations in Sydney to estimate equation 2.5 and shows that retail margin is significantly increased by travel delay in traffic. Column 2 to 4 exploit subsamples whose variation in traffic delay is more likely to be caused by congestion and commuter traffic. Column 2 excludes observations associated with speeding traffic: when the observed traffic speed is above the legal speed limit. Consequently, this subsample excludes variations in traffic delay that reflect speeding behavior of drivers and not travel time externality due to congestion. Column 3 excludes weekends and public holidays since traffic during these times are mostly due to leisure travels and not to commuter traffic. Column 4 excludes both speeding traffic observations and weekend and public holiday observations. The results of column 4 shows that a 1 Min/KM increase in local traffic delay leads to an increase in the margin of regular gasoline by 0.31 cents per liter which corresponds to 4% of the subsample mean. To put this result in context, a 1 Min/KM traffic delay is similar to the typical delay experienced by drivers during peak commuting hours (8am inbound and 5pm outbound) in my sample. All specifications show that margins of regular gasoline increased when travel in traffic is delayed. The effects are larger when restricting the samples to travel delays that are due to obstructed traffic flow on working days. My preferred specification is column 4, which I will use in the remainder of the paper except when specified.

2.5.2 Effect on other types of gasoline

Table 2.4 presents estimates of the effect of traffic congestion on different types of gasoline. Column 1 replicates my preferred specification using regular gasoline as the outcome variable. Column 2 to 3 present the effect of traffic congestion on the margins of mid-grade and premium gasoline. The results show that the estimated coefficient on traffic congestion have the same sign as regular gasoline but are not statistically significant for mid-grade and premium gasoline. One possible explanation for these results is that gasoline companies employ a multi-product pricing strategy similar to that discussed in Hilleke and Butscher (1997) where companies engage in price competition only over lower-positioned products not over higher-positioned products. Compared to mid-grade and premiums gasoline, regular gasoline can be considered as a lower-positioned product based on its lower quality and price. Regular gasoline is lower in quality in terms of octane content.[8] Regular gasoline is also a cheaper fuel than mid-grade and premium gasoline. Based on my sample, the price of regular gasoline is 11% lower than mid-grade gasoline and 16% lower than premium gasoline. Yet, heterogeneous pricing response to traffic congestion between gasoline companies may be another explanation for the insignificant average effect for mid-grad and premium gasoline. In the following section, I explore heterogeneous response to traffic congestion by station brands.

[8]In Australia, regular gasoline has an octane content of 91%, mid-grade gasoline 95% and premium gasoline 98%.

2.5.3 Effect by station brand

After establishing that traffic congestion has a positive effect on gasoline margins, I now examine if this effect represents an industry-wide response to traffic congestion or the response of specific gasoline companies. It is possible that not all gasoline companies respond to traffic congestion. One reason may be that not all gasoline companies have the same pricing strategy or the capacity to continuously monitor and price in unexpected variations in traffic congestion. Intuitively, we expect larger gasoline companies to lead the response to traffic congestion as they are more likely to employ sophisticated pricing strategies. I follow Luco (2019) and identify gasoline companies by the brand of the gas station. Informal conversation with a number of station managers in Sydney reveals that prices of branded gas stations are set centrally by pricing specialists in their corporate head office while prices of unbranded gas stations are typically set by their individual owners. This insight suggests that stations who share the same brand should follow a similar pricing strategy and subsequently exhibit similar margin response to traffic congestion.

Table 2.5 presents the heterogeneous effects of traffic congestion by station brands. To parse out the effect by brands, I estimate a regression model that interacts $TrafficDelay$ in my preferred specification with brand dummies. Column 1 of table 2.5 presents the results of brand-specific response for regular gasoline. It shows that the overall response is driven by three brands which are 7-Eleven, Woolworths and Coles Express. Column 2 and 3 reports the brand-specific response for mid-grade and premium gasoline. They suggest that the margin of mid-grade and premium gasoline at Coles Express stations are responding to traffic congestion. A feature for these three brands is that they are strong players in both supermarket and the retail gasoline industry.[9] One possible explanation for their response to traffic congestion can therefore be attributed to their ability to leverage pricing expertise from their supermarket business which is another highly competitive market. It is also somewhat unsurprising that both Woolworths and Coles Express share similar response to traffic congestion as there was precedent of two companies matching each other's pricing

[9] Woolworths and Coles are the two largest supermarket companies in Australia while 7-Eleven is a global leader in convenience store business.

strategy[10]. What's more, they are also the top three retail gasoline companies in Australia: together they represent approximately 40% of all gas stations Australia in 2016 according to ACCC (2018). The dominant market presence of these three brands means that their pricing decision are more likely to influence other companies in the market than smaller brands.

2.5.4 Dynamic effects of traffic congestion

The analysis so far has focused on establishing the contemporaneous effect traffic congestion has on margins. However, it is possible for gasoline companies to form expectations about future traffic congestion based on past traffic patterns and weather forecasts. This implies that margins may respond to both contemporaneous and expected traffic congestion. On the other hand, it is also possible for traffic congestion to have a persistent effect on margins. This can happen if some stations are price-followers and hence have a delayed response after price-leaders have updated their price in response to a change in traffic congestion.

In this section, I examine the dynamic effect of traffic congestion on margins. This is important for two reasons. First, the effect of future traffic congestion provides a placebo test for my identification strategy. Specifically, if the variation in traffic congestion I exploit is indeed quasi-random then future traffic congestion should have no impact on current margins. Second, the dynamic effects can also reveal the the speed with which the market responds to unanticipated shocks to traffic condition. The high-frequency nature of my data allows me to measure this response time in unit of hours.

To test the impact of future and past traffic delay on current margins, I estimate a dynamic model that adds a vector of lead values of traffic delay ($[FutureTrafficDelay]$) and a vector of lagged values of traffic delay ($[PastTrafficDelay]$) to the specification in column 4 of table 2.5. $[PastTrafficDelay]$ is a vector of 6 lead values of $TrafficDelay_{jt}$ from 1, 2, 3, 4, 24 and 168 hours after time t. They represent future observations of traffic delay at trip j, 1 to 4 hours, 1 day and 1 week after time t. Similarly, $[PastTrafficDelay]$

[10] Both have been investigated by ACCC in 2014 for their fuel shopper docket discount scheme. For details, please refer to ACCC (2015)

is a vector of 6 lagged values of $TrafficDelay_{jt}$ that are past observations of traffic delay at trip j, 1 to 4 hours, 1 day and 1 week prior to time t. Coefficient on the variables in $[FutureTrafficDelay]$ in this model represents the impact of future shocks in traffic delay on current margins and the coefficient on the variables in $[PastTrafficDelay]$ represents the impact of past shocks in traffic delay on current margins.

Along with their 95% confidence interval, figure 2.5 graphs the coefficients on contemporaneous traffic delay observed at time t, future traffic delay at time $t+k$ and past traffic delay at time $t-k$, where k is the lead and lag hours from time t. Reassuringly, estimated effects of future traffic congestion are all indistinguishable from zero. This result supports the identification assumption that variation in traffic congestion is approximately random given the controls and fixed effects included in my preferred specification. On the other hand, traffic delay seems to have a persistent effect for about at least 1 hour as traffic delayed observed 1 hour prior still has a significant but smaller effect on current margins. There are two possible explanations for the persistent effect of traffic congestion, First, some unexpected traffic delay may be caused by traffic incidents that last more than an hour. For example, in the event of a traffic accident or vehicle breakdown, involved vehicles often need to be left in traffic for some time obstructing traffic flow until the arrival of the towing crew. Another possible explanation for the persistent effect is the presence of price leaders and price followers in the market. Under this explanation, the contemporaneous effect of traffic congestion measures the margin response of price leaders in the market as they respond to shocks to traffic congestion as soon as they occur while it takes within an hour for the remainder of the market to match the price changes of the price leaders.

Combined with the brand-specific effects estimated in the previous section, the results from this analysis provide suggestive evidence that some gasoline companies are exploiting changes in market condition at the hourly frequency. Specifically, they let their margins to reflect changes in traffic condition in real-time (within the hour). This type of dynamic pricing response to traffic congestion offers an explanation for the reported phenomenon[11] in Canada that some gas stations are raising prices slightly during peak traffic hours and

[11] News reported by DaSilva (2019).

lowering them back in off-peak traffic hours within a single day.

2.6 Alternative explanations for the effect traffic congestion on gasoline margins

Peak-load pricing

Peak-load pricing strategy has been suggested as an alternative explanation for the positive effect of traffic congestion on gasoline margins. Peak-load pricing is a type of dynamic pricing that has been most prominently applied in the electricity market where price can ramp up quickly during periods of high demand (e.g., on a hot day). Under this pricing strategy, prices are responding to changes in demand volume rather than changes in competitive pressure. One way that traffic congestion could be correlated with demand volume is because traffic congestion is caused by the large number of vehicles in traffic. As the number of traveling vehicles increases there may be more consumers who need to purchase gasoline hence an increase in demand. My empirical strategy accounts for peak-load pricing effect by including contemporaneous traffic density as a control in all of my specifications. Because traffic density measures the corresponding number of vehicles for every observation of traffic congestion, my estimated effects of traffic congestion should be free from effect of additional demand for gasoline during periods of busier traffic.

Dynamic price discrimination by consumer type

Another possible reason that may have caused the margins to increase with traffic delay is dynamic price discrimination. Gasoline companies may implement dynamic price discrimination by charging a higher price during certain times of the day. One example of this pricing strategy is to charge higher price during business hours as business travelers may have higher willingness-to-pay for gasoline than leisure travelers. This is a type of third-degree price discrimination which has been observed in the airline industry. For example, Puller and Taylor (2012) show that airfares are cheaper during weekends and they attribute this phenomenon to price discrimination between business and leisure travelers. In addition, Siekmann (2017) finds that intraday price cycles in Germany is associated with higher prices during business hours than leisure hours of the day. My preferred specification controls for the effect of this type of pricing practice by exploiting variations in traffic delay on only business days. In addition, hour-of-the day fixed effects are included in all my specification to control for unobserved effect each hour of the day may have on all stations.

2.7 Chapter conclusion

Motivated by the implied relationship between consumer travel cost and the intensity of competition from spatial competition models, this paper provides a first attempt to quantify the impact of traffic congestion on competition in a consumer market with spatially differentiated firms. This paper shows that traffic congestion dampens competition in the retail gasoline market. Based on a hourly panel of gasoline price and traffic data in Sydney, I find that retail margins of regular gasoline increased significantly by 4% with an additional 1 Min/KM travel delay in traffic. I also find that this effect is only present for regular gasoline but not for more premium types of gasoline indicating that gasoline companies may employ different pricing strategies by product quality. The effect of traffic congestion is also found to be heterogeneous by station brand with 7-Eleven, Coles Express and Woolworths stations more likely to respond to traffic congestion. Furthermore, a placebo test based on the effect of future traffic congestion confirms that the randomness in the variations I exploit for identification. On the other hand, my analysis also suggests that gasoline companies are capable of responding to unanticipated and temporary changes in traffic congestion.

This paper contributes primarily to the literature on quantifying the impact of traffic congestion and the literature on gasoline pricing. I identify a novel effect of traffic congestion that has not been previously investigated. This paper also sheds new light on the pricing efficiency of firms in the retail gasoline company that they may be responding to shocks in market on the hourly basis. The main finding from this paper suggests that policies for ameliorating traffic congestion can generate a double-dividend effect as consumers, especially those with lower income, can benefit from the reduction in welfare transfer gasoline firms caused by traffic congestion. For antitrust agencies, this paper analyses one dimension in which gasoline companies may exploit algorithm pricing to derive market power as real-time traffic congestion data is publicly available in many countries around the world.

Figures and Tables in Chapter 2

Figure 2.1: GEOGRAPHIC LOCATIONS OF SAMPLED GAS STATIONS SHOWN ON GOOGLE MAP

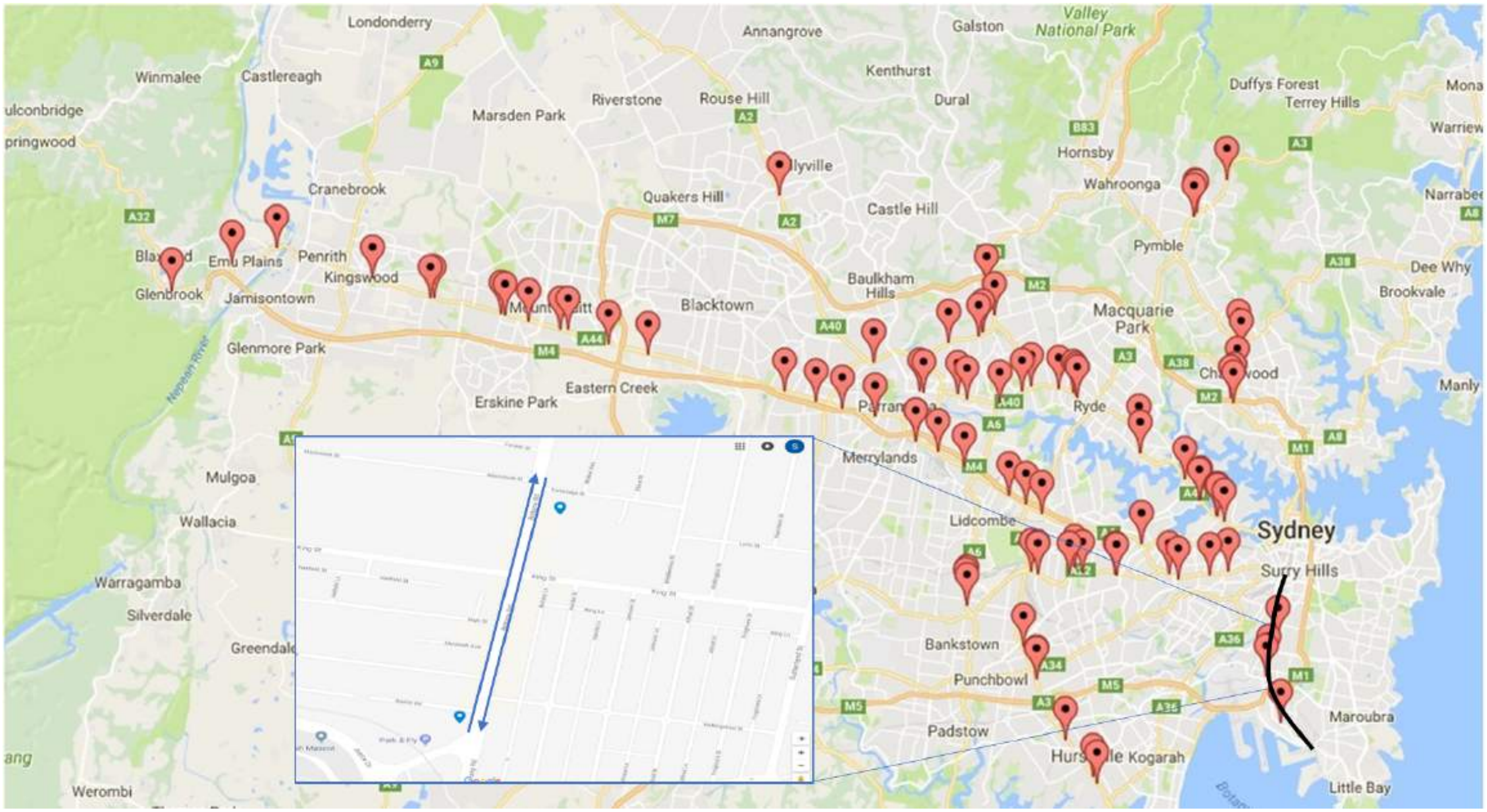
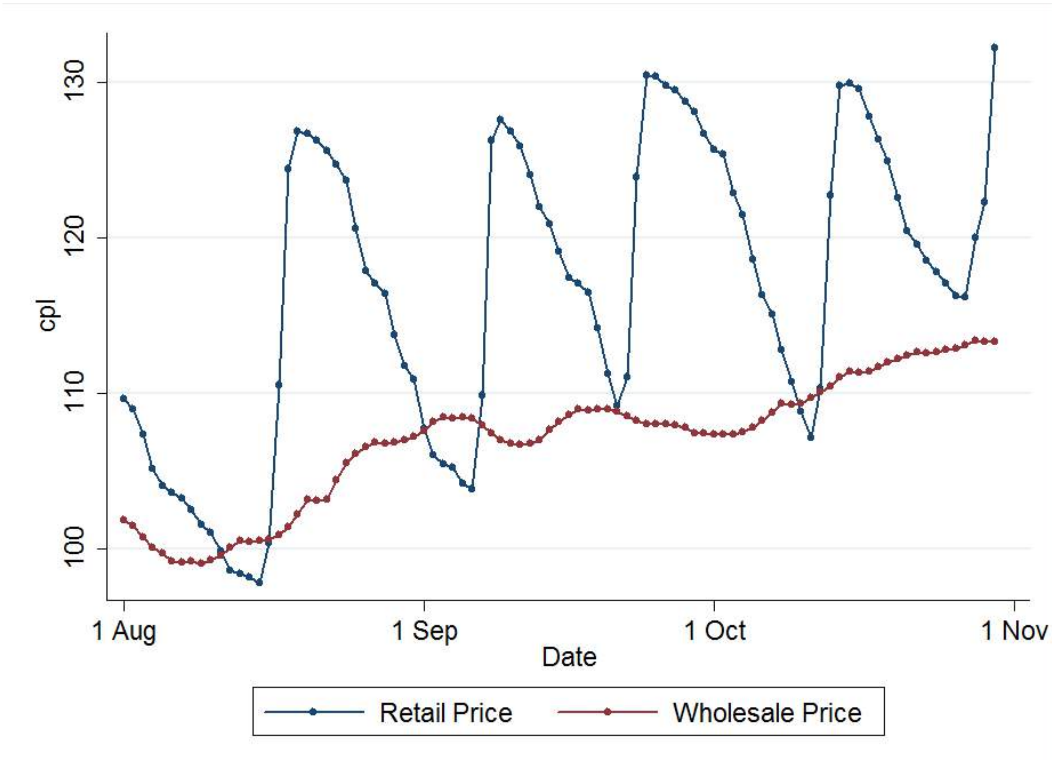


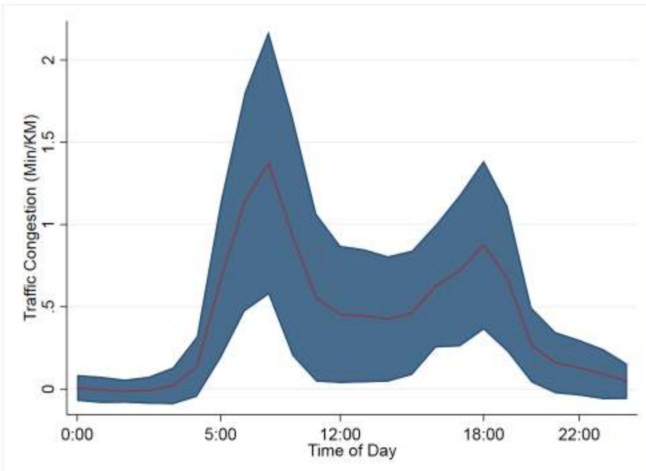
Figure 2.2: GASOLINE PRICE CYCLES IN THE DATA



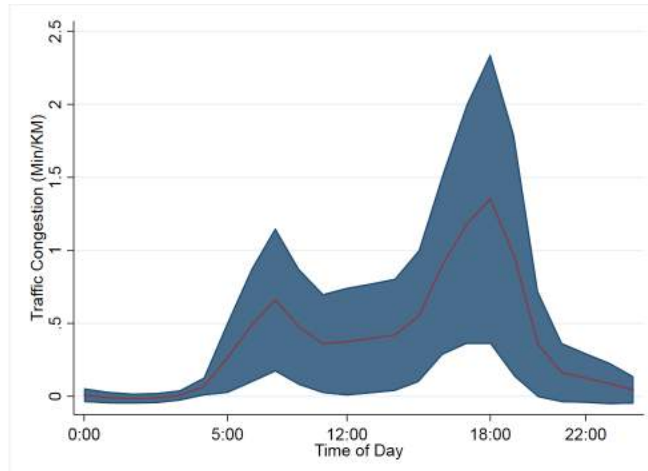
Note. Each marker represents the daily average regular gasoline price (U91) for all stations in the.

