Essays on Information, Competition, and Pricing Dynamics in the Retail Gasoline Market

Woo-Hyung Hong

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Reading Committee:

Fahad A. Khalil, Chair

Robert Halvorsen

Christopher M. Anderson

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Abstract

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Woo-Hyung Hong

Chair of the Supervisory Committee:
Caster Professor Fahad A. Khalil
Department of Economics

This dissertation studies the role of information in market performance, and pricing dynamics observed in the retail gasoline market. In Chapter 1, we empirically test whether smartphones, as information-providing devices, can improve market performance and reduce price dispersion. We treat the introduction of smartphones in the Korean gasoline market as a natural experiment to investigate the impact of smartphones on competition among gas stations. Smartphones provided consumers with direct access to price information through OPINET, a government-sponsored Internet website. Our results indicate that the adoption of smartphones is associated with dramatic decreases in price dispersion and average price-cost margins, thereby creating consumer gains. Additionally, we found a sudden decline in entries and a slow increase in exits after the introduction of smartphones.

Chapter 2 investigates how and why a link between market power and asymmetric pricing occurs. Exploiting unique island panel data from the Korean gasoline market, we propose geographical separation as a reliable measure of market power. Our findings confirm a positive correlation between market power and price-response asymmetry. We provide direct evidence of tacit collusion by investigating sticky pricing behaviors and suggest that the tacit collusion is the main channel through which market power influences asymmetric pricing. Additionally, we examine the effect of station heterogeneity on asymmetric pricing to provide

further evidence of tacit collusion even in relatively competitive environments.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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DEDICATION

To my wife, Kyounghee Ryu, and my two daughters, Amy and Ashley.

Chapter 1

DO SMARTPHONES SPUR COMPETITION? EVIDENCE FROM THE KOREAN RETAIL GASOLINE MARKET.

1.1 Introduction

As Stigler (1961) emphasized, limited or costly access to information can lead to excess price dispersion and an inefficient allocation of goods. Under these circumstances, the introduction of technology that improves access to relevant information can have important implications for market agents' behaviors and market performance, leading to increases in efficiency.

In this paper, we explore the introduction of smartphones in the Korean retail gasoline market as a proper natural experiment and investigate the impact of smartphones on competition among gas stations. The recent dramatic growth in the mobile phone industry, specifically the introduction of smartphones, has brought tremendous changes to our daily lives. In particular, smartphones have functioned as excellent information-providing devices. In the Korean retail gasoline market, smartphones have provided consumers with direct access to gas prices at every station in the country with the assistance of a pre-existing information channel called OPINET, a government-sponsored Internet website. Thus, smartphones have reduced search costs for consumers, thereby increasing competition among gas stations. Furthermore, the market serves as an experimental setting because the introduction of smartphones can be regarded as an exogenous event in the sense that the effect of smartphones on this market is unintended and at least *ex-ante* unexpected before their release.[1]

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[1] One sole concern regarding the potential endogeneity of the event is that consumers' decision of whether to purchase a smartphone is not random. If there are unobserved shocks that could affect stations' pricing decisions and individual smartphone adoption decisions, the effect of smartphones on price dispersion and

The conceptual framework for our analysis relies on clearinghouse search models (Varian, 1980; Stahl, 1989, 1996; Guimãraes, 1996; Chandra and Tappata, 2011), which yield the theoretical implication that the presence of high search costs reduces competition and causes an inefficient allocation of goods across markets. The model predicts that the market converges to competitive outcomes as consumers become perfectly informed. Therefore, the introduction of information technology, which substantially improves access to relevant information, should result in less price dispersion and lower price-cost margins. This enhanced competition among sellers improves welfare.

This paper investigates the impact of the introduction of smartphones, as a natural experiment, to assess the role of information in the functioning of markets. Our results are consistent with theory and indicate that the adoption of smartphones is associated with a *gradual* and significant one-third decrease in price dispersion. In addition, average price-cost margins decreased by 7.67 won (the Korean currency) per liter (approximately 2.64 cents per gallon) after the introduction of smartphones. A rough calculation based on 2010 gasoline consumption in Korea estimates savings from the reduction in price-cost margins to be approximately 78.5 million dollars per year, indicating significant consumer gains. Additionally, we explore the heterogeneous effects of smartphones on price dispersion, which allows us to pin down the equilibrium relationship between price dispersion and search intensity, which is non-monotonic in theory.

Further, we extend our argument to gas station entry and exit decisions, which is also a contribution to the information and price-dispersion literature. We find new results that the reinforcement of competition among sellers, stimulated by the introduction of smartphones, is associated with a dramatic decrease in the number of entries and a slow increase in the number of exits. The empirical analysis uses an ordered Probit model, as suggested by conventional empirical models, and verifies that the entry probability significantly decreases

average margins will be biased. However, it is unlikely that consumers purchase smartphones for the purpose of reducing search costs in the presence of either demand or supply shocks in the gasoline market. Therefore, we can presume that the exogeneity condition holds in this research design.

while the exit probability marginally increases after the introduction of smartphones in this market.