Figure 2.3: TRAFFIC CONGESTION BY DIRECTION AND TIME OF DAY

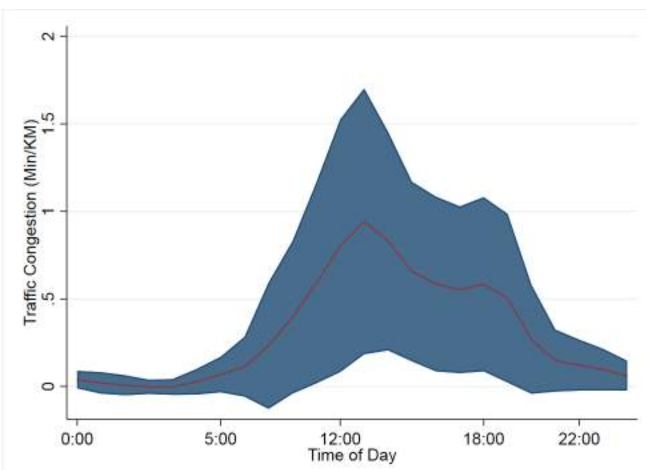
(a) Workdays (Inbound)



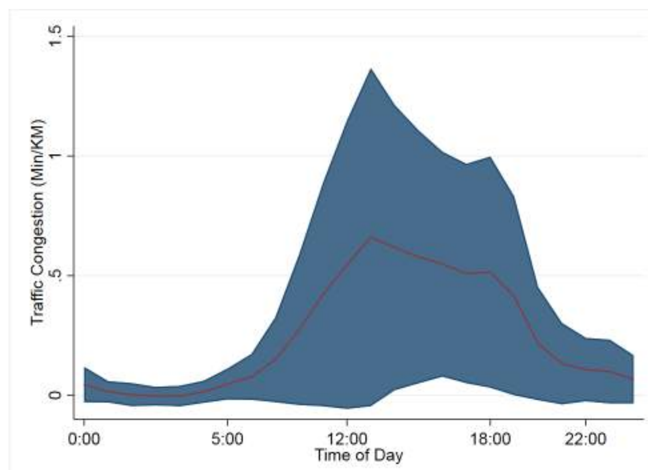
(b) Workdays (Outbound)



(c) Weekends & public holiday (Inbound)

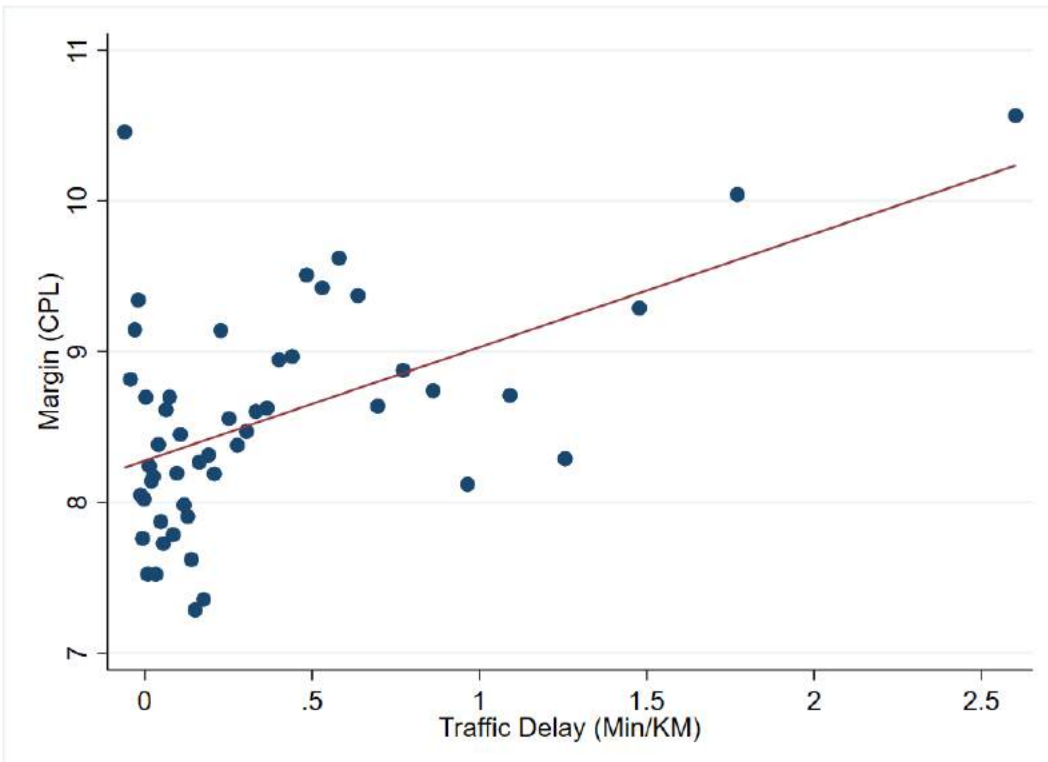


(d) Weekends and public holidays (Outbound)



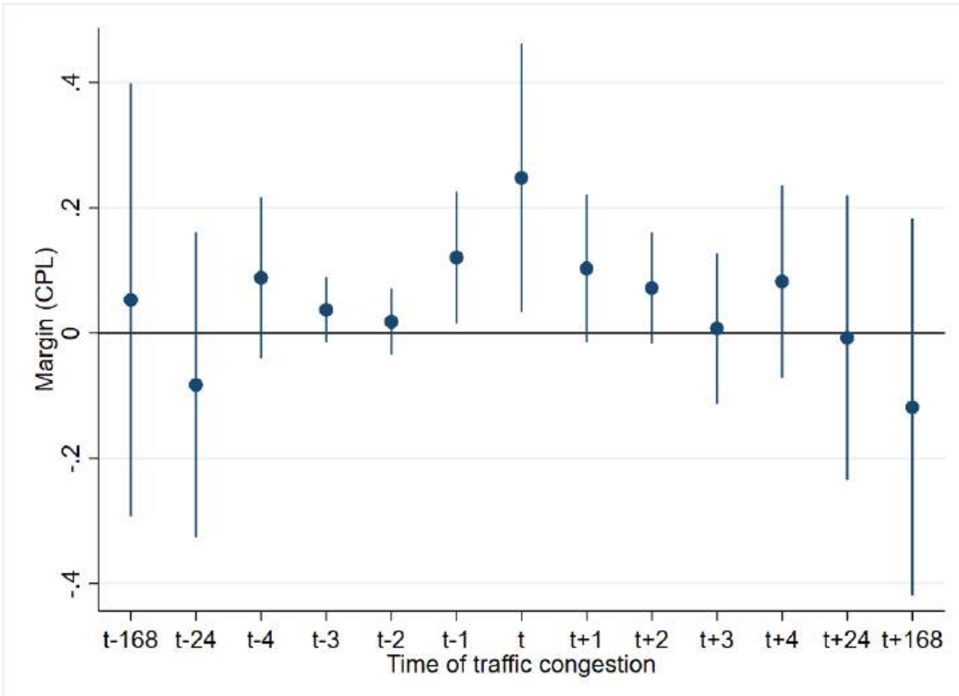
Note. Traffic congestion is measured as travel time delay compared to the travel time under the legal speed limit.

Figure 2.4: DESCRIPTIVE EVIDENCE - BINNED SCATTER PLOT OF GASOLINE MARGIN ON TRAFFIC DELAY



Note. Each point in the scatter plot represents the average margin OF regular gasoline and average traffic delay for an eqaul-sized bin of traffic speed observations. The

Figure 2.5: THE EFFECT OF FUTURE, CURRENT AND PAST TRAFFIC DELAY ON CURRENT GASOLINE MARGINS



The figure shows the estimated coefficients and confidence intervals for leads and lags of traffic congestion. Each dot represents the point estimate for the effect of traffic delay observed at the time $t + k$ where positive ks represent the number of hours into the future from time t and negative ks represent the number of hours in the past from time t. The confidence band shown in the figure are that of 95

Table 2.1: SAMPLED ROUTES

Trip	Road Name	Segment - In	Length (km)	Matched Stations (In)	Matched Stations (Out)
1	Parramatta Road	Ashfield to Sydney	7.7	2	2
2	Parramatta Road	Harris Park to Concord	9.5	1	3
3	Victoria Road	Parramatta to Rozelle	19.7	7	7
4	Liverpool Road	Liverpool to Ashfield	24	2	3
5	Old Windsor Road	Kings Langley to Wentworthville	5.3	0	1
6	Botany Road	Haymarket to Matraville	11.9	2	0
7	Pacific Highway	Lane Cove to North Sydney	5.1	3	0
8	Pacific Highway	Roseville to Lane Cove	3	4	1
9	Mona Vale Road	Mona Vale to Pymble	20.1	1	1
10	Great Western Highway	Parramatta to Emu Plains	28.1	6	7
11	King Georges Road	Strathfield South to Blakehurst	12.5	0	2
12	Rookwood Road	Auburn to Bankstown	7.5	1	1
13	Cumberland Highway	Carlingford to North Parramatta	6.7	1	3
		Total No. of Stations		**30**	**31**

Table 2.2: SUMMARY STATISTICS

Variable	**Unit**	**Mean**	**S.D.**	**N**
Price Variables				
Wholesale Prices	AUD¢/L	107.7	4.9	147,776
Retail Prices	AUD¢/L	116.2	10.6	147,776
Margin	AUD¢/L	8.5	10.2	147,776
Traffic Variables				
Speed	KM/Hour	48.0	13.7	147,776
Speed Limit	KM/Hour	59.4	7.1	147,620
Traffic Delay	Min/KM	0.36	0.53	147,332
Traffic Density	'000 VKT/Hour	0.023	0.023	147,332

Notes* AUD¢/Liter stands for Australian cents per liter. 100 Australian cents is equivalent to 1 Australian dollar. KM/Hour stands for kilometers per hour. '000 VKT/Hour stands for thousands Vehicle-Kilometers-Travelled per hour. Min/Hour stands for Minutes per Hour.

Table 2.3: EFFECT OF TRAFFIC CONGESTION ON MARGINS

	Dependent variable: $Margin_{ijt}$			
	(1)	(2)	(3)	(4)
	All observations	No speeding traffic	Workdays	No speeding traffic & workdays
Traffic Delay	0.290**	0.268**	0.328**	0.315**
	(0.127)	(0.123)	(0.141)	(0.141)
No. of Stations within 5 KM	0.0651	0.399	0.294	0.622
	(0.245)	(0.394)	(0.634)	(0.713)
Traffic Density	-3.998	-6.716**	-1.340	-1.781
	(2.590)	(3.204)	(3.277)	(4.133)
Rainfall	-0.0551	-0.0291	-0.102*	-0.0670
	(0.0433)	(0.0370)	(0.0601)	(0.0467)
Traffic Delay (1 day prior)	0.0247	-0.00235	-0.00593	-0.0696
	(0.0657)	(0.0621)	(0.111)	(0.105)
Traffic Delay (2 days prior)	0.0484	-0.00122	0.0263	-0.0245
	(0.0766)	(0.0742)	(0.110)	(0.105)
Traffic Delay (3 days prior)	-0.127*	-0.0893	-0.109	-0.0654
	(0.0712)	(0.0655)	(0.108)	(0.102)
Traffic Delay (1 week prior)	0.0254	0.0180	0.0172	0.00493
	(0.155)	(0.149)	(0.157)	(0.152)
Traffic Delay (2 weeks prior)	-0.236*	-0.189	-0.199	-0.151
	(0.131)	(0.131)	(0.134)	(0.132)
Constant	9.512***	7.954***	7.452**	5.890
	(1.265)	(1.972)	(3.296)	(3.610)
Station FE$\times$ Month FE	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes
Hour-of-Day FE	Yes	Yes	Yes	Yes
Mean margins (AUD¢/liter)	8.54	8.38	7.94	7.79
Effect as percentage of the mean	3.4%	3.2%	4.1%	4.0%
N	107,791	92,164	75,396	64,305
R^2	0.800	0.803	0.778	0.784

Notes* The dependent variable in all regressions is the retail margin of regular gasoline measured in Australian cents per litre. Standard errors are clustered two-way at station i and the route j level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.4: EFFECTS ON DIFFERENT TYPES OF GASOLINE

	Dependent variable: $Margin_{ijt}$		
	(1)	(2)	(3)
Gasoline type	Regular	Mid-grade	Premium
Traffic Delay	0.315**	0.123	0.179
	(0.141)	(0.135)	(0.129)
N	64,305	63,335	81,173
R^2	0.784	0.820	0.823

Notes* The dependent variable in all regressions is margin$_{it}$, measured in Australian cents per litre. Specification in all columns replicate that of column 4 of table 3. Standard errors are clustered two-way at station i and the route j level.
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: EFFECTS BY STATION BRAND

	Dependent variable: $Margin_{ijt}$		
	(1)	(2)	(3)
Gasoline type	Regular	Mid-grade	Premium
Traffic Delay×7-Eleven	0.354**	0.0896	0.163
	(0.176)	(0.249)	(0.185)
Traffic Delay×BP	0.0476	0.118	0.0725
	(0.188)	(0.175)	(0.189)
Traffic Delay×Caltex	0.179	-0.0786	0.0440
	(0.207)	(0.157)	(0.159)
Traffic Delay×Woolworths	0.346**	0.134	0.211
	(0.149)	(0.172)	(0.163)
Traffic Delay×Coles Express	0.561**	0.365*	0.437**
	(0.219)	(0.214)	(0.216)
Traffic Delay×United	0.315	0.118	0.195
	(0.257)	(0.311)	(0.258)
Traffic Delay×Independent	0.0560	-0.179	-0.138
	(0.313)	(0.250)	(0.360)
N	64,305	63,335	81,173
R^2	0.784	0.820	0.823

Notes* The dependent variable in all regressions is margin$_{it}$, measured in Australian cents per litre.Specification in all columns replicate that of column 4 of table 3. Standard errors are clustered two-way at station i and the route j level.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Is the Effect of Consumer Search Cost on Price Dispersion Non-monotonic? Evidence from the Retail Gasoline Industry

A theme in the consumer search literature is to understand the implications of consumer search behavior for market outcomes. In his seminal paper "Information of Economics", Stigler (1961) claims that price dispersion is a manifestation of ignorance in the market. The intuition is that some firms can charge higher prices than others to exploit uninformed consumers in the market. In consumer search models, search cost avoidance is used to rationalize why some consumers decide against searching thus choosing ignorance over knowledge. Succinctly, consumer search literature posits that observed price dispersion for homogeneous goods can be attributed to the presence of consumer search cost in the market.

However, there is a dearth of research papers that empirically investigate the effect of search cost on price dispersion. This can be attributed at least three empirical difficulties. The first difficulty is that search cost is generally observable. One solution in the literature is the use of a proxy variable for search cost.[1] A popular proxy in the literature is to

[1]The alternative method is to structurally estimate search cost from price data. See, for example, Hong

compare the level of price dispersion between online and offline markets. The idea behind this approach is that online search cost is lower (entails mouse clicks) compared to searching offline (entails traveling to stores). However, research by Ellison and Fisher Ellison (2005) and Ellison and Ellison (2009) has raised concern that online and offline search cost may not be directly comparable since online sellers can employ new obfuscation strategies such as "bait-and-switch" that are unavailable to sellers in offline markets.

Another well-known issue is the non-monotonic relationship between equilibrium price dispersion and search intensity. This issue is highlighted in Chandra and Tappata (2011) who use a version of consumer search model to show that equilibrium price dispersion has an inverse-U relationship with search intensity. Brown and Goolsbee (2002) and Pennerstorfer et al. (Forthcoming) provide empirical evidence for this relationship in life insurance and retail gasoline market respectively. The non-monotonic relationship between equilibrium price dispersion and search intensity implies that the relationship between equilibrium price dispersion and search cost may also be non-monotonic and especially when search intensity is linearly dependent on search cost. Consequently, establishing the empirical relationship between equilibrium price dispersion and search cost requires researchers to accommodate non-monotonicity between the two variables.

This paper aims to establish the *global* relationship search cost on equilibrium price dispersion in the context of retail gasoline market. My empirical strategy for identifying the effect of search cost in this market relies on the variation in traffic congestion. The rational for this approach is based on two empirical facts. The first fact is established by transport engineering literature that travel time and gasoline consumed both increase when traffic flow is obstructed[2]. The second is established by Castilla and Haab (2013) who find that the majority of consumers who search for cheaper gasoline do so while they drive and their search cost is a function of the amount of gasoline consumed while driving and the time spent searching for prices. Together, these two empirical facts imply that search cost for consumers in the retail gasoline market is always increasing in the severity of traffic congestion.

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and Shum (2006).

[2]c.f. Tobin (1979) and Jereb, Kumperščak, and Bratina (2018)

My empirical analysis uses high-frequency traffic and gasoline price data from Sydney, New South Wales (NSW). The traffic dataset is collected by Road and Maritime Services (RMS)[3] and in which I observe hourly traffic speed and traffic volume for 36 road segments in Sydney over a 3-month period from 1 August to 31 October 2016. The price data for the same period is collected by NSW Fair Trading[4]

There are several advantages with using this data set to identify the empirical effect of search cost on price dispersion. The first one is its high-frequency nature which allows for the exploitation of intraday variation in traffic congestion. Traffic congestion can vary both spatially and temporally. In an urban setting, traffic congestion for the same location can vary significantly within a day due to commuter traffic and the occurrence of traffic accidents. The hourly frequency of my data allows me to exploit these intraday variations in traffic congestion. Second, because I observe both the actual traffic speed and the free-flow traffic speed defined by the legal speed limit, I am able to quantify traffic congestion as travel time delay in traffic, or more succinctly, traffic delay which is a continuous variable. This continuous measure allows me to test for a variety of non-monotonic relationship between search cost in traffic and equilibrium price dispersion between gas stations. In addition, the panel nature of the data allows me to control for unobserved effects across space and time with fixed effects. Finally, my price data includes the complete history of prices for every sampled gas stations which means that the sampling concern described in Lewis (2008) and Pennerstorfer et al. (Forthcoming) is not an issue in this paper. [5]

I preface my empirical analysis with a conceptual framework based on the consumer search model presented in Chandra and Tappata (2011). With this conceptual framework, I show that search cost and equilibrium price dispersion follows an inverse-U relationship. Using price data for regular gasoline, my empirical results suggest that the impact of traffic congestion on equilibrium price dispersion is indeed not monotonic. Specifically, I find that the effect is inverse-U shaped: for low levels of traffic delay, equilibrium price dispersion is

[3] The state road transport authority.

[4] A state government division for regulating retail business practices

[5] Lewis (2008) relies on price data reported by roaming spotters and Pennerstorfer et al. (Forthcoming) relies on random sampling by the Austrian government: data in both studies are subject to omission of price data from one or more stations in a local market.

increasing in traffic delay and for high levels of traffic delay, equilibrium price dispersion is decreasing in traffic delay. The turning-point of this relationship is at 1.39 minute per kilometer in terms of traffic delay or 42% of the average legal speed limit in my sample. This result is robust to alternative definitions of price dispersion, the inclusion of high-frequency time fixed effects, correcting standard errors for spatial and serial correlations, and alternative definitions of local markets. However, the effect of traffic delay on equilibrium price dispersion differ across gasoline types. For mid-grade gasoline, the result is at best inconclusive: price dispersion appears to be monotonically increasing in traffic delay in one measure of price dispersion but inverse U-shaped for others. For premium-grade gasoline, the estimates are all statistically indistinguishable from zero.

3.1 Related literature

Within the large empirical literature that links price dispersion to consumer search behavior[6], this paper is related specifically to the literature that investigates how price dispersion responds to the "cost" of search, which has largely relied on comparing price dispersion between online and offline prices in a variety of consumer markets[7]. For offline-only markets, the idea that traffic quality between firms may affect spatial search cost has been discussed in Sherman and Weiss (2017) who use different days of the week to examines the effect of pedestrian traffic on price differences between outdoor grocery sellers. This paper contributes towards this literature by relying actual observations of traffic congestion to study the effect of consumer search cost on equilibrium price dispersion in an offline-only market.

This paper is also related to the literature that empirically investigates the non-monotonic relationship between equilibrium price dispersion and search. Brown and Goolsbee (2002) find that price dispersion in the life insurance market follows a cubic-relationship to the share of internet users in the population. They proxy search intensity with the ratio of the number of consumers with low search cost (internet users) to the total number of consumers

[6] Baye, Morgan, Scholten, et al. (2006) provides an excellent review of this literature.

[7] (c.f. Brynjolfsson and Smith (2000), Clay, Krishnan, and Wolff (2001), Ancarani and Shankar (2004), Degeratu, Rangaswamy, and Wu (2000) , Orlov (2011) and Sengupta and Wiggins (2012))

in the market. Also employing a ratio of consumer numbers as a proxy for search intensity is Pennerstorfer et al. (Forthcoming) who find that equilibrium price dispersion in the retail gasoline market has an inverse U-shaped relationship with the share of informed consumers (long-distance commuters) in the retail gasoline market.[8]

Finally, this paper is related to the literature that examines the determinants of equilibrium price dispersion in the retail gasoline market. Other determinants that have already been examined include the number of rivals (Barron, Taylor, and Umbeck (2004) and Lewis (2008)), waiting time at the station (Png and Reitman (1994)), price transparency (Luco (2019)) and informedness of consumers (Pennerstorfer et al. (Forthcoming)). In summary, to the best my knowledge, this paper is the first to establish the global relationship between equilibrium price dispersion and search cost in the retail gasoline market.

The remainder of the paper is organized as follows. Section 3.1 presents the related literature. Section 3.2 presents a modified version of the a consumer search model to illustrate the predicted relationship between search cost and price dispersion. Section 3.3 describes the data and the construction of key variables. Section 3.4 describes the empirical strategy and the results. Section 3.6 provides robustness tests. Section 3.7 concludes.

3.2 Traffic congestion and consumer search cost - a conceptual framework

Search cost is defined in Baye, Morgan, Scholten, et al. (2006) to be consist of "*consumers' opportunity cost of time in searching for lower prices plus other costs associated with obtaining price quotes from competing firms*". This definition implies that, holding everything else fixed, the search cost will be higher in the market if all consumers have to spend more time for their search. In the context of retail gasoline market, Castilla and Haab (2013) find that 75% of gasoline consumers search while they drive and this finding allows them to

[8]Pennerstorfer et al. (Forthcoming) argue that compared to short-distance commuters defined as commuters who live and work within the local market, long-distance commuters defined as commuters who travel beyond the the boundary of at least one local market for work, are better informed because they can sample price from more stations during their commute.

conclude that search cost in this market should be a function of the time spent on searching in traffic. Since travel time in traffic is dependent on traffic condition, the search cost over the same distance of road will therefore be higher when traffic is congested. stations.[9].

I use a modified version of the consumer search model in Chandra and Tappata (2011) to illustrate how equilibrium price dispersion will respond to traffic congestion. In their model, the equilibrium search intensity in the market is determined by the share of informed consumers called "shoppers" (consumers with zero search cost) and the level of search cost facing nonshoppers (uninformed consumers who must incur search cost to obtain information) in the market. In the context of retail gasoline market, shoppers can be considered as consumers who search online while nonshoppers are consumers who search while they drive. I modify their modeling assumption on the propensity to search for nonshoppers (consumers with positive search cost) to better suit the context of the retail gasoline market. Specifically, I model the realization of search cost in the market as a random and common draw to all consumers but each consumer has differing indifference level. The common draw assumption is to suit the empirical reality that traffic congestion increases the travel time for all drivers on the same road at the same rate. The indifference level reflects the maximum amount of time a consumer is willing to spend for searching, which is decreasing in the valuation of time by individual consumers. This modification reflects the empirical observation that consumers searching within a local spatial market experience similar increase in the time spent on search due to traffic congestion but their search decisions depend on their individual opportunity cost of time.

3.2.1 The Model

Assume a homogeneous-good market with n firms engage in price competition and have the same constant marginal cost of c. There is a unit mass of consumers with inelastic demands and common valuation of v. A fraction of λ consumers are "shoppers". The remaining consumers are nonshoppers who decide between remaining ignorant or engage in

[9]Reduce traffic flow as a result of traffic congestion is known to cause additional fuel consumption per distance traveled. c.f. Tobin (1979) and Jereb, Kumperščak, and Bratina (2018)

costly search to know all prices in the market. To search, each nonshopper need to incur a positive, common and exogenous search cost s. Each nonshopper however differs in their indifference level ω_i so that a nonshopper i searches only if $\omega_i \geq s$. Nonshoppers draw their indifference level from a continuous distribution $G(\omega_i)$ with $\omega_i \in [0, \bar{\omega}]$. The total number of informed consumers in the market is the sum of shoppers and nonshoppers who search. Denoting the fraction of informed consumers in the market as μ, the equilibrium fraction of informed consumers in the market can be expressed as $\mu = \lambda + (1 - G(s))(1 - \lambda)$. This definition of μ also helps distinguish this paper from Pennerstorfer et al. (Forthcoming). This paper aims to identify the empirical relationship between price dispersion and s while the goal of Pennerstorfer et al. (Forthcoming) is to identify the equilibrium relationship between price dispersion and μ through the variation of a proxy for λ.

Varian (1980) shows that, for a given μ, there is a unique Nash Equilibrium in which firms play mixed strategies. In each period, firms simultaneously draw prices from

$$F(p; \mu, c, v, n) = 1 - \left[\frac{(1-\mu)}{\mu n}\frac{(v-p)}{(p-c)}\right]^{1/(n-1)}$$

where $p \in \left[p^* = \frac{cn\mu + (1-\mu)v}{1+(n-1)\mu}, v\right]$.

Price dispersion as Gains from Search associated with equation (1) can be written as

$$GS = E\left[p - p_{min} \mid \mu; c, v, n\right] = \int_{p^*}^{v} p\left[1 - n\left[1 - F(p; \mu, c, v, n)\right]^{n-1}\right] dF \qquad (3.1)$$

Using numerical integration, Chandra and Tappata (2011) shows that the non-monotonic relationship between μ and GS has an inverse-U shape. Given the monotonic relationship assumed between s and μ, it is straightforward to see that s should follow an inverse-U relationship with GS. Following Chandra and Tappata (2011), I plot the corresponding values between s and GS in figure 3.1 which confirms the inverse-U relationship: price dispersion first increases in search cost s from 0 to $\hat{s}$ and then decreases in s from $\hat{s}$ to 1. [10].

[10] The parameter values used are $n = 5, \lambda = 0$, $v = 2$, $c = 0$, $G(s) = I_s(2, 2)$, where I_s is a beta cumulative distribution function.

3.3 Data and Descriptive Evidence

3.3.1 Traffic data

Central to my empirical strategy is the assumption that search cost in the retail gasoline market increases in traffic congestion. Traffic delay refers to the extra travel time drivers experience during their journey as a result of slower than normal traffic flow. In the same spirit of Chandra and Tappata (2011) , the validity of this proxy exploits the fact that search cost is higher for stations located further away[11]. Because consumers typically drive in traffic to access gasoline stations, for them, the temporal distance between stations will vary depend on local traffic condition. The time-varying nature of traffic condition implies that for consumers who search while they drive will face higher search cost when the local road network is experiencing greater levels of traffic delay.

Until mid-2017, the RMS Roads Report provided hourly observations of traffic speed and traffic density for 60 trips in NSW. [12].

An example of how information is presented in the RMS Roads Report is shown in figure (3.2). For each trip, Roads Report provides its description in words, its location on the map, direction and traffic observations. Using a web data scraper, I collected a sample of three months from August to October 2016 for all trips with hourly traffic speed and traffic density observations in the Roads Report.

3.3.2 Measuring traffic congestion

I follow Anderson (2014) and measure the intensity of traffic congestion in terms of traffic delay

$$TrafficDelay_{jt} = \frac{FreeflowSpeed_j}{ActualSpeed_{jt}} - 1 \tag{3.2}$$

where $FreeflowSpeed_j$ is the legal speed limit[13] of trip j and $ActualSpeed_{jt}$ is the observed average traffic speed for road segment j at time t. For example, an observed speed of 30

[11] Chandra and Tappata (2011) assumes that search is free between stations that are located immediately next to each other (in the same corner); search is costly if otherwise.

[12] A trip is defined in the Roads Report represents a direction-specific subsection of a major road.

[13] Reported in the Roads Report by RMS

kilometer per hour (kmh) on a trip with a free-flow speed of 60 kmh corresponds to a traffic delay of 1 minute per kilometer (Min/KM).

3.3.3 Price data

The price data is collected by NSW Fair Trading via a government-developed price comparison online tool called FuelCheck. FuelCheck contains the full history of station-level prices for every fuel type sold in the state of NSW from August 2016. My main analysis focus on the price of regular gasoline (U91) which is the most commonly available gasoline in Australia. Since 2013, all gas stations in NSW have been required by law to display the price of their top two selling fuel on a price board visible to the passing drivers. In 2016, U91 accounted for approximately 30% of gasoline sales in NSW making it a top seller (Australia (2018)). The popularity of U91 means that its price is more likely to be displayed on price boards making it easier, and hence more probable, for consumers to compare its price between stations while driving than other gasoline varieties.

An advantage of the FuelCheck data is its high quality in terms of timeliness and accuracy thanks to the legal requirement that all gas stations must report new prices to FuelCheck as soon as they change their in-stone prices. Consumers can report mismatches between online price and in-store price directly via the FuelCheck mobile app and fines are issued to non-compliant stations.

FuelCheck also provides the geographic information of each gas station which allows me to spatially match gas stations to traffic data. Retail prices are nominal and measured in Australian cents per liter. Because prices in my sample exhibit little within-hour variation, my empirical approach examines how equilibrium price dispersion responds to traffic congestion at the hourly level.

3.3.4 Measuring price dispersion

I now describe how I construct measures of price dispersion, my outcome of interest. Below I explain how I define local markets, construct "residual" prices, and the various measures of price dispersion employed.

Local markets

In order to construct measures of equilibrium price dispersion, local markets must first be defined. Barron, Taylor, and Umbeck (2004) and Lewis (2008) propose that competition in the retail gasoline market is mostly local so that a local market should only include direct competitors that are located closely to each other. A simple method of market delineation based on this argument involves assigning stations to local market i if they are located within an euclidean distance to station i. Alternatively, the literature has also identified local gasoline market by subsections of the road network. For example, Haining (1983) provides theoretical argument and empirical evidence that price interaction between gasoline stations are defined by principal roadways. Cooper and Jones (2007) also define local spatial markets by commuting route to study pricing pattern for gasoline. Houde (2012a) argues that competition among stations may not be solely localized since consumers can substitute between stations far away from each other but close to a common commuting path. In addition, Houde (2012a) suggests that spatial market definition should be related to the road network and the direction of the traffic flow.

According to the RMS Roads Report, each trip in the report represents a section of a major communing route in NSW. Based on this description, I follow Houde (2012a) and define a local market to include all stations located immediately on the left hand side of a trip. Because each trip represents a single direction of a road, this definition of local markets assumes that stations located on opposite sides of the same road compete in separate local markets. Figure 3.3 illustrates the stations (black dots) in two local markets: 6 stations in the local market defined by the trip of Pennant Hills Road (Carlingford to Wahroonga) and 2 stations in the local market defined by the trip of Pennant Hills Road (Wahroonga to Carlingford).

Residual prices

Even though automobile fuel is homogeneous in terms of its physical characteristics, gas stations differ not only in their location, but also in terms of services provided and other characteristics. Thus, a simple explanation for the observed existence of price dispersion relies on station heterogeneity. The challenge is to obtain a measure of price dispersion after removing the main source of heterogeneity. I follow the literature[14] and obtain the residuals of a price equation and interpret these residuals as the price of a homogeneous product. To obtain "cleaned" prices I exploit the panel nature of my data following Lach (2002) and run a two-way fixed effects panel regression of "raw" fuel prices (p^r_{it}) using seller (ζ_i) and time (χ_t) fixed effects:

$$p^r_{it} = \alpha + \zeta_i + \chi_t + u_{it} \tag{3.3}$$

I focus on the residual variation, interpret the residual price $p_{it} \equiv \hat{u}_{it}$ as the price of a homogeneous product after controlling for time-invariant store specific effects and fluctuations in price common to all stores.

Measures of price dispersion

To examine the impact of search cost on price dispersion I need to summarize the price distribution in a (local) market as a single metric. Several measures of price dispersion have been proposed in the literature. I will first focus on the "Gains from Search" (GS, also known as "value of information"). This is a commonly used measure and the testable prediction in section 3.2 is also based on this metric. The measure has a very intuitive interpretation: it corresponds to a consumer's expected benefit of being informed. The GS is defined as the difference between the expected price and the lowest expected price in the market. If the local market assigned to road segment j is defined by m_j, then the GS for local market j at time t is given by $GS_{jt} = E\left[p^{m_{jt}}\right] - E\left[p^{m_{jt}}_{min}\right]$. I follow Chandra and Tappata (2011) and use the average local market price $\bar{p}^{m_{jt}}$ as the estimate for $E\left[p^{m_{jt}}\right]$ while the estimate of $E\left[p^{m_{jt}}_{min}\right]$ is given by $p^{m_{jt}}_{(1)}$ (i.e. the first order statistic of prices sampled in market m_j). Subsequently, price dispersion measured as GS in market m_j at time t is given by equation 3.4:

$$GS_{jt} = \bar{p}^{m_{jt}} - p^{m_{jt}}_{min} \tag{3.4}$$

[14] See e.g. Sorensen (2000), Brown and Goolsbee (2002), Lewis (2008), Chandra and Tappata (2011) or Luco (2019)

Baye, Morgan, Scholten, et al. (2006) acknowledges the estimated empirical relationship between price dispersion and consumer search may depend on how price dispersion is measured. To address this concern, I test if the inverse-U relationship is robust for alternative measures of price dispersion in section 4.

After spatially matching gas stations to local markets defined by trips, observations from local markets that contain fewer than two gas stations are dropped because by construction there is no equilibrium price dispersion in these markets. Among the 60 trips where traffic data is observed, 36 contain at least 2 gas stations which means that my sample is based on equilibrium price dispersion from 36 local markets. Measures of price dispersion is then calculated using station-level price data for each local market at the hourly frequency. The sample for regular gasoline is an hourly panel of 46,085 observations over a three-month period from 1 August to 31 October 2016. The summary statistics based on the sample of regular gasoline is presented in table 3.1.

3.4 Methodology and results

3.4.1 Estimation strategy

In this section, I describe how I estimate the relationship between equilibrium price dispersion and traffic congestion. I exploit the panel nature of the data and include market fixed effects in all of my specifications to control for time-invariant market heterogeneity. This prevents cross-sectional variations from driving my results. Time-invariant market characteristics (such as location and the number of traffic lights) will not bias my estimates. To investigate the impact of traffic congestion on equilibrium price dispersion, I estimate the following regression model:

$$\begin{aligned} GS_{jt} = \beta_0 + \beta_1 TrafficDelay_{jt} + \beta_2 TrafficDelay_{jt}^2 \\ + X_{jt}\theta + (\gamma_j \times \tau_{month}) + (\tau_{workday} \times \tau_{hour}) + \epsilon_{jt} \end{aligned} \tag{3.5}$$

where j indexes local market and t indexes time; GS_{jt} is a Gains from Search measure of price dispersion defined in equation 3.4; $Delay_{jt}$ is the observed traffic congestion defined by 3.2; X_{jt} is a vector of control variables including a quadratic function of contemporaneous traffic density, a quadratic function of the number of active competing stations in the local market and the average wholesale gasoline cost; $\gamma_j \times \tau_{month}$ are interactive fixed effects between market and monthly fixed effects; $\tau_{workday} \times \tau_{hour}$ are interactive fixed effects between workday fixed effects[15] and hour-of-the-day fixed effects.

Traffic density measures the number of vehicles passing through a trip within an hour. Controlling for traffic density is necessary for isolating the travel time effect of traffic congestion on price dispersion. Traffic density is correlated with traffic delay because the flow of traffic is slowed when the capacity of the road is reached. Through its impact on demand for travel, the price of gasoline is also know to influence traffic density (Burger and Kaffine (2009)). Traffic density is therefore included as a control to address the concern that gasoline price and traffic delay may be simultaneously determined. The number of active competing stations is included as a control because gas stations may have different business hours so that equilibrium price dispersion may be simply driven by the number of prices available in the market. Finally, the daily state-wide average of wholesale gasoline price is included as a control for the effect of daily common cost shocks on equilibrium price dispersion.

In the preferred specification, I include $\gamma_j \times \tau_{month}$ to provide additional control for unobserved month-to-month variation in market heterogeneity such as local income and unemployment rate. Finally, $\tau_{workday} \times \tau_{hour}$ are included to control for repeating within-day traffic cycles for both workdays and non-workdays (weekends and public holidays).

The empirical model, equation (3.5) implies that when the relationship between traffic congestion and equilibrium price dispersion is non-monotonic, the estimate of β_1 and β_2 should be significantly different from zero. The null hypotheses to be tested are $\mathrm{H}_0 : \beta_1 = 0$ and $\mathrm{H}_0 : \beta_2 = 0$ and the alternative hypotheses are $\mathrm{H}_1 : \beta_1 \neq 0$ and $\mathrm{H}_1 : \beta_2 \neq 0$. In addition, if consumer search cost in the retail gasoline market is indeed increasing in traffic congestion then consumer search model in section 3.2 implies that the equilibrium price

[15] A workday is a day that is not a Saturday, a Sunday or a public holiday.

dispersion in my sample should have an inverse-U relationship with traffic congestion. An inverse-U relationship can be inferred from a significantly positive estimate of β_1 and a significantly negative estimate of β_2.

For robust inference, I cluster the standard errors of my regressions at the local market level. Furthermore, to address the concern that clustering standard errors might lead to incorrect inference when cluster size is small, I implement the six-point bootstrap-weight distribution approach proposed by Webb (2014).

3.5 Estimation results

Panel A of table 3.2 displays the estimated coefficients for equation 3.5 based on the GS measure of price dispersion. Column 1 only includes the local market fixed effects. Column 2 adds traffic density, wholesale gasoline price and the number of active local competitors as covariates to column 1. Column 3 allows for month-specific local market fixed effects. Column 4 adds day-type-specific hour fixed effects to the specification in column 3. Column 4 is my preferred specification. In all four specifications, $\hat{\beta}_1$ and $\hat{\beta}_2$ are statistically significant at the 10% level which implies the presence of a non-monotonic relationship between GS and $TrafficDelay$. The signs of the coefficient estimates of β_1 and β_2 in table 3.2 are consistent with a relationship that has an inverse-U shape. Based on the coefficient estimates in my preferred specification, I plot the net relationship between the predicted GS and traffic delay in figure 3.4. Figure 3.4 shows that GS increases with traffic delay when traffic delay is low and decreases with traffic delay when traffic delay is high. The corresponding marginal effect of $TrafficDelay$ on GS is therefore $0.280 - 0.199Delay$.

An additional check of the inverse-U relationship is to ensure that the estimated turning point $-\frac{\hat{\beta}_1}{2\hat{\beta}_2}$ falls within the sample range of $TrafficDelay$. Panel B of table 3.2 reports that, based on the 95% confidence interval derived using the Fieller method[16], estimated turning-points based on all specifications in table 3.2 fall within the sample range of $TrafficDelay$, confirming the inverse-U shaped relationship between price dispersion and traffic delay.

[16] According to Lye and Hirschberg (2012), the confidence intervals derived based on the Fieller method is less susceptible to bias than the delta method.

Based on the estimates in column 4, the following can be inferred: 1) a local market displays the highest level of price dispersion when traffic delay is about 1.40 Min/KM, 2) the average level of traffic congestion has a positive effect on equilibrium price dispersion, and 3) the turning-point value of traffic delay represents the 94th percentile of traffic delay observations in my sample.

3.5.1 Non-parametric evidence of the inverse-U relationship

A possible concern for the inverse-U shaped relationship implied by the coefficients estimates on $TrafficDelay$ in table 3.2 is driven by the quadratic function of $Delay$ in the regression model. To address this concern, I follow Chetty, Friedman, and Rockoff (2014) and use a binned scatterplot[17] to visualize the relationship between GS and $TrafficDelay$. Figure 3.5 is a binned scatterplot with the residuals from the following regression equation on the vertical axis and $TrafficDelay$ on horizontal axis.

$$GS_{jt} = \beta_0 + X_{jt}\theta + (\gamma_j \times \tau_{month}) + (\tau_{workday} \times \tau_{hour}) + \epsilon_{jt} \tag{3.6}$$

The variation in the residuals from equation 3.6 represents the residual variation in GS after controlling for the covariates and fixed effects in 3.5. The rational behind this approach is that if the inverse-U relationship is not driven by the quadratic specification of $TrafficDelay$ in 3.5, then binned scatterplot should present corroborating visual evidence for this relationship between the residual variation from equation 3.6 and $TrafficDelay$. Reassuringly, the inverse-U relationship is clearly visible in the binned scatterplot shown in figure 3.5. It shows that for the majority of time, price dispersion measured as GS increases with traffic delay while the downward portion in the inverse-U relationship is associated very high levels of traffic delay greater than 2 Min/Km. It is therefore a concern that the inverse-U shape is driven by outliers that are potentially measurement errors.

My sample contains some of the most congested roads in Sydney (e.g, Pacific Highway

[17]Binned scatter plot is a convenient non-parametric way to identify relationship between two variables in large panel datasets such as the one in this paper. It first divides the sample into equal sized bins based on observations of the explanatory variable. Each dot on a binned scatterplot represents the mean of outcome variable in each bin and the corresponding mean of the the explanatory variable in the same bin.

and Alison Road) and it is therefore unsurprising extreme delays are found in my sample. In fact, drivers on these roads frequently experience delays greater than 4 Min/KM during commuting peak hours. Extreme traffic congestion are chronic and common in Sydney as they have been repeatedly reported in the press (For example, O'Rourke (2014)). Nevertheless, as a robustness check in section 3.6, I drop the top and bottom 1% of observations based on traffic delay and show that the inverse-U shaped relationship is not dependent on presence of outliers.

3.5.2 Mechanism - opportunity cost of time

The result so far suggests that the relationship between equilibrium price dispersion in the retail gasoline market and traffic congestion is consistent with the relationship between equilibrium price dispersion and consumer search cost implied by my conceptual model. In this section, I test the assumption that the opportunity cost of time is one of the channels through which traffic congestion affects consumer search cost in the the retail gasoline market. Following Chandra and Tappata (2011), I do this by estimating the effect of traffic congestion on equilibrium price dispersion of mid-grade gasoline (P95) and premium gasoline (P98). Chandra and Tappata (2011) postulate that consumer search cost increases in the grade of gasoline. This association is based on the assumption that, on average, consumers of a higher grade of gasoline are wealthier and hence have higher opportunity cost for their time.

Assuming there is no cross-grade substitution, consumer types can be modeled as having grade-specific distribution of indifference level $G_h(\omega_i)$ where $h \in \{\text{U91,P95,P98}\}$. Because indifference level represents the maximum amount of time a consumer is willing to spent on searching, a higher opportunity cost will imply a lower indifference level. An increase in opportunity cost therefore implies a leftward shift of $G_h(\omega_i)$. In other words, for every realization of search cost s, the probability of searching decreases in the grade of gasoline. This implies that the share of consumers who search on the margin is decreasing in the grade of gasoline. In the extreme case, no consumer will search if the lower bound of their indifference level is sufficiently high. If opportunity cost of time is the indeed the channel through which traffic congestion affects consumer search cost, then for higher grades gasoline, we should expect price dispersion to be less dependent on traffic congestion and hence a flatter relationship between price dispersion and traffic congestion.

Figure 3.6 plot the net relationship between GS and $Delay$ for regular, mid-grade and premium gasoline. Figure 3.6 shows that compared to regular gasoline, the inverse U-shape becomes flatter for mid-grade gasoline and completely flat for premium gasoline. This pattern is consistent with the explanation that search decision by consumers with higher opportunity cost is less sensitive to traffic congestion because fewer of them will spend time searching in traffic.

3.6 Robustness tests

In this section, I provide a number of robustness tests for my main result presented in column 4 of table 3.2. Specifically, I examine if the inverse-U relationship is robust to alternative measures of price dispersion, GS constructed from raw instead of cleaned prices and the removal of outliers from the sample.

3.6.1 Alternative measures of price dispersion

Baye, Morgan, Scholten, et al. (2006)) acknowledges that the estimated empirical relationship between price dispersion and consumer search cost may depend on how price dispersion is measured. It is therefore possible that the inverse-U relationship may not hold between traffic congestion and measures of equilibrium price dispersion other than GS. To address this concern, I re-estimate equation 3.5 to with alternative measures of equilibrium price dispersion. The alternative measures considered are standard deviation and interquartile range which are two common measures of equilibrium price dispersion examined in the gasoline pricing literature[18]. Figure 3.7 plot the net effect of traffic congestion on Gains from Search, standard deviation and interquartile range. Comparing to the Gains from Search measure, the inverse-U shape appears more apparent for the interquartile range measure

[18]c.f. **pennerstorfer2017information** points out that interquartile range is a better measure for price dispersion than standard deviation and sample range as it is less susceptible to outliers in the price data.

and less apparent for the standard deviation measure. Nevertheless, it can be concluded from figure 3.7 that traffic congestion has an inverse-U relationship with equilibrium price dispersion measured as Gains from Search, standard deviation and inter interquartile range.

3.6.2 Raw prices

It is possible that the regression model, equation 3.3, for generating residual prices is misspecified. To ensure that my results are not driven by this specification error, I re-estimate my preferred specification with raw prices instead of residual prices. Based on the coefficient estimates from this regression, the implied net relationship between $Delay$ and GS is presented in figure 3.8b. When compared to the main result which is reproduced in figure 3.8a, the relationship shown in figure 3.8b is flatter but still inverse-U shaped. This difference is expected because a larger share of variation in raw price dispersion is explained by factors other than search cost such as location, branding and service differences between gas stations. In spite of this, figure 3.8b suggests that the inverse-U relationship is robust to potential misspecification of equation 3.3.

3.6.3 Dropping extreme traffic delay

To address the aforementioned concern that the curvature of the relationship is driven by outliers of extreme traffic delay, I re-estimate my preferred specification with a subsample which drops the top and bottom 1% observations of traffic delay. Compared to the net relationship in the full sample in figure 3.9a, figure 3.9b shows that the curvature of the inverse-U relationship is reduced after dropping observations associated with extreme traffic delay. Visually, the inverse-U relationship appears to survive the removal of extreme values of traffic delay. To confirm this, I formally verify the presence of an inverse-U relationship in the restricted sample by applying the statistical test in Lind and Mehlum (2010).[19] The test verifies if the slope of the relationship between $TrafficDelay$ and GS is significantly positive for low values of $TrafficDelay$ and significantly negative for high values of $TrafficDelay$.

[19] Lind and Mehlum (2010) argues that while a positive linear and a negative quadratic term supports a concave relationship between two variables, it is not sufficient to guarantee an inverse-U shaped relationship since the relationship may be concave but still monotone in relevant range.

The null hypothesis in this test is that the relationship is either linear or U-shape and the alternative hypothesis is that the relationship is inverse-U shaped. The test produced a p-value of 0.0365 which implies that the null is rejected. Based on the visual and statistical evidence presented, it can be concluded that the inverse-U relationship is robust to dropping extreme values of traffic delays.

3.7 Chapter conclusion

This paper provides an empirical examination on the global relationship between consumer search cost and equilibrium price dispersion. Based on a modified version of consumer search model presented in Chandra and Tappata (2011), I predict that the relationship between search cost and equilibrium price dispersion is non-monotonic and inverse-U shaped. I test this prediction in the retail gasoline market by estimating the global effect of traffic congestion on equilibrium price dispersion observed between gas stations along the same side of a major road in New South Wales. My empirical strategy exploits the fact that traffic congestion can increase consumer search cost in the retail gasoline market.

I find that traffic congestion and equilibrium price dispersion for regular gasoline has a non-monotonic relationship which is inverse U-shaped. The turning point for this relationship corresponds to a traffic delay of 1.40 Min/KM. Equilibrium price dispersion in this result uses the Gains from Search measure constructed from residual prices after controlling for time-invariant station heterogeneity and time-varying common shocks. The same inverse-U relationship is obtained when equilibrium price dispersion is measured as standard deviation and interquartile range. Consistent with the income hypothesis by Setiawan and Sperling (1993), I find this relationship is weaker for mid-grade gasoline and insignificant for premium gasoline. These results are consistent with the interpretation that wealthier consumers are less likely to search in traffic due to their higher opportunity cost of time.

This paper is the first empirically establish a non-monotonic relationship between consumer search cost and equilibrium price dispersion in the retail gasoline market. For future empirical investigations into the impact of search cost on equilibrium price dispersion in other markets, my findings highlight the need to allow for non-monotonic relationship in their empirical strategies.

My results can also be appreciated by antitrust agencies who monitor the level of price competition in the retail gasoline market. Following the interpretation of turning-point location by Chandra and Tappata (2011), my finding suggests that pricing of regular gasoline is more consistent with competitive pricing for 94% of the time and more consistent with monopolistic pricing for 6% of the time. This inference is made based on the fact that the estimated turning-point value of traffic delay corresponds to the 94th percentile of all traffic delay observations in my sample.

Figures and Tables in Chapter 3

Figure 3.1: SEARCH COST (s) AND GAINS FROM SEARCH

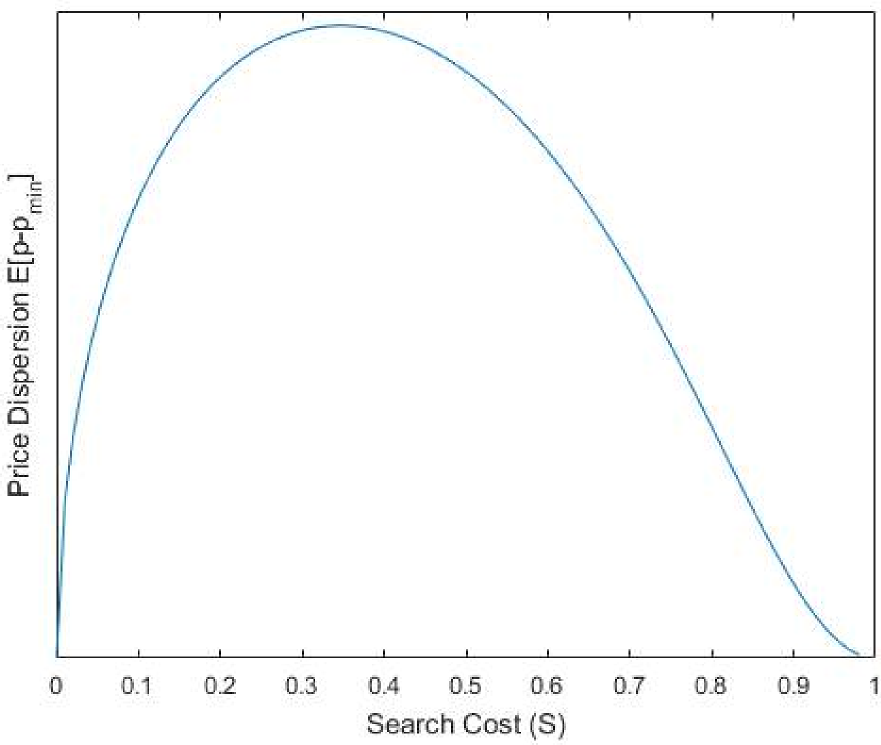


Figure 3.2: ROADS REPORT

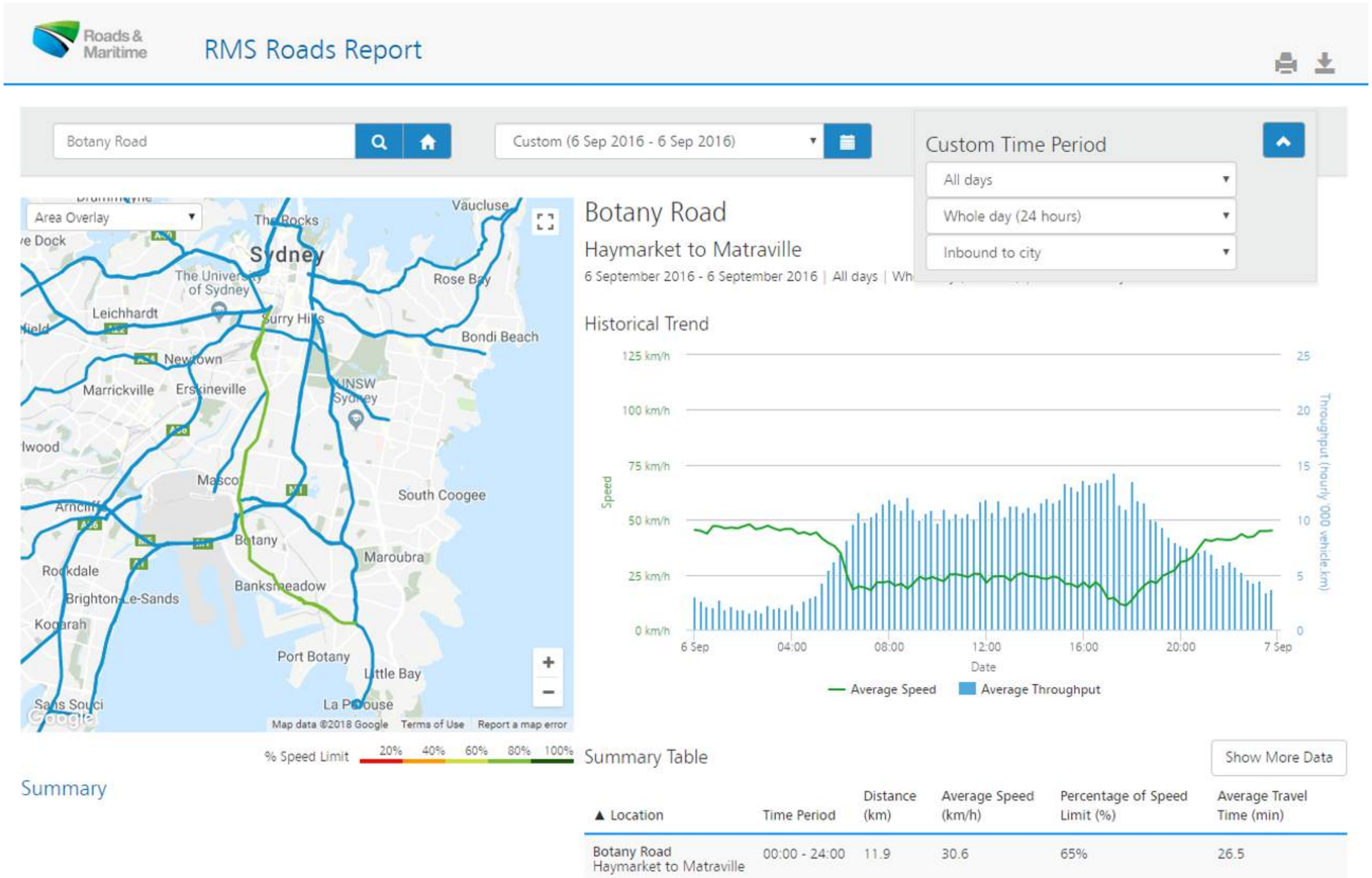
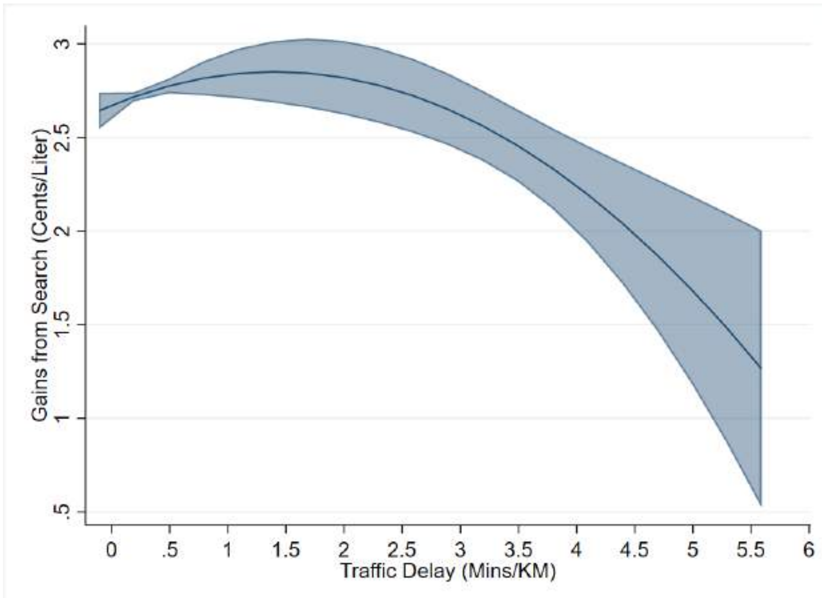


Figure 3.3: TWO EXAMPLES OF LOCAL MARKET

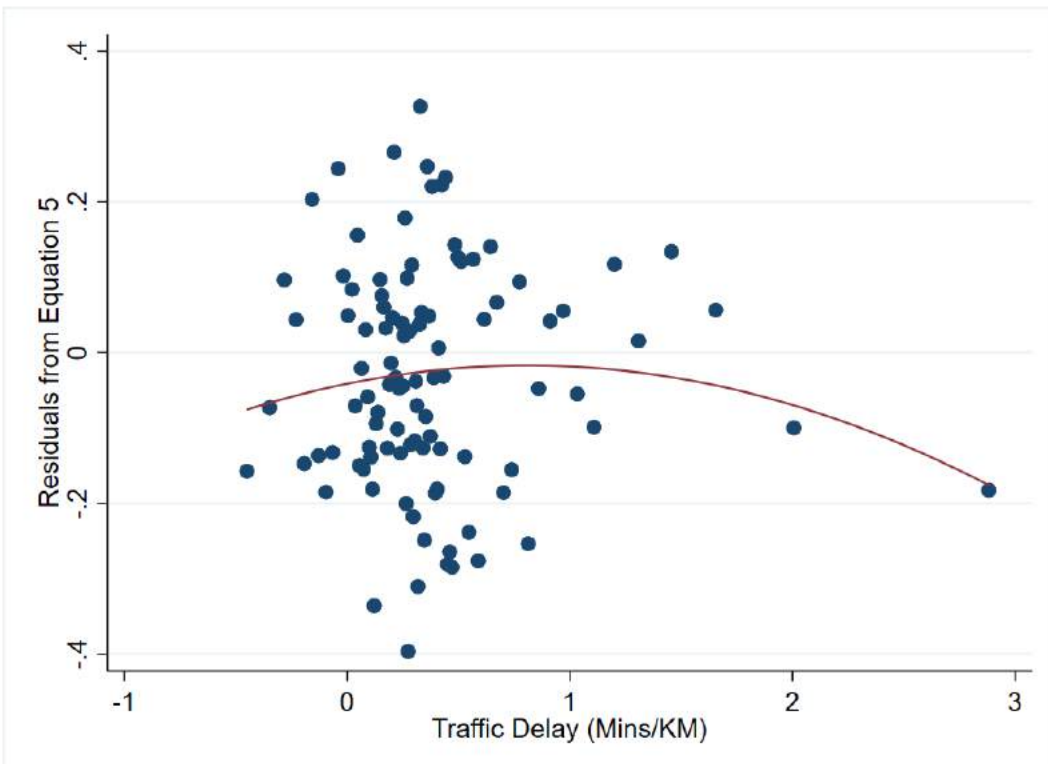
Note. Gas stations are shown as black dots.

Figure 3.4: NET RELATIONSHIP BETWEEN TRAFFIC DELAY AND GAINS FROM SEARCH



Note. This graph is based on the specification of column 4 in table 2. Price dispersion in this diagram is based on the Gains from Search measure

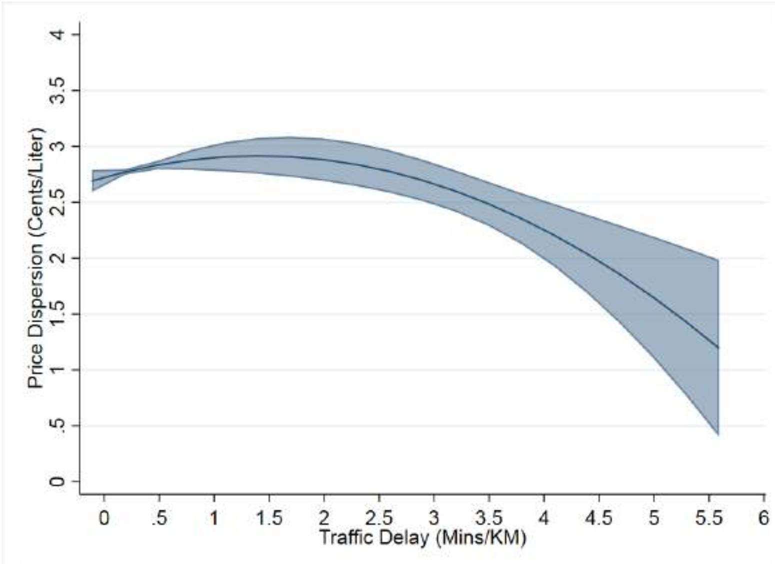
Figure 3.5: BINNED SCATTERPLOT OF of *GS* ON *Delay*



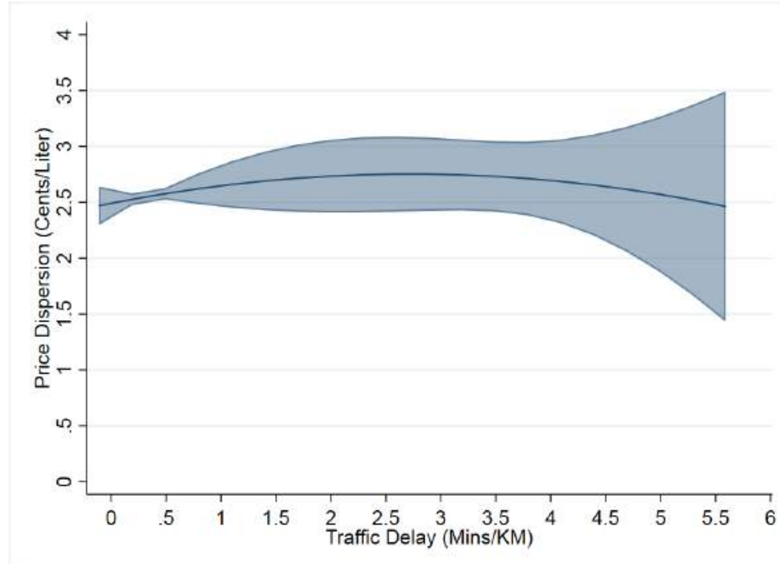
Note. The figure is a binned scatter plot in which observations are organised into 100 equal sized bins and each point in the figure represents the average of 460 observations. The curve is a quadratic line of best fit

Figure 3.6: NET RELATIONSHIP BETWEEN TRAFFIC DELAY AND GAINS FROM SEARCH BY GASOLINE TYPE

(a) Regular gasoline (U91)



(b) Mid-grade gasoline (P95)



(c) Premium gasoline (P98)

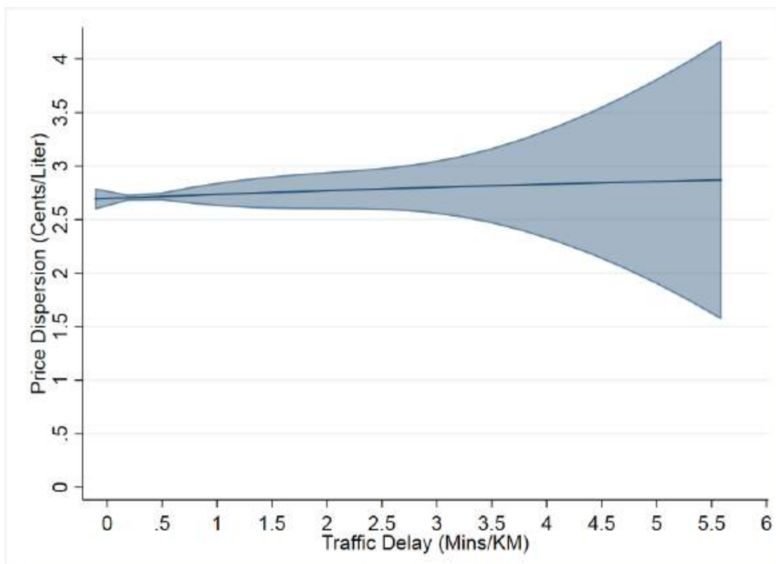
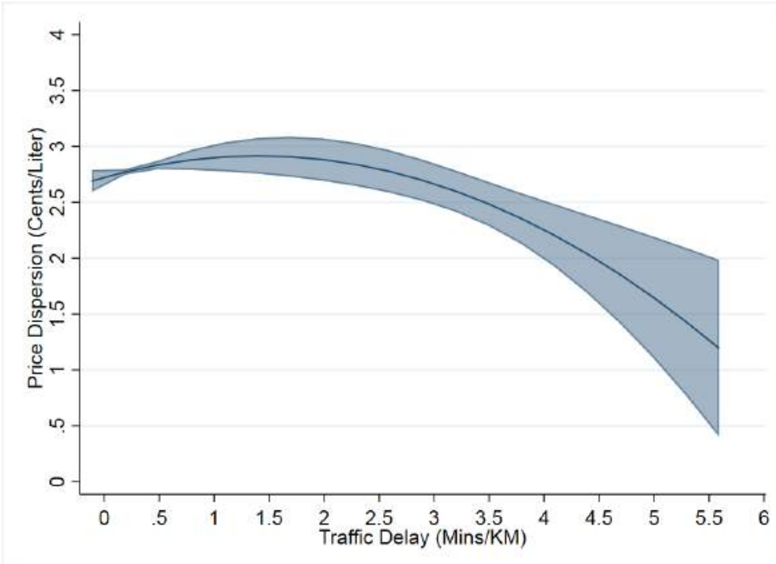
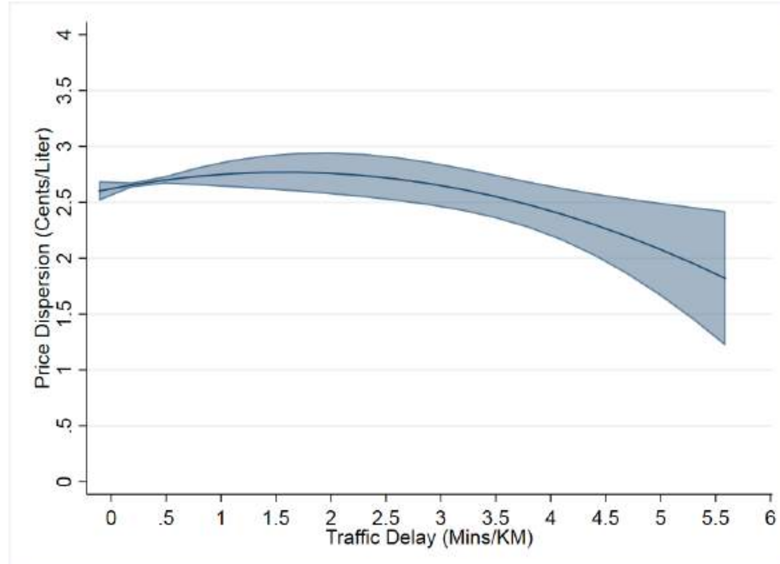


Figure 3.7: ROBUSTNESS TEST - ALTERNATIVE MEASURES OF PRICE DISPERSION

(a) Gains from Search (baseline)



(b) Standard Deviation



(c) Interquartile Range

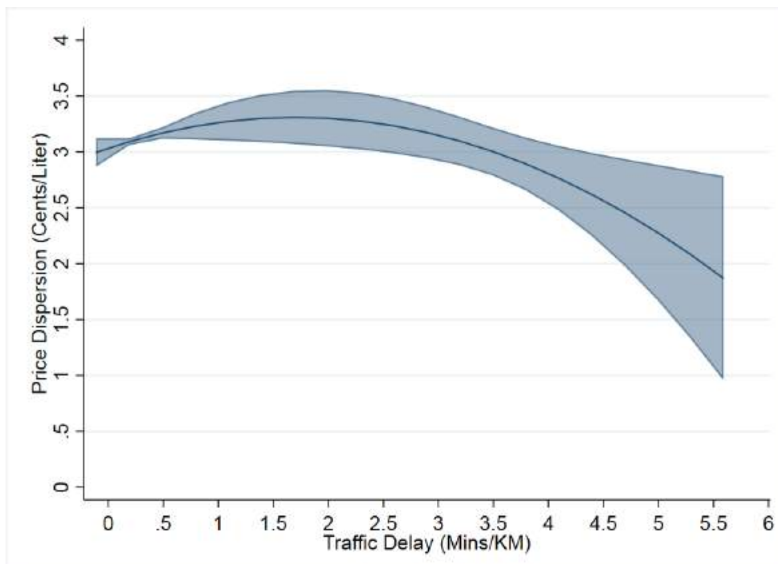
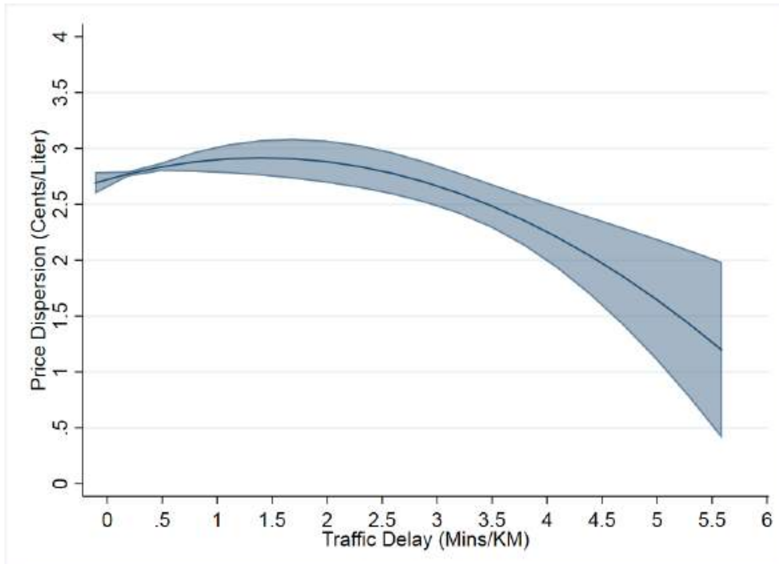


Figure 3.8: ROBUSTNESS TEST - RAW PRICES

(a) Residual prices



(b) Raw prices

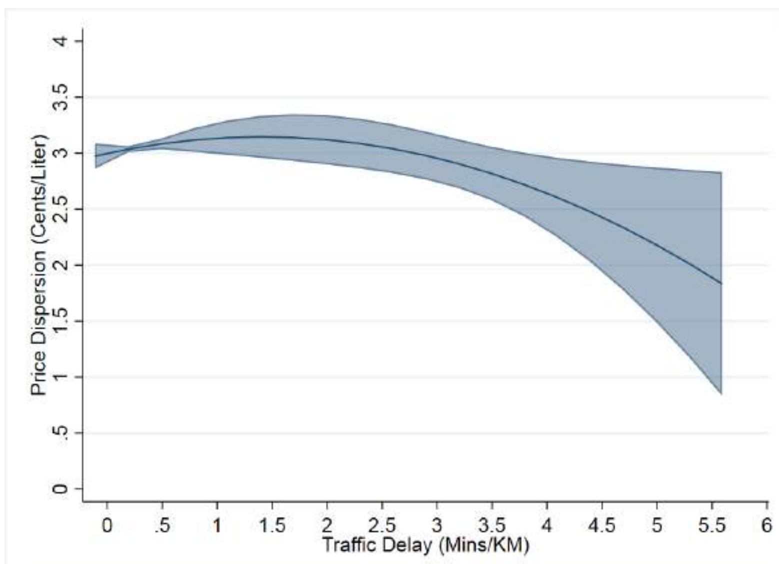
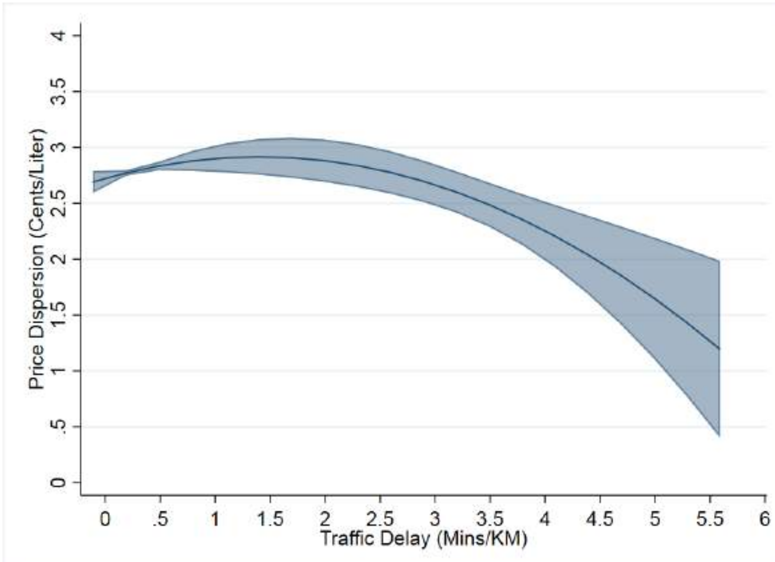


Figure 3.9: ROBUSTNESS TEST - DROPPING EXTREME TRAFFIC DELAY

(a) Full sample



(b) Sub-sample - dropping outliers of traffic delay

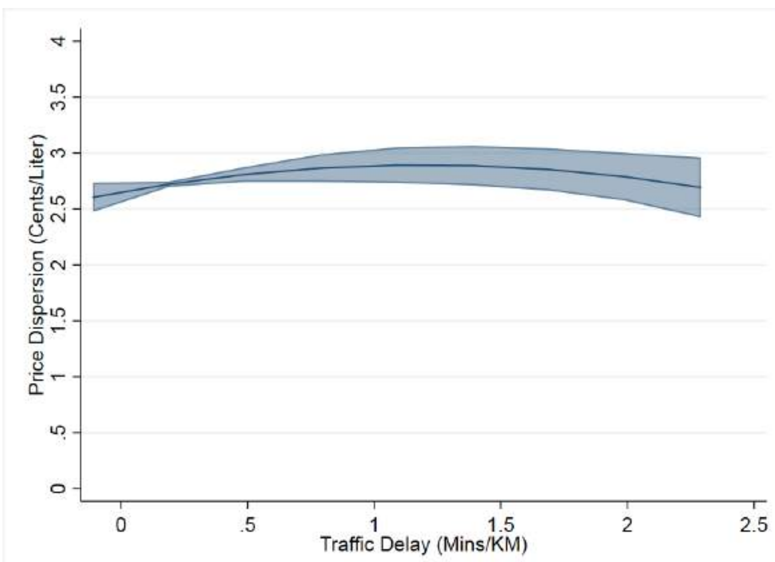


Table 3.1: SUMMARY STATISTICS

Variable	Unit	Mean	Std. Dev.	Min.	Max.	Observations.
Price data - Residual Prices						
Average Price	Cents per litre	0.066	5.733	-21.634	24.297	46085
Price dispersion						
Gains from Search	Cents per liter	2.786	3.732	0.002	24.771	46085
Standard Deviation	Cents per liter	2.72	3.114	0.003	19.005	46085
Sample Range	Cents per liter	5.641	6.374	0.005	36.332	46085
Price data - Raw Prices						
Average Price	Cents per litre	115.466	10.344	93	140.45	46085
Price dispersion						
Gains from Search	Cents per litre	3.111	4.373	0	27.12	46085
Standard Deviation	Cents per litre	2.997	3.633	0	20.295	46085
Range	Cents per litre	6.107	7.306	0	37	46085
Traffic data						
Traffic Speed	Kilometre per Hour	47.314	12.674	8.175	84	46085
Traffic Volume	Vehicle-Kilometres-per-hour	8.721	6.464	0.1	41.45	46085
Speed Limit	Kilometres per Hour	59.765	6.658	50.513	79.971	46085
Traffic Delay	Minutes per Kilometre	0.387	0.543	-0.117	5.823	46085
Number of stations observed				120		
Number of Markets				36		
Average Number of Stations in a Market				2.7		

Table 3.2: NON-MONOTONIC EFFECT OF TRAFFIC CONGESTION ON EQUILIBRIUM PRICE DISPERSION OF REGULAR GASOLINE

Dependent Variable	Gains from Search			
	(1)	(2)	(3)	(4)
Panel *A*				
$TrafficDelay$	0.230**	0.234**	0.258***	0.255**
	(0.0917)	(0.102)	(0.0934)	(0.118)
$TrafficDelay^2$	-0.0770***	-0.0790***	-0.0862***	-0.0907***
	(0.0247)	(0.0267)	(0.0248)	(0.0320)
Wholesale price	N	Y	Y	Y
Traffic density	N	Y	Y	Y
No. of active station	N	Y	Y	Y
Market FE	Y	Y	N	N
Month-specific market FE	N	N	Y	Y
Day-type-specific hour FE	N	N	N	Y
Panel *B*				
Turning point ($\hat{s} = \frac{-\hat{\beta}_1}{2\hat{\beta}_2}$)	1.49	1.48	1.50	1.40
95 percent C.I. of the turning point	[0.69,1.92]	[0.46,1.89]	[0.85,1.83]	[-0.086,1.78]
N	45,196	45,196	45,196	45,196
R^2	0.112	0.133	0.192	0.195

Notes* This table presents the estimated effect of traffic on price dispersion. The depdendent variable is price dispersion measured as Gains from Search constructed from residual prices from equation (2). Standard errors are clustered at the local market level. Inferences in panel A is based on bootstrapped stdandard errors following the six-point bootstrap-weight distribution approach proposed by Webb(2014). In Panel B, confidence intervals of the turning points are derived using the Fieller method. *** p<0.01, ** p<0.05, * p<0.1

Chapter 4

Reference-Dependent Demand, Price Cycle and Competition in Retail Gasoline Market

4.1 Introduction

Asymmetrical price cycles have been found in retail gasoline markets around the world including the United States, Canada ,Germany and Australia. While a significant amount of research has studied this phenomenon, an ongoing research question in the literature revolves around whether it is an outcome of competitive or cooperative pricing strategy by gasoline firms. Answering this question is of particular interest to governments who have raised concern that gasoline price cycles are collusive in nature (Parliament of Australia (2006) and Hydro and Pellatt (2006)). Research papers offering empirical evidence for competition such as Eckert (2003), Noel (2007a), Noel (2007b), Atkinson (2009), Lewis (2009) Wang (2009) and Linder et al. (2018) aim to demonstrate that gasoline price cycles are a manifestation of the non-cooperative dynamic price equilibrium known as the Edgeworth Cycle (EC) formalized in Maskin and Tirole (1988). On the other hand, researchers have also found evidence of tacit collusion in some gasoline markets with price cycles. For example, in separate markets, gasoline companies are found to coordinate their prices through focal-point in price timing (Foros and Steen (2009)), price leadership by large firms (Lewis (2012)), and price experimentation and signaling (Byrne and De Roos (2019)).

This paper contributes towards answering this question by examining whether pricing behavior under gasoline price cycle is dependent on the price elasticity of demand for gasoline. The rational for this test is based on the prediction by Noel (2008) that, under an EC equilibrium, price cycles are longer when aggregate demand for the good is more price elastic. The intuition for this prediction is that firms will, under the EC equilibrium, respond to more elastic demand by lowering their undercutting aggressiveness resulting in a longer period of time to reach the bottom of a cycle. Hence, this paper attempts to establish whether gasoline price cycle is consistent with EC through estimating the impact of demand elasticity on its cycle length and undercutting aggressiveness.

The ideal data for my empirical analysis would include direct observations of demand elasticity for gasoline or the price and demand data for estimating them. In the absence of such data, my empirical analysis exploits a proxy variable constructed using only gasoline price data. This proxy variable measures whether current average gasoline price is higher or lower than a historical average of past prices. The relevance of this proxy is based on the idea of reference-dependent demand in behavioral economies which suggests that reference-dependent demand becomes more price elastic when consumers believe the price they face is higher than their reference-price: a psychological price threshold. Hence, the validity of my proxy variable relies heavily on the assumption that demand for gasoline is reference-dependent. This assumption has been tested by a number of empirical papers including Lewis and Marvel (2011), Castilla and Haab (2015) and Levin, Lewis, and Wolak (2019). Findings from these papers are supportive of this assumption, in the sense that, higher gasoline prices are found induce consumer behavior that can interpreted as having more price sensitive demand. It is important to note that all conclusions made for the effect of aggregate demand elasticity are therefore inferred from the estimated impact of the proposed proxy variable.

To preview my results, I find that positive deviations from the reference-price increased the length of gasoline price cycle by 3.5 days (13% of the sample mean). After establishing its impact on cycle length, I then investigate if positive deviation from the reference-price has any effect on undercutting aggressiveness. Using the magnitude of average price cut from each price cycle as a measure for undercutting aggressiveness, I find that positive deviations from the reference-price decreased undercutting aggressiveness by 0.72 cents per liter (22% of the sample mean). To control for the impact of wholesale cost of gasoline on pricing decisions, I also show that positive deviations from the reference-price has a similar impact on the magnitude of average *margin* cut. Based on the assumption that demand for gasoline is reference-dependent, I infer from these results that estimated pricing behavior under gasoline price cycle in my sample is consistent with predicted pricing behavior under the EC. Additionally, I show that gas stations of all brands reduced their undercutting aggressiveness when demand is inferred to be more elastic suggesting that my conclusion is valid for all gasoline companies in my sample. Finally, I show that my results are robust to alternative definitions of reference-price based on a variety of time horizons of past prices.

The rest of the papers is organized as follows. Section 4.2 describes related literature and theory to be empirically tested. Section 4.3 describes the data and offers descriptive evidence. Section 4.4 presents the empirical strategy. Section 4.4.2 presents the results. Section 4.5 concludes.

4.2 Literature and hypotheses

The EC equilibrium formalized by Maskin and Tirole (1988) is widely acknowledged in the literature as the leading theory that explains the asymmetrical price cycles observed in the retail gasoline market. In their model, Maskin and Tirole (1988) assume two firms are engaged in price competition over a homogeneous product for an infinite number of periods[1]. An EC consists of three phases in the order of *Restoration*, *Undercutting* and *War-of-Attrition*. The *Restoration* phase is completed over one period with a large price increase from the bottom of the previous cycle; the *Undercutting* phase is comprised of multiple periods of small price cuts resulting in a graduate decline in price towards the

[1] One firm can change its price in each period and the two firms alternate in setting price every period. They also face fixed demand and have fixed production cost.

marginal cost; the cycle ends with the *War-of-Attrition* phase defined by one or several periods of static price prior to the *Restoration* phase of the next cycle. Importantly, the *Undercutting* phase of an EC is theorized by Maskin and Tirole (1988) to be driven by a competitive process of firms taking turns to undercut each other to steal market share. Consequently, an EC can be interpreted as an outcome of competition.

Previous research (Eckert and West (2004), Noel (2007a), Noel (2007b), and Wang (2009)) that attempted to establish observed gasoline price cycle as EC has commonly relied on the implied role of small firms in generating EC according to Eckert (2003). In his model, Eckert (2003) shows that EC is more likely to be found in markets that have a significant difference in outlet numbers between two firms. The intuition for this approach is that the small firm (the firm that has the lower share of outlets in a market) is more likely to lead price cuts that trigger the *Undercutting* phase of EC. The empirical implication is that gasoline price cycle is consistent as EC if it is more likely to be found in markets with a greater share of small firms.

In Noel (2008), the author predicts that the shape of EC should respond to aggregate demand elasticity. Specifically, cycle length is expected to increase in the aggregate demand elasticity. Noel (2008) explains that this is because the speed at which prices fall during the *Undercutting* phase decreases if consumers are more price sensitive. The intuition is that a smaller price cut can now steal the same amount of demand as a larger price cut when consumers are less price sensitive. Based on this prediction, Isakower and Wang (2014) use the difference in demand elasticity of Liquefied Petroleum Gas (LPG) and gasoline to explain the difference in their price cycle length.

Due to the lack of gasoline demand data, this paper proposes to infer price elasticity of demand from price data by assuming that demand for gasoline is reference-dependent. This assumption has been examined by Lewis and Marvel (2011), Castilla and Haab (2015) and Levin, Lewis, and Wolak (2019). The contribution of this paper over these papers is on the salience of reference-dependence for the supply-side. My results suggest that reference-dependence may have a role in explaining price-rigidity. Specifically, strategic consideration of firms towards reference-dependence of demand may affect downward price stickiness in the retail gasoline market, which corroborates with the finding by Douglas and Herrera (2010) who attributes upward price stickiness in the wholesale gasoline market to the strategic consideration of firms towards fair pricing.

Combining the predictions of Noel (2008) and my approach to infer aggregate elasticity of demand from price data, my empirical analysis aims to test the following two hypotheses:

H1: Cycle length should *increase* when the current price is above consumers' reference price.

H2: Undercutting aggressiveness should *decrease* when the current price is above consumers' reference price.

4.3 Data

4.3.1 Data source

My empirical tests are based on station-level retail price data of regular gasoline[2] from New South Wales (NSW), Australia. The sample range covers a 28-month period from January 1, 2017 to June 30, 2019. The data were originally collected and published by FuelCheck - an online fuel price transparency tool managed by the NSW government[3]. All gas stations were required by law to update their prices in FuelCheck whenever they change their prices at the pump. The FuelCheck data therefore contains the universe of retail prices for all gasoline types from all 2228 active gas stations in NSW over the sample period. Importantly, because I observe the timestamp for each price update, this allows me to interpolate the raw data of price updates into a daily panel of station-level prices.

4.3.2 Identifying stations with price cycles

Because I am examining the length of price cycles at the station level, it is therefore necessary to first identify gas stations whose dynamic price path follow a cyclical pattern. To do this,

[2]Regular gasoline is known as United 91 or U91 in New South Wales. Mid-grade gasoline and premium gasoline are known locally as P95 and P98 respectively.

[3]The data were downloaded from the website: https://data.nsw.gov.au/data/dataset/fuel-check.

I follow the method proposed by González and Hurtado (2018) who use a cycling ratio[4] to identify cycling stations. This method distinguishes cycling stations from non-cycling one if their cycling ratio is sufficiently high. The rational of this method is based on the expected relationship between price restorations and price cuts implied by EC that the size of average price restorations should be significantly larger than that of price cuts. Their method is chosen for this study instead of the "median price change" method proposed by Lewis (2009) because it avoids the classification errors the later method can generate with station-level price data.[5]

Following the advice of González and Hurtado (2018), I classify stations whose cycling ratio is equal or greater than 1.5 as cycling stations (the average size of price restorations is at least 50% larger than the average size of their price cuts). This results in a total of 1309 cycling stations and 898 non-cycling stations in my sample. It should be noted that cycling ratio cannot be computed for a total of 97 stations in my sample due to them having constant or monotonically changing prices over the sample period. These stations are classified as non-cycling stations. Figure 4.1 shows the dynamic price path of cycling stations and figure 4.2 shows non-cycling stations based on their daily cross-sectional means. As expected, the price path of cycling stations exhibits the asymmetrical price cycle implied by the EC equilibrium. In contrast, asymmetrical price cycle is absent for the non-cycling stations. The focus of this study is subsequently on the cycling stations identified here.

4.3.3 Measuring price cycle length

Having identified the cycling stations in my sample, I now describe how I measure the length of individual price cycles of these stations. Because the restoration phase marks the start of a new EC, I measure the length of a price cycle as the amount of time elapsed between two successive dates on which the price has increased. Mathematically, this can be represented in equation 4.1 where t_k represents the date on which $\left(P_t^i - P_{t-1}^i\right) > 0$ has occurred for the kth time since the start of the sample period for station i. By this definition, the sequence

[4] For each gas station, the ratio equals to the average of all observed price increase divided by the absolute value of the average of all observed price cut over the sample period

[5] Please refer to González and Hurtado (2018) for a detailed comparison between their method and that of Lewis (2009) in identifying price cycles at the station level

of price cycles for station i is indexed by k. Inn other words, the kth price cycle starts with kth price increase and finishes with the next or $(k+1)$th price increase. In addition, because each price increase takes 1 period (day) to complete, the kth price cycle for station i therefore starts on $\left(t_k^i - 1\right)$ and ends on date $\left(t_{k+1}^i - 1\right)$. The difference between these two dates is therefore that the length of a price cycle. Formally, cycle length can be expressed as:

$$CycleLength_k^i = \left(t_{k+1}^i - 1\right) - \left(t_k^i - 1\right) = t_{k+1}^i - t_k^i \tag{4.1}$$

Equation 4.1 is also illustrated graphically in figure 4.3. The first, second and third price cycle (k=1, 2 and 3) in figure 4.1 has a total cycle length of 5 days, 3 days, and 2 days respectively.

Using the terms of a EC, $CycleLength_k^i$ can also be expressed as the combined length of the restoration phase, undercutting phase and war-of-attrition phase. Formally,

$$CycleLength_k^i = \sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_+\right] + \sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_-\right] + \sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_0\right]$$

where $\sum_{t_k^i}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_+\right]$ represents the length of restoration phase[6] and τ_+ is the subset of dates in the sample at which station i has a price increase or when $p_{t+1}^i > p_t^i$; $\sum_{t_k^i}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_-\right]$ represents the length of undercutting phase and τ_- is the subset of dates in the sample at which station i has a price cut or when $p_{t+1}^i < p_t^i$; $\sum_{t_k^i}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_0\right]$ represents the length of war-of-attrition phase and τ_0 is the subset of dates in the sample at which station i has no price change or when $p_{t+1}^i = p_t^i$.

The summary statistics of cycle length in the final sample is shown in panel A of table 4.1. The final sample includes a total of just under 43610 station-level price cycles. The sample mean of cycle length is 27 days. Cycle length in my sample also exhibits substantial variation indicated by the large standard deviation of 58 days. Table 4.1 also shows that, on average, gas stations cut prices on 5 of the 27-day price cycle and left prices unchanged on the other 22 days of the price cycle. This suggests that the "median price change"

[6] By construction, $\sum_{t_k^i}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_+\right] = 1$ for all i and k in my data.

method would have indeed classified many cycling stations as non-cycling in my sample. The summary statistics of the restoration phase are not reported as they all last for 1 day by construction.

4.3.4 Inferring aggregate demand elasticity of gasoline

Because I only have access to gasoline price data, my empirical strategy relies an inferred measure of aggregate price elasticity of demand. This inference is based on the prospect theory in behavioral economic (Kőszegi and Rabin (2006) and Bordalo, Gennaioli, and Shleifer (2013)) that the demand elasticity for some products is reference-dependent. Reference-dependent demand means that demand is more price elastic if consumers believe the price they face is higher than their reference-price. The reference-price is a psychological price threshold that consumers have, which may represent consumers' expected price for a product. If demand is reference-dependent and other salient factors for demand elasticity stay fixed, then aggregate demand can be inferred as relatively more price elastic if the current average price in a market is higher than consumers' reference-price in that market.

The validity for this inference in the retail gasoline market rests on the assumption that gasoline demand is reference-dependent. Empirical evidence that supports this assumption has been documented in a number of recent papers. For example, using gasoline price and quantity data, Levin, Lewis, and Wolak (2019) find that demand for retail gasoline becomes three times more elastic when the current price is above a reference-price based on historical prices. Additionally, Lewis and Marvel (2011) use observational data to demonstrate that consumers are more price sensitive and subsequently search more intensively for cheaper gasoline when price is rising than when it is falling. Furthermore, using survey data, Castilla and Haab (2015) show that consumers are more price sensitive and hence willing to search more intensively for cheaper gasoline when they are presented with a higher price than their reference-price. A common finding from these papers is that price becomes a more salient factor for consumers when the price is higher than prices they observed in the past. Based on these papers, I argue that consumer demand for gasoline is reference-dependent.

4.3.4.1 Definition of local gasoline markets

To infer aggregate demand elasticity, I rely on reference-dependence of gasoline demand at the local market level. Following Van Meerbeeck (2003) and Clemenz and Gugler (2009), I spatially divide the state of New South Wales into local gasoline markets by census area. Specifically, each local gasoline market corresponds to the area defined by the geographical boundary of Statistical Area Level 3 (SA3) prescribed by the Australian Bureau of Statistics (ABS). SA3 is based on areas serviced by a major transport and commercial hub in metropolitan cities. In rural areas, SA3s represent communities with distinct and similar social economic characteristics. These characteristics of SA3 imply that stations located within them are probably competing for the same group of consumers and hence can be considered as competing in the same market. Figure 4.4 illustrates the spatial delineation of local markets by SA3 areas. Figure 4.4a presents the state map of NSW, the spatial boundaries of its local gasoline markets and the position of gasoline stations. Figure 4.4a is the corresponding map for the urban area of Greater Sydney.

4.3.4.2 Definition of reference-price

Following Castilla and Haab (2015) and Levin, Lewis, and Wolak (2019), I define reference-price as the expected price by consumers which is approximated by an average of past prices. To construct reference-prices at the local market level, I first aggregate the daily panels of station-level prices into daily panels of market-level prices according to equation 4.2 which states that the price for market m on day t (p_t^m) is simply the average of station-level prices (p_t^i):

$$p_t^m = \frac{1}{N_t^m} \sum p_t^i, \; \forall i \in m, \tag{4.2}$$

where N_t^m is the number of observed prices in market m on day t.

The reference-price, $\overline{p}\,(h)_t^m$, for each local markets m on date t can therefore be represented by equation 4.3 as follows:

$$\overline{p}\,(h)_t^m = \frac{1}{h} \sum_{t-h}^{t} p_{mt} \tag{4.3}$$

where h represents the time horizon of past prices in days from day t of the sample. The difference between market price from the market reference-price is therefore

$$p_t^m - \overline{p}\left(h\right)_t^m$$

The corresponding $p_t^m - \overline{p}\left(h\right)_t^m$ for each station-level gasoline price cycle can be expressed as

$$p_{t_k^i}^m - \overline{p}\left(h\right)_{t_k^i}^m \tag{4.4}$$

I now construct the proxy measure for aggregate demand elasticity $\left(HighPrice_{t_k^i}^m\right)$ as follows :

$$HighPrice\left(h\right)_{t_k^i}^m \equiv \mathbf{1}\left(p_{t_k^i}^m - \overline{p}\left(h\right)_{t_k^i}^m\right) \tag{4.5}$$

where $\mathbf{1}\left(p_{t_k^i}^m - \overline{p}\left(h\right)_{t_k^i}^m\right)$ is an indicator variable that equals to one if $p_{t_k^i}^m - \overline{p}\left(h\right)_{t_k^i}^m$ is greater than zero, and equals to zero if otherwise.

This definition of $HighPrice$ therefore allows me to infer that the aggregate demand for gasoline in market m at time t_k^i is relatively more price elastic if $HighPrice\left(h\right)_{t_k^i}^m = 1$ and relatively less inelastic if $HighPrice\left(h\right)_{t_k^i}^m = 0$. Because the exact horizon of time over which consumers form price expectations is unknown, I base my main result on a reference-price calculated as the moving average of the past 360 days which is also the focus in Levin, Lewis, and Wolak (2019). As a robustness check, I present estimates based on reference-prices determined using a range of different time horizons of past prices.

The summary statistics of proxy $HighPrice\left(360\right)_{t_k^i}^m$, market price ($p_{t_k^i}^m$), market reference-price ($\overline{p}\left(360\right)_{t_k^i}^m$) and the deviations from market reference-price ($p_{t_k^i}^m - \overline{p}\left(360\right)_{t_k^i}^m$) are presented in panel B of table 4.1. The mean for all deviations from the reference-price (based on the past 360 days) is approximately 7 cpl. Furthermore, approximately 22% of the price cycles in the sample had a negative deviation from the reference-price.

4.3.5 Variables for characterizing within-cycle price dynamics

In this section, I describe the variables I use to measure price variations within each cycle. These variables are restoration amplitude, undercutting amplitude and undercutting aggressiveness.

Restoration amplitude is the size of the price increase that marks the start of a new cycle. It can be calculated as the absolute difference between the the peak price ($p^i_{t_k}$) of the current cycle and the trough price of the previous cycle ($p^i_{t_k-1}$). Equation 4.6 presents the formal expression for $RestoAmp^i_{t_k}$ which is the restoration amplitude for the kth cycle of station i:

$$RestoAmp^i_k = p^i_{t_k} - p^i_{t_k-1} \tag{4.6}$$

Undercutting amplitude is the sum of of all price cuts in each cycle. It can be calculated as the difference between the peak price ($p^i_{t_k}$) and trough price ($p^i_{t_{k+1}-1}$) of the current cycle. Equation 4.7 presents the formal expression for $UnderAmp^i_{t_k}$ which is undercutting amplitude for the kth cycle of station i:

$$UnderAmp^i_k = p^i_{t_k} - p^i_{t_{k+1}-1} \tag{4.7}$$

Undercutting aggressiveness describes how fast price is falling during the undercutting phase. It is easy to see that, for the same undercutting amplitude, undercutting is more aggressiveness if the undercutting phase is completed with a smaller number of price cuts implying a larger average price cut. Following Noel (2007b), I measure undercutting aggressiveness as the absolute size of expected price cut per cycle $\left(\mathbb{E}\left[\left|\Delta_- p^i_k\right|\right]\right)$ that can be calculated with sample data as the absolute size of the average price cut per cycle $\left(\overline{\left|\Delta_- p^i_k\right|}\right)$. Formally, undercutting aggressiveness for the kth cycle of station i is defined as:

$$UnderAgg^i_k = \overline{\left|\Delta_- p^i_k\right|} = \frac{UnderAmp^i_k}{\sum_{t^i_k-1}^{t^i_{k+1}-1} \mathbf{1}\left[t \in \tau_-\right]} \tag{4.8}$$

In my empirical analysis, I will also test the impact of $HighPrice$ on a measure of undercutting aggressiveness based on the retail margins $\left(UnderAmpMargin_k^i\right)$. This is to obtain the net variations in $UnderAgg$ that is not due to variations in the input cost of gasoline. To construct $UnderAmpMargin_k^i$, I first calculate the undercutting amplitude in terms of retail margins as show in equation 4.9:

$$UnderAmpMargin_k^i = \left(p_{t_k}^i - \overline{wp}_{t_k}\right) - \left(p_{(t_{k+1}-1)}^i - \overline{wp}_{t_k}\right) \tag{4.9}$$

where $\overline{wp}_{t_k}$ represents the average wholesale gasoline price in NSW at time t_k.

$UnderAggMargin_k^i$ is therefore the average margin cut per cycle as shown in equation 4.10:

$$UnderAggMargin_k^i = \frac{UnderAmpMargin_{t_k}^i}{\sum_{t_k^i}^{t_{k+1}^i} \mathbf{1}\left[t \in \tau_-\right]} \tag{4.10}$$

Panel C of table 4.1 presents the summary statistics on $RestAmp$, $UnderAmp$, $UnderAgg$, and $UnderAggMargin$.

4.3.6 Visualizing the hypotheses

To clarify the empirical relationship I am investigating, I now present my hypotheses graphically using the the variables I defined in the previous section. Figure 4.5 shows a hypothetical price cycle (1st cycle of station i in local market m) whose pattern is consistent both with H1 and H2. It shows that, with identical restoration amplitude, undercutting amplitude, marginal cost, the cycle length is 2 periods longer (H1) under the scenario where $HighPrice_{t_1^i}^m = 1$ than under the counterfactual scenario where $HighPrice_{t_1^i}^m = 0$. Consistent with H2, the hypothetical case also shows that the undercutting aggressiveness under scenario A is a third of that under scenario B.

Recall that Noel (2008) cites lower undercutting intensity as the reason why it anticipates the length of a competitive price cycle to be longer when aggregate demand is relatively more elastic. This implies that empirical evidence supporting H1 can be insufficient for concluding that observed gasoline price cycles are consistent with the predictions of Noel (2008). For my empirical analysis, if all stations respond to variations in $HighPrice$ over time only by adjusting their undercutting aggressiveness, then testing H1 alone is sufficient to verifying the predictions of Noel (2008). However, it is entirely possible that stations may also respond to $HighPrice$ by adjusting the length of their *War-of-Attrition* phase. Figure 4.6 depicts an extreme case where the effect of $HighPrice$ is consistent with H1 but not with H2 where the effect of $HighPrice$ comes entirely from extending the length of the *War-of-Attrition* phase leaving undercutting aggressiveness unaffected. This hypothetical example therefore highlights the need to examine both H1 and H2 when relying on the prediction of Noel (2008) to compare empirical price cycles to EC.

4.3.7 Descriptive evidence

To investigate how gasoline price cycle length and undercutting aggressiveness vary with my proxy for gasoline demand elasticity, I divide my sample into two groups: cycles with positive deviations from the reference-price and cycles with zero and negative deviations from the reference-price. Table 4.2 displays the average cycle length and undercutting aggressiveness. In support of H1, the average cycle length associated with elastic demand in my sample is 7 days longer than the average cycle length associated with inelastic demand. In support of H2, the average undercutting aggressiveness associated with elastic demand in my sample is 0.6 cpl lower than the undercutting aggressiveness associated with inelastic demand. The p-values for the corresponding t-tests also suggest that these differences are statistically significant. Together, these results suggest that pricing behavior by gas stations in NSW is consistent with the predictions of Noel (2008). In the next section, I use regressions to isolate and confirm the effects of my proxy for gasoline demand elasticity implied by the descriptive evidence.

4.4 Panel Analysis

4.4.1 Empirical model for estimating the impact on cycle length

Using $HighPrice$ as a proxy for aggregate demand elasticity for gasoline, I exploit the panel structure of the data to estimate its impact on the length of gasoline price. I do this by estimating a fixed effects model represented in equation 4.11 below:

$$
\begin{aligned}
CycleLength_k^i = \beta_0 &+ \beta_1 HighPrice\,(360)_{t_k^i}^m + \beta_2 OwnPriceDev_{t_k^i} \\
&+ \beta_4 RestAmp_k^i + \beta_5 UndercutAmp_k^i \qquad (4.11)\\
&+ \Delta\overline{wp}_k^i + N_{t_k^i}^m + \beta_{t_k} + \beta_i + \epsilon_{it_k} \qquad (4.12)
\end{aligned}
$$

where $CycleLength_{ik}$ represents cycle length defined by equation 4.1. $HighPrice\,(360)_{t_k^i}^m$ is my variable of interest as defined in equation 4.5. β_1 is hence my coefficient of interest which measures the impact on cycle length when $HighPrice\,(360)_{t_k^i}^m$ equals to 1. The objective of equation 4.11 is to identify the effect of a higher-than-expected market-average price on the price cycle length of gas stations. To do this I use station (β_i) fixed effects to control for static spatial unobserved effects, brand (β_b) fixed effects to control for brand-specific unobserved effects and time fixed effects β_{t_k} to flexibly control for common shocks. An immediate source of endogeneity associated with this identification strategy arises from the fact that the construction of $HighPrice\,(360)_{t_k^i}^m$ also relies on the the contemporaneous pricing decision of station i. Hence, I include the deviation of station i's price from the market reference-price ($OwnPriceDev_{it_{ik}}$)[7] to isolate the variation in $HighPrice\,(360)_{t_k^i}^m$ that is independent of the pricing decision of station i. Next, I include restoration amplitude and undercutting amplitude of the cycle to control for dynamic cycle heterogeneity for individual stations.

Finally, I include $\Delta\overline{wp}_k^i$ and $N_{t_k^i}^m$ for supply side factors that may affect cycle length. $\Delta\overline{wp}_k^i$, which is calculated as $\overline{wp}_{t_k^i-1} - \overline{wp}_{t_{k+1}^i-1}$, represents the change in the average wholesale price of gasoline in NSW over the span of cycle k for station i. $N_{t_k^i}^m$ is the number of active stations at time t_k^i in market m.

Identification of the causal effect of $HighPrice\,(360)_{t_k^i}^m$ based on equation 4.11 therefore will come from within-station variations of $HighPrice\,(360)_{t_k^i}^m$. In order to interpret the estimated β_1 as causal, I will need to rely on the assumption that the variation in $HighPrice\,(360)_{t_k^i}^m$ is as good as random after the inclusion of the control variables and the

[7] $OwnPriceDev_{it_{ik}} = p_{it_{ik}} - p_{mt_{ik}}^{Ref}$

fixed effects as specified in equation 4.11.

4.4.2 Estimated impact on cycle length

Table 4.3 presents the impact of higher-than-expected market price on cycle length . Fixed effects and control variables are added progressively from column 1 to 3. The specification in Column 1 estimates without any fixed effects or controls. Column 2 adds spatial, brand and time fixed effects to column 1. Finally, column 3 adds a vector of covariates to column 2 including restoration amplitude , wholesale cost of gasoline, undercutting amplitude and the number of gas stations in the local market. All specifications show that cycles become longer when $HighPrice\,(360)^{m}_{t^{i}_{k}}$ equals 1 than when $HighPrice\,(360)^{m}_{t^{i}_{k}}$ equals 0. These results are in favor of accepting H1 as true in my sample. Column 3 is my preferred specification for estimating the impact of $HighPrice$ on cycle length. Based on the estimated $\hat{\beta}_1$ in column 3 and the my interpretation for $HighPrice$, it can be inferred that elastic aggregate demand increased cycle length by approximately 3.5 days which represents a 13% increase based on the sample mean.

4.4.3 Empirical model for estimating the impact on undercutting aggressiveness

Having established that $HighPrice$ has a positive effect on cycle length, I now investigate if undercutting aggressiveness also responds to $HighPrice\,(360)^{m}_{t^{i}_{k}}$ as predicted by H2. To do this, I estimate the impact of $HighPrice$ on undercutting aggressiveness with the following fixed effects model below:

$$
\begin{aligned}
Y_k^i = {} & \beta_0 + \beta_1 \tilde{\eta}\,(360)_{t_k^i}^m + \beta_2 OwnPriceDev_{t_k^i} \\
& + \beta_3 RestAmp_k^i + \beta_4 UndercutAmp_k^i \\
& + \beta_5 \Delta \overline{wp}_k^i + \beta_6 N_{t_k^i}^m + \beta_7 \sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_0\right] \\
& + \beta_{t_k} + \beta_i + \epsilon_{it_k}
\end{aligned} \tag{4.13}
$$

The outcome of interest Y_{ik} in equation 4.13 represents alternative measures of undercutting aggressiveness in price ($UnderAgg_k^i$) and in retail margin ($UnderAggMargin_k^i$) which are defined in equation 4.8 and equation 4.10. The variable of interest, control variables and fixed effects from equation 4.11 are carried forward to equation (4.13) with one addition. Equation 4.13 adds $\sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_0\right]$ which is the length of the *War-of-Attrition* phase in each cycle. $\sum_{t_k^i - 1}^{t_{k+1}^i - 1} \mathbf{1}\left[t \in \tau_0\right]$ is included to account for cycle heterogeneity over the lengths of their *War-of-Attrition* phase. Standard errors are clustered at the market m level. Again, the estimated β_1 can only be interpreted as the causal effect of $HighPrice\,(360)_{t_k^i}^m$ on undercutting aggressiveness based on the assumption that the variation in $HighPrice\,(360)_{t_k^i}^m$ is as good as random after the inclusion of the control variables and the fixed effects as specified in equation

The results for the estimated effect of $HighPrice\,(360)_{t_k^i}^m$ on undercutting aggressiveness is presented in table 4.4. Column 1 and 2 of table 4.4 estimate the impact of $HighPrice\,(360)_{t_k^i}^m$ on undercutting aggressiveness in price. Column 1 estimates this effect without any fixed effects or controls. In this simple model, the estimated coefficient on $HighPrice\,(360)_{t_k^i}^m$ is negative and significant which is consistent with H2. Column 2 is my preferred specification which estimates the marginal effect of $HighPrice\,(360)_{t_k^i}^m$ based on the full specification of equation 4.13. It suggests that the undercutting aggressiveness decreased by approximately 0.7 cpl or 22% of its sample mean when $HighPrice\,(360)_{t_k^i}^m$ equals to 1.

Column 3 and 4 of table 4.13 estimate the impact of $HighPrice\,(360)_{t_k^i}^m$ on $UnderAggMargin_k^i$. Again, column 3 estimates the relationship without any fixed effects or controls and column

4 has the full specification as per equation 4.13. Based on column 4, undercutting cutting aggressiveness in retail margin decreased by 0.8 cpl or 18% of its sample mean when $HighPrice\,(360)^m_{t^i_k}$ equals to 1.

All estimates in table 4.4 are negative and statistically significant at the one percent level. They all support H2 that stations undercut each other less aggressively when the value of $HighPrice\,(360)^m_{t^i_k}$ suggests that aggregate demand is more elastic.

4.4.4 Heterogeneous responses by brand

To better understand how a higher-than-expected market price influence gasoline pricing decisions, I now examine whether the estimated effect of a higher-than-expected market price on undercutting aggressiveness reflect a common pricing practice across firms or the pricing strategy of specific gasoline companies. This insight could be interesting as DellaVigna and Gentzkow (2019) found that most large chain businesses in US tend to overlook differences in local market demand elasticity and set suboptimal uniform prices across their stores. DellaVigna and Gentzkow (2019) attributes this paradox to management inertia and suggests gasoline industry is an exception to this phenomenon. This analysis therefore can supplement DellaVigna and Gentzkow (2019)'s comment on the retail gasoline industry by testing if pricing practice is consistently flexible across gasoline companies. I do this by estimating the heterogeneous responses to $HighPrice\,(360)^m_{t^i_k}$ by the brand of each gas station. Specifically, I estimate the following regression equations:

$$\begin{aligned} Y^i_k = {} & \beta_0 + \beta_1 HighPrice\,(360)^m_{t^i_k} + \beta_b \left(HighPrice\,(360)^m_{t^i_k} \times Brand^i_t \right) \\ & + \beta_2 OwnPriceDev_{t^i_k} + \beta_3 RestAmp^i_k + \beta_4 UndercutAmp^i_k \\ & + \beta_5 \Delta \overline{wp}^i_k + \beta_6 N^m_{t^i_k} + \beta_7 \sum_{t^i_k - 1}^{t^i_{k+1}-1} \mathbf{1}\left[t \in \tau_0\right] \\ & + \beta_{t_k} + \beta_i + \epsilon_{it_k} \end{aligned} \tag{4.14}$$

Equation 4.14 has the same outcome and explanatory variables as 4.13 but with an added interaction term between $HighPrice\,(360)^m_{t^i_k}$ and brand dummies $\left(Brand^i_t\right)$. β_b is therefore a vector of coefficients that represents the differential responses in undercutting aggressiveness of each brand of stations from the brand of stations in the omitted group. As a reference, columns 1 and 3 of 4.5 reproduces columns 4 and 5 of table 4.4 respectively. Columns 2 and 3 estimate equation 4.14 with 7-Eleven brand of stations as the omitted group. Column 2 shows that, on average, $HighPrice\,(360)^{m}_{t^{i}_{k}}$ has a negative and significant impact on the size of average price cut for all brands in the sample. When compared to the impact on undercutting aggressiveness in prices for 7-Eleven stations, the impact on other brands is either similar or stronger. The the same inference can be made based on the result in column 4 whose outcome variable is undercutting aggressiveness in margins. These results are consistent with the interpretation that the negative response of undercutting aggressiveness to $HighPrice\,(360)^{m}_{t^{i}_{k}}$ is a common pricing practice and not the exclusive strategy of any particular company. Importantly, the pervasive effect of $HighPrice\,(360)^{m}_{t^{i}_{k}}$ also suggests that gasoline price cycles is consistent with EC for all brands in my sample.

4.4.5 Robustness to alternative definitions of reference-price

A key assumption that has been maintained so far is that reference-price is equivalent to the moving average of prices in the past 360 days. In this section, I test the sensitivity of my results to alternative definitions of reference-price. I do this by estimating the impact of $HighPrice$ based on a range of price history. Table 4.6 reports the main effects estimated with reference-prices based on the past 30 ,60, 90, 120, 240 and 360 days.

Panel A, B and C of table 4.6 presents the effect on cycle length, average price cut per cycle and average margin cut per cycle respectively. For cycle length, the impact of $HighPrice$ is statistically significant at the 1% level for 60 days and 90 days, at the 5% level for 240 days and 360 days, and at the 10% level for 30 days and 120 days. For undercutting aggressiveness measured in price and margin, the impacts are significant (at the 1% level) for all alternative definitions of reference-price considered.

Reassuringly, the estimates based on the alternative reference-prices also confirm that higher-than-expected market price increased cycle length and decreased undercutting aggressiveness. Interestingly, the magnitude of the point estimates for the three outcomes are the largest in magnitude when the reference-price is based on a price history of the last 60 days. Importantly, the results in table 4.6 suggest that my main results are robust to these alternative specifications of reference-price.

4.5 Chapter conclusion

Based on testable implications from Noel (2008) and Levin, Lewis, and Wolak (2019), I investigate if changes in aggregate demand elasticity has the same impact on gasoline price cycle as it does on EC. My empirical strategy relies on a proxy variable based on the deviations from consumers' reference-price to infer the aggregate demand elasticity for gasoline. Using station-level data from 2017 to 2019, I first establish cycle length increased when the demand for gasoline is inferred as relatively more price-elastic. I then establish that, consistent with predicted pricing behavior under the EC equilibrium, undercutting aggressiveness decreased when the demand for gasoline is inferred as relatively more price-elastic. These results are consistent with the intuition that firms following a competitive price cycle equilibrium, i.e. EC, will undercut each other less aggressively when consumers are more price sensitive and resulting in longer cycle length. What's more, these pricing responses are found across all brands in my sample suggesting that it is a common pricing practice for the industry.

Because aggregate demand elasticity have the same impact on pricing dynamic within gasoline price cycles as it is predicted to have on EC, the results in this paper can be interpreted as new evidence that supports the EC explanation for gasoline price cycles. These findings, however, are not sufficient to rule out other explanations for gasoline price cycles such as collusion. Hence, it is not the claim of this paper that EC is the only explanation for the gasoline price cycles examined.

My finding also sheds new light on the dynamic determinants of gasoline cycle length. This knowledge could be of interest to consumer-welfare agencies[8] who wish to enable consumers to make better informed purchase decisions. For example, such agencies could pro-

[8] The Australian Competition & Consumer Commission, for example, monitors gasoline price cycles in Australia and provides ongoing advice to consumers on the optimal time to fuel up.

vide forecasts of gasoline price cycles so that consumers can time their purchase closer to the trough of the cycle. In practice, when building a forecasting model for gasoline cycle length, the findings in paper suggest that the forecaster should consider including a measure of price elasticity of demand (e.g. the proxy proposed in this paper) as a predictor in addition to the length of past cycles and other predictors.

Figures and Tables in Chapter 4

Figure 4.1: DYNAMIC PRICE PATH OF CYCLING STATIONS

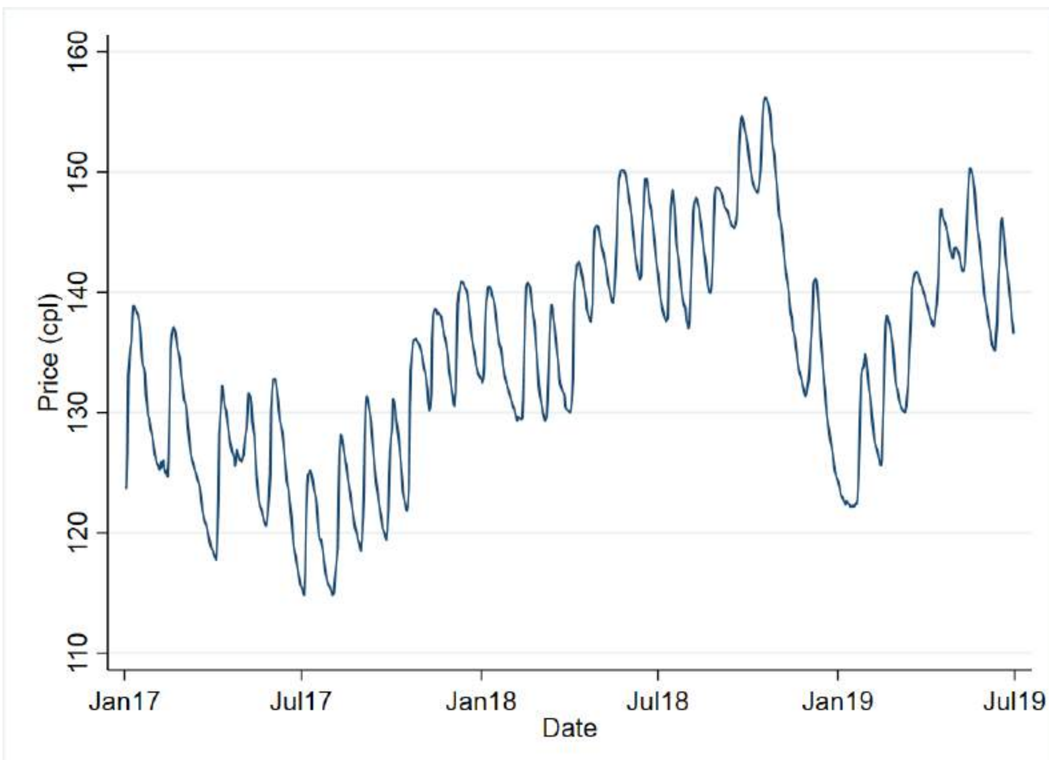


Figure 4.2: DYNAMIC PRICE PATH OF NON-CYCLING STATIONS

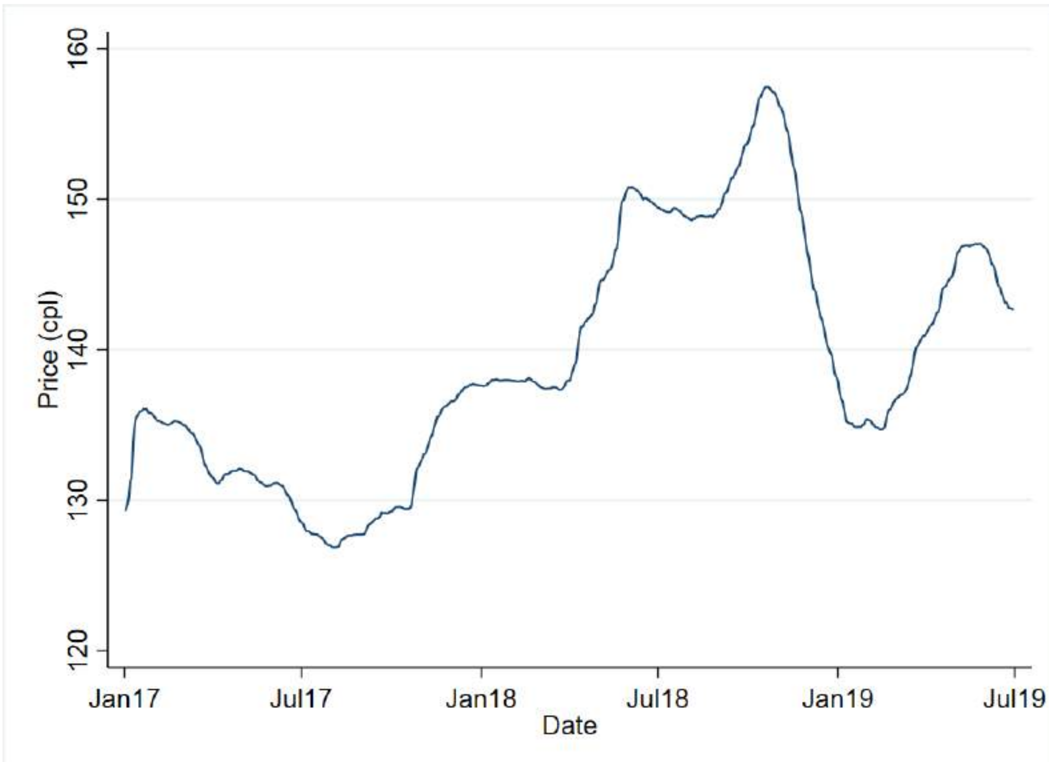


Figure 4.3: TIMELINE OF GASOLINE PRICE CYCLES

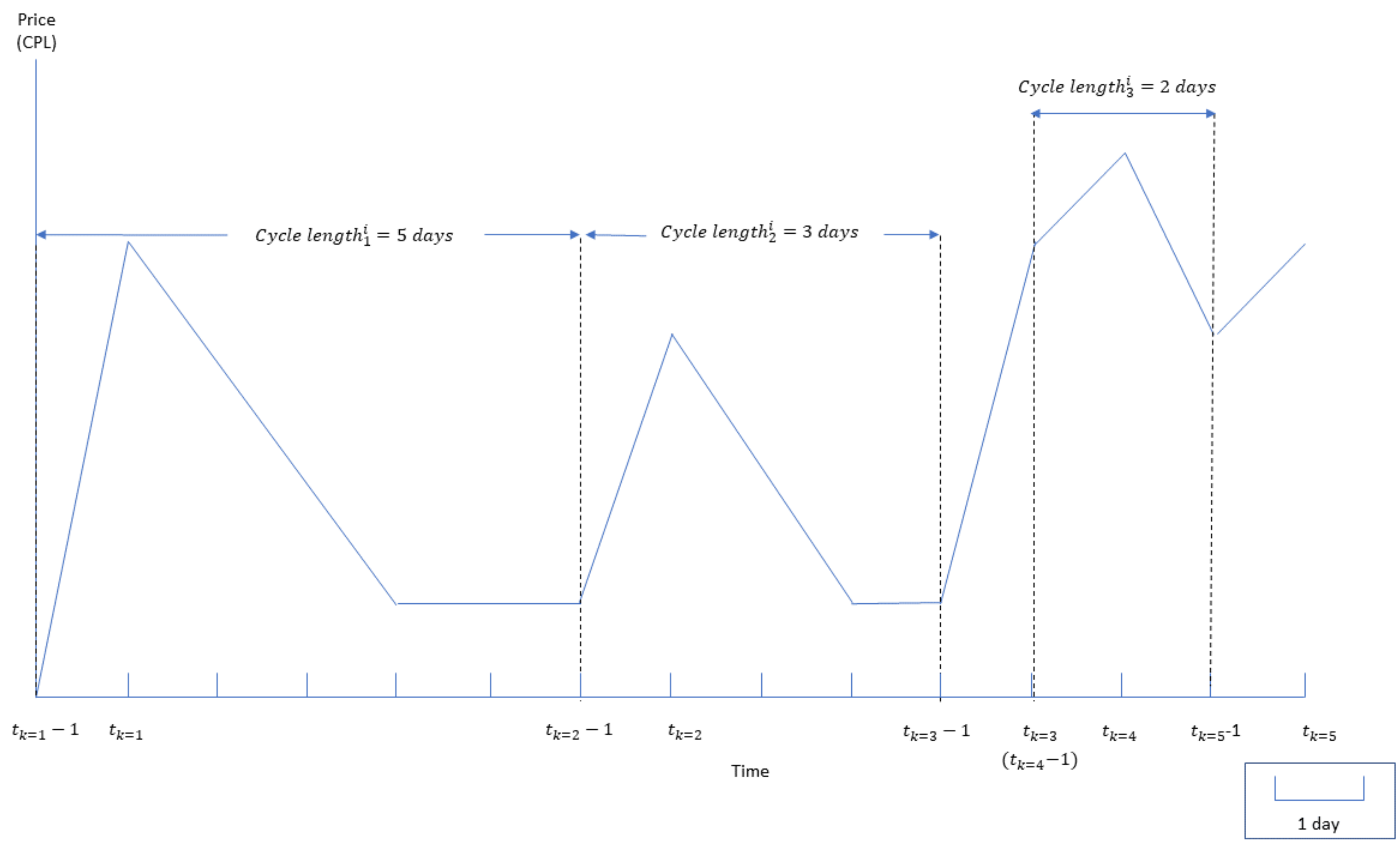
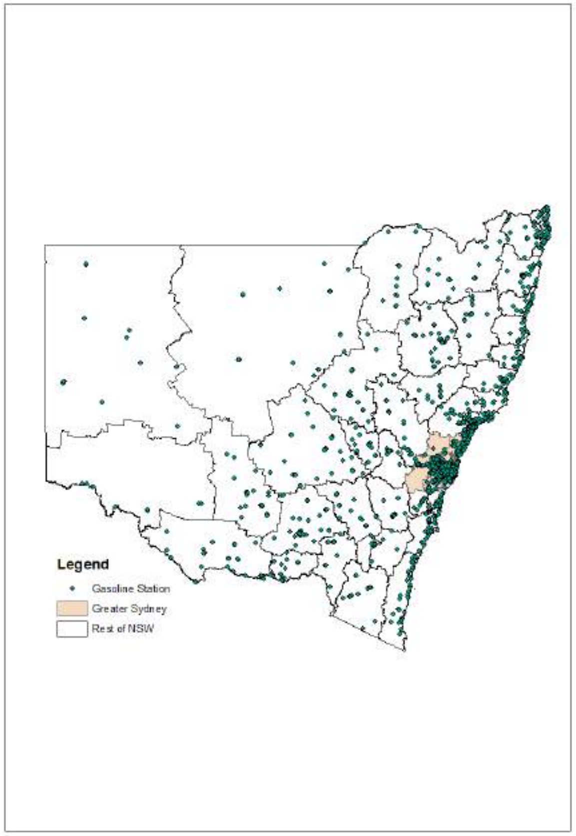


Figure 4.4: GAS STATIONS IN LOCAL MARKETS DEFINED BY SA3 BOUNDARIES IN NSW AND SYDNEY

(a) NSW



(b) Sydney

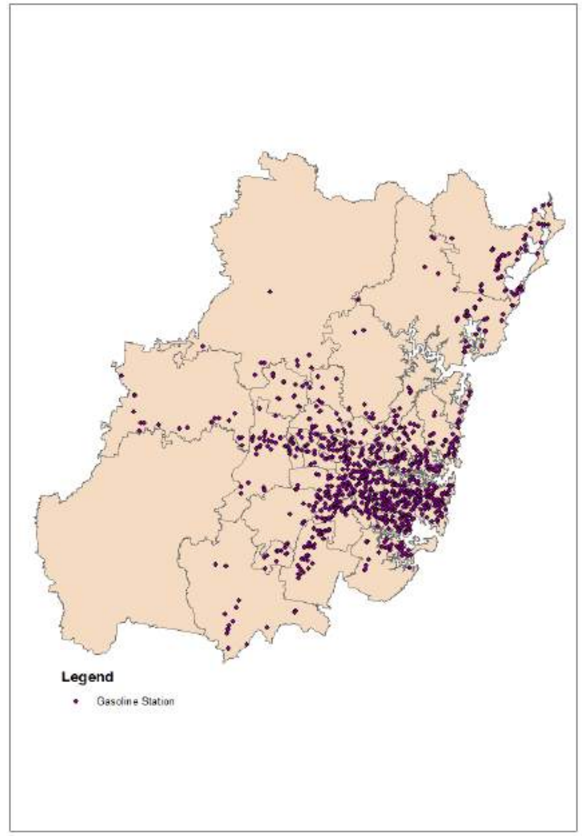


Figure 4.5: GRAPHIC REPRESENTATION WHEN BOTH H1 AND H2 ARE TRUE

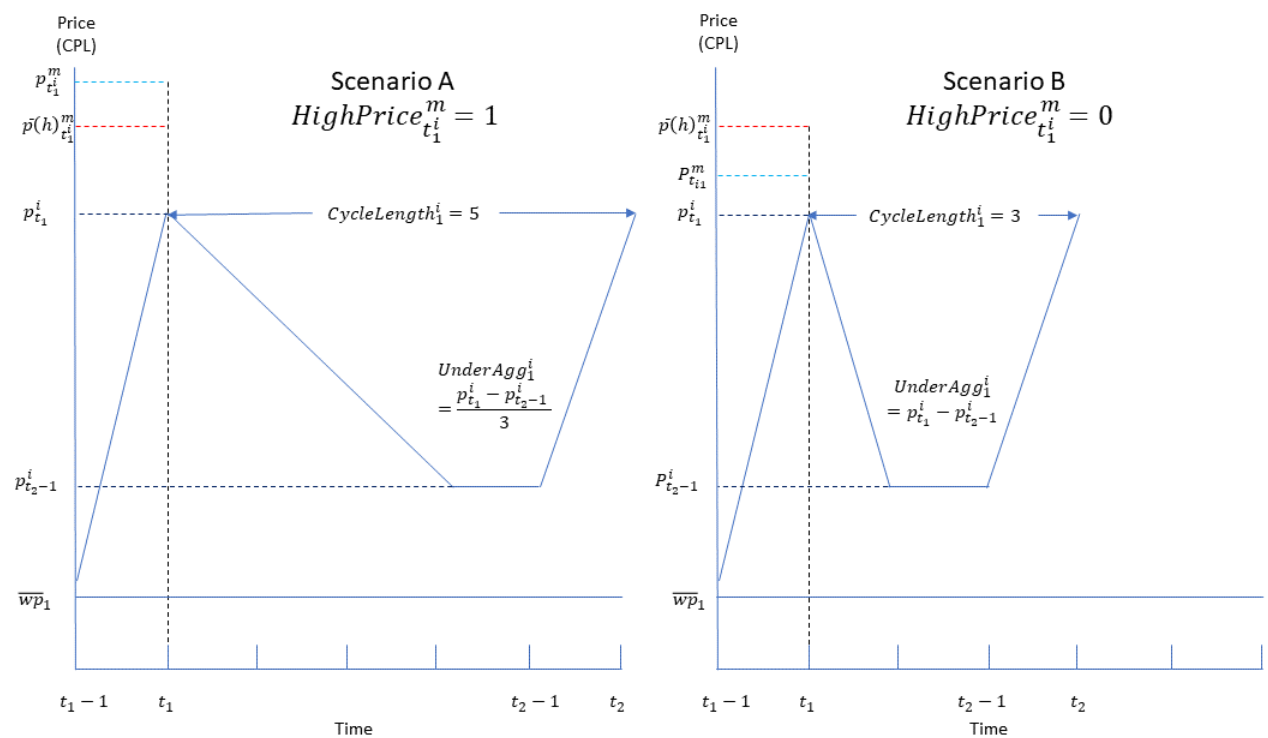


Figure 4.6: GRAPHIC AL REPRESENTATION WHEN H1 IS TRUE AND H2 IS FALSE

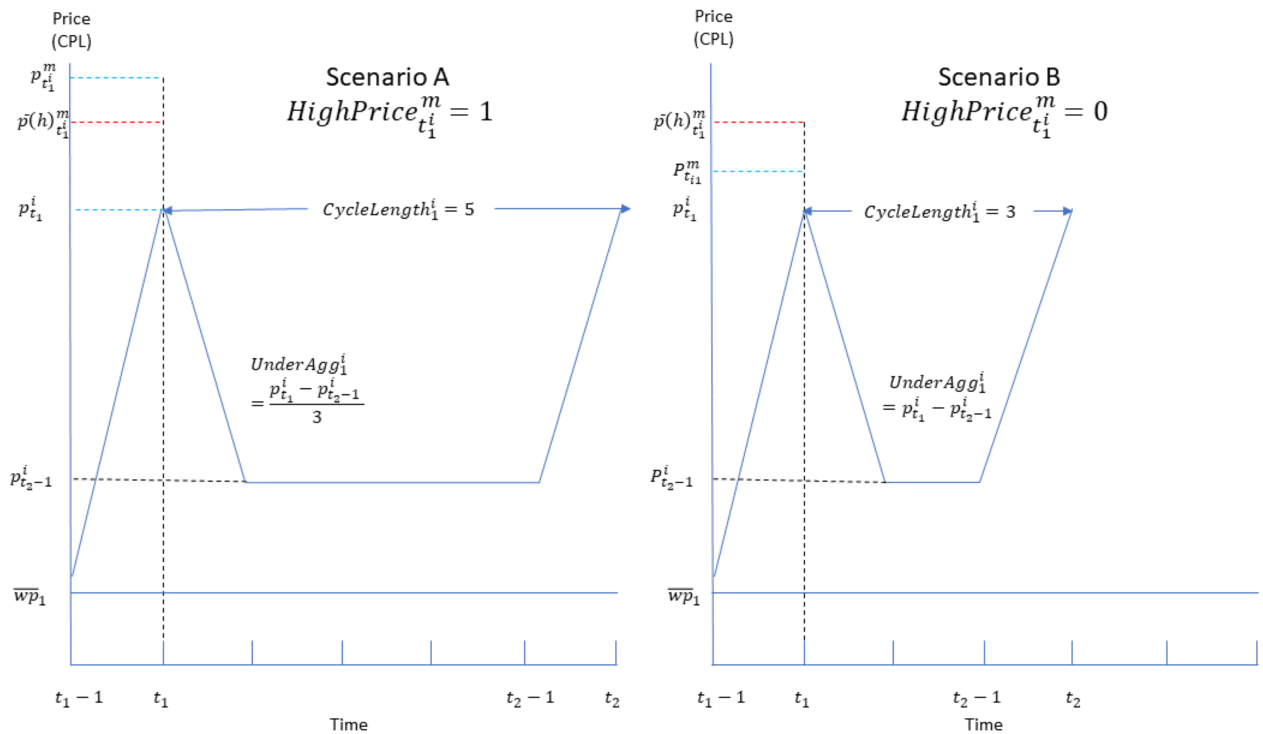


Table 4.1: SUMMARY STATISTICS

Variable	Mean	Std. Dev.	N
Panel:A			
Full cycle in days	27.107	57.562	43610
Undercutting phase in days	5.135	5.835	43610
War of attrition phase in days	20.972	56.814	43610
Panel:B			
$HighPrice$	0.742	0.438	43610
Market price (Cents per Liter)	137.965	10.44	43610
Reference-price* (Cents per Liter)	131.912	7.01	43610
All deviations from reference-price (Cents per Liter)	6.053	9.159	43610
Positive deviations from reference-price (Cents per Liter)	10.371	5.571	32354
Negative deviations from reference-price (Cents per Liter)	6.356	5.315	11256
Panel:C			
Restoration amplitutde (Cents per Liter)	12.684	9.888	43610
Undercutting amplitutde (Cents per Liter)	17.73	10.701	30188
Undercutting Aggresiveness by Price (Cents per Liter per day)	3.265	3.359	30188
Undercutting Aggresiveness by Retail Margin (Cents per Liter per day)	4.273	5.288	30150
Number of sampled dates		910	
Number of sampled stations		1347	
Number of sampled local markets		88	

Notes* *Reference-price is based on moving average of daily market prices in the past 360 days.

Table 4.2: MEANS OF CYCLE LENGTH AND UNDERCUTTING AGGRESSIVENESS BY *HighPrice*

	Cycle Length (Days)	Undercutting Aggressiveness (cpl)
$HighPrice = 0$	25.14	3.798
	(0.4126)	(0.0496)
$HighPrice = 1$	32.10	3.228
	(0.3020)	(0.0175)
Difference in Means	-6.966	0.5692
	(0.5499)	(0.0418)
p-value for the t-test	0.000	0.000

Table 4.3: EFFECT OF HIGHER-THAN-EXPECTED MARKET PRICE ON CYCLE LENGTH

Dependent variable:	Cycle length (days)		
	(1)	(2)	(3)
$HighPrice$	4.11***	6.770***	3.511***
	(0.524)	(0.891)	(0.616)
Own-price deviation			0.0397
			(0.0355)
Restoration amplitutde			-0.139***
			(0.0286)
ΔWholesale cost			0.0197
			(0.0493)
Undercutting amplitutde			1.191***
			(0.0556)
Number of stations in local market			0.523**
			(0.231)
Station FE	No	Yes	Yes
Brand FE	No	Yes	Yes
Date FE	No	Yes	Yes
Effect as percentage of the mean cycle length	15.1%	25.0%	13.0%
N	28,336	28,323	27,134
R^2	0.003	0.335	0.609

Notes* This table investigates the effect of elastic aggregate demand on price cycle length. Estimation in this table is based on the sub-sample of stations whose cycling ratio is greater or euquals to 1.5 and price cycles that contain at least price cut betwee price restorations. The dependent variable in all regressions is $CycleLength_{i(k-1)}$, measured in calendar days. Reference-price in this table is based on the average market prices in the past 360 days. Standard errors are clustered at the market m level. *** p<0.01, ** p<0.05, * p<0.1

Table 4.4: EFFECT OF HIGHER-THAN-EXPECTED MARKET PRCE ON UNDERCUTTING AGGRESSIVENESS

	Expected price cut		Expected margin cut	
	(1)	(2)	(3)	(4)
HighPrice	-0.418***	-0.724***	-0.802***	-0.868***
	(0.0827)	(0.204)	(0.116)	(0.224)
Own-price deviation		0.0825***		0.0737***
		(0.0149)		(0.0169)
Restoration amplitutde		0.0446***		0.0455***
		(0.00773)		(0.00813)
ΔWholesale cost		0.0505***		0.150***
		(0.0159)		(0.0218)
Undercutting amplitutde		0.0274*		0.0271*
		(0.0141)		(0.0154)
Number of stations in local market		-0.000155		0.00213
		(0.0727)		(0.0754)
Station FE	No	Yes	No	Yes
Brand FE	No	Yes	No	Yes
Date FE	No	Yes	No	Yes
Effect as percentage of the mean cycle length	-12.8%	-22.2%	17.0%	18.4%
N	19,091	18,018	19,075	18,002
R^2	0.003	0.408	0.006	0.438

Notes* This table investigates the effect of elastic aggregate demand on price cutting aggresiveness by gas stations. Estimation in this table is based on the sub-sample of stations whose cycling ratio is greater or euquals to 1.5 and price cycles that contain at least price cut betwee price restorations. The dependent variable in column (1) and (2) is the average pice cut per cycle , measured in cents per liter. Reference-price in this table is based on average market prices in the past 360 days. Standard errors are clustered at the market m level. *** p<0.01, ** p<0.05, * p<0.1

Table 4.5: DIFFERENTIAL EFFECTS BY STATION BRANDS

Dependent variable	Average price cut		Average margin cut	
	(1)	(2)	(3)	(4)
$HighPrice$	-0.630***	-0.355**	-0.900***	-0.461**
	(0.174)	(0.174)	(0.168)	(0.194)
$HighPrice$×Mobil		-0.130		-0.187
		(0.689)		(0.726)
$HighPrice$×BP		-0.504***		-0.707***
		(0.194)		(0.228)
$HighPrice$×Caltex		-1.101***		-1.243***
		(0.245)		(0.262)
$HighPrice$×Caltex Woolworths		-0.220		-0.298
		(0.228)		(0.258)
$HighPrice$×Shell		0.107		-0.454
		(0.572)		(0.780)
$HighPrice$×Shell Coles		0.00577		-0.0169
		(0.276)		(0.303)
$HighPrice$×Metrol		-0.105		-0.370
		(0.207)		(0.233)
$HighPrice$×Budget		-0.579**		-0.738***
		(0.246)		(0.282)
$HighPrice$×Speedway		-0.336		-0.942**
		(0.374)		(0.453)
$HighPrice$×United		0.441*		-0.00837
		(0.243)		(0.314)
$HighPrice$×Independent		-0.0626		-0.384
		(0.212)		(0.276)
N	18,016	18,016	18,000	18,000
R^2	0.419	0.422	0.441	0.443

Notes* This table investigates the differnetial effects of higher-than-expected market price by the brands of gas stations. Estimation in this table is based on the sub-sample of stations whose cycling ratio is greater or euquals to 1.5 and price cycles that contain at least price cut betwee price restorations. The dependent variable in column (1), (2) and (3) are cycle length measured in calendar days, the size of average price cut per cycle measured in cents per liter and the size of average margin cut per cycle measured in cents per liter. Reference price in this table is based on average market prices in the past 360 days. All regressions in this table include the fixed effects and covariates as column (4) of table 2. The percentage in parentheses next to the brand variable are the share of stations under that brand in the sample. Standard errors are clustered at the market m level. *** p<0.01, ** p<0.05, * p<0.1

Table 4.6: EFFECT OF HIGHER-THAN-EXPECTED MARKET PRICE WITH ALTERNATIVE PREFERENCE-PRICE

	(1)	(2)	(3)	(4)	(5)	(6)
h	30 Days	60 Days	90 Days	120 Days	240 Days	360 Days
Panel:A						
	Dependent variable: Cycle length					
$HighPrice(h)$	0.349	0.856*	1.645***	0.727*	1.943***	3.510***
	(0.463)	(0.440)	(0.587)	(0.406)	(0.577)	(0.616)
Panel:B						
	Dependent variable: Average cut in retail price per cycle					
$HighPrice(h)$	-0.625***	-0.690***	-0.816***	-0.458***	-0.859***	-0.868***
	(0.124)	(0.160)	(0.179)	(0.117)	(0.171)	(0.224)
Panel:C						
	Dependent variable: Average cut in retail margin per cycle					
$HighPrice(h)$	-0.642***	-0.726***	-0.816***	-0.451***	-0.796***	-0.724***
	(0.115)	(0.156)	(0.169)	(0.101)	(0.149)	(0.204)
N	27,973	26,999	25,793	24,873	22,179	17,878
R^2	0.491	0.510	0.471	0.478	0.495	0.587

Notes* This table investigates the effect of higher-than-expected market price on cycle length and undercutting aggresiveness by gas stations. Estimation in this table is based on the sub-sample of stations whose cycling ratio is greater or euquals to 1.5. The reference-price on which the $HighPrice$ variable is based on varies in each column by the time horizon of past prices. The regression models estimated in Panel A have the same dependent variable, covariates and fixed effects as column 3 of table 3. The regression models estimated in Panel B have the same dependent variable, covariates and fixed effects as column 3 of table 4. The regression models estimated in Panel C have the same dependent variable, covariates and fixed effects as column 4 of table 4. Standard errors are clustered at the market m level. *** p<0.01, ** p<0.05, * p<0.1

Chapter 5

Conclusion

Observed prices in the retail gasoline market may reflect more than just supply cost and product differentiation via static characteristics of the gas station. Historically, direct government intervention is only called for when there has been suspicion of collusive pricing. However, rapid advancement in technology has created a new advantage for gasoline companies in the form of algorithm pricing (Schechner (2017)). Algorithm pricing is an enhanced version of dynamic pricing strategy that allows gasoline companies to charge a price that is "always right": price is optimized continuously for maximizing profit by complex algorithms as soon as one or more of monitored market conditions have changes. Antitrust agencies such as the U.S. Federal Trade Commission (McSweeny and O'dea (2017)) has expressed concern that such pricing practice is potentially harmful for consumer welfare and may require changes in its enforcement practice. Findings from this dissertation therefore speak directly to this concern as they document possible channels through which gasoline companies may implement algorithm pricing.

The analysis in chapter 2 shows that gasoline companies may price in hourly changes in consumer travel cost. Specifically, unexpected variations in local traffic delay is found to have a positive and significant effect on the retail margins of gasoline. Further indication that this may be a manifestation of algorithm pricing is the finding that this type of margin response is limited to gasoline brands owned by leaders in the supermarket industry - another industry that is reportedly practicing dynamic pricing strategies (Adams (2017)).

Gasoline companies may also let their price to reflect dynamic changes in consumer search cost. Chapter 3 finds that traffic delay has an inverse-U relationship with the equilibrium price dispersion in this market which is consistent with the predicted relationship between search cost and equilibrium price dispersion by a consumer search model.

Analysis in chapter 4 suggests that gasoline companies may be monitoring dynamic changes in the price sensitivity of consumers. It finds that gasoline companies cut their price at a slower pace within a gasoline price cycle if current demand is inferred to be more price elastic.

In addition to highlighting possible channels for algorithm pricing in the retail gasoline industry, the findings of this dissertation also have policy implications. Specifically, chapters 2 and 3 suggest that consumers can benefit from policies that address traffic congestion as they will also promote competition and reduce search cost in the retail gasoline market. For antitrust policies, chapter 3 suggests that gasoline is priced competitively for about 94% of the time and chapter 4 establishes new empirical evidence that the observed gasoline price cycle is consistent with a theory of competitive price cycle.

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