As noted by Aker (2010) and Goyal (2010), there are relatively few empirical studies on the impact of information on market performance. Most closely related to this paper, Jensen (2007) and Aker (2010) investigate how sellers' use of mobile phones improved market efficiency in India and Niger and find that the addition of mobile phone coverage was associated with a substantial reduction in price dispersion and an increase in welfare for market participants. However, the Korean gasoline market differs from the markets they focused on and is more consistent with theoretical models, in that consumers, instead of sellers, are the ones who search prices using the phones when optimizing their choices. This is also the case for Goyal (2010), who investigates a setting in which consumers compare prices through Internet kiosks in soy markets in rural Central India and derives similar implications regarding price dispersion. While the above papers targeted developing countries, Brown and Goolsbee (2002) explore the effects of Internet comparison shopping sites on the U.S. insurance market and provide evidence that information improves market performance even in a developed economy.

With frequent and observable price changes, the market for gasoline has already been noted to have desirable properties to study the relationship between price dispersion and consumer search in the context of a developed economy. In an insightful paper, Chandra and Tapatta (2011) rely on product differentiation in the gasoline market to model varying search intensities for different grades of gasoline by assuming that search costs are higher for higher grades. They show that price dispersion is also higher for higher grades. Pennerstorfer *et al.* (2014) obtain similar results on search intensity and price dispersion, relying on spatial variation in the proportion of informed consumers by assuming that commuters have better information about gasoline prices. In contrast, in this paper, we study the change in price dispersion over time due to the direct reduction of search costs as a result of the introduction of the smartphone.[2] We rely on a unique feature of the Korean gasoline market, OPINET,

[2]Another strand of the empirical literature on gasoline prices focuses on the relationship between price

which is a transparent information channel providing consumers with reliable price data free of charge. Smartphones distribute this information to consumers, thereby contributing to the dramatic reduction in search costs for consumers.

The contributions of this paper are twofold. First, the analysis and results shed light on the important role of information in the efficiency of markets. While some prominent empirical studies on this subject have focused on developing markets, this paper presents efficiency results for a developed economy. In this respect, this paper contributes to the growing literature that emphasizes the role of information, especially in a highly industrialized market system. Second, to the best of our knowledge, this is the first study that explicitly treats the introduction of smartphones as an exogenous natural experiment. Their introduction can be treated as an exogenous event, in that it is uncorrelated with economic shocks in the gasoline market and its effect on the market is unintended and at least *ex-ante* unexpected. Furthermore, this event can be broadly applied to other relevant research designs that study the role of information.

The remainder of this paper proceeds as follows. Section 1.2 provides background information on the Korean gasoline market: OPINET and the adoption of smartphones in Korea. In Section 1.3, we present a simple search model and derive testable predictions in our analysis. In Section 1.4, we describe the data and the identification strategy. Section 1.5 presents the main empirical results on price dispersion and average price-cost margins. In Section 1.6, we extend our argument to station entry and exit decisions. Section 1.7 concludes.

1.2 Backgrounds: OPINET and smartphones

To encourage consumer search behavior in the retail gasoline market, on April 15, 2008, the Korean government introduced the Oil Price Information Network (OPINET). Specifically,

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dispersion and the number of sellers (or seller density), which is ambiguous in theory. Barron, Taylor, and Umbeck (2004) demonstrate that the relationship is positive, whereas Lewis (2008) finds that it is negative using a more localized dispersion measure. Lach and Moraga-Gonzalez (2009) investigate the asymmetric effect of seller density on price and demonstrate that low price is falling while high price is rising with the number of sellers and thus the price distribution becomes more dispersed.

OPINET, operated by the Korea National Oil Corporation (KNOC), provides consumers with real-time gasoline price information and detailed characteristics for all stations in the country.[3] This information is provided to consumers free of charge, and the price information is highly accurate, precise, and reliable because the website uses a credit card payment system to collect the information. Once a consumer purchases gasoline with a credit or debit card, information such as the gasoline price per liter, the name of the station, and its address is automatically and electrically sent to financial network providers and stored in their databases. Then, OPINET publishes and updates the information from the databases every 6 hours.

The website became widely popular among Korean consumers shortly after its launch. It experienced serious server overload soon after it went live due to excessive connections.[4] Since then, there have been two additional server overloads, one on Nov. 29, 2011 and another on Feb. 23, 2012, for the same reason. This evidence supports our argument that OPINET was both well known among consumers and continuously used by consumers when selecting a gas station.

Recent technological progress in the mobile phone industry led to tremendous growth known as the smartphone revolution. The technology was widely and rapidly adopted after its invention, especially in Korea. Figure 1.1 depicts the number of smartphone users over time and illustrates that the adoption of smartphones has been remarkably rapid since the introduction of the iPhone in Korea on November 28, 2009.[5] In February 2010, the release

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[3]The station characteristics that OPINET collects include geographical location, discount information, brand, and whether the station is self-service and/or has such facilities as a convenience store, car wash, and auto repair shop.

[4]A Korea Herald article on April 15, 2008 reports that OPINET experienced a server overload because approximately 0.3 million users had attempted to access the website simultaneously.
http://news.heraldcorp.com/view.php?ud=200804150181&md=20100403225726_AE

[5]The iPhone was unveiled to the public on January 9, 2007 and went on sale in the United States on Jun 29, 2007. Apple initially released the iPhone in the U.S. and European countries and made it available in other countries after iPhone 3GS was announced on June 8, 2009. Approximately two years were required before the iPhone become available to Korean customers. Thus there was sufficient time before the iPhone's release for awareness of its uses and features to spread among potential customers in Korea. This implies that the adaptation speed of this innovative technology was sufficiently rapid that the effect

of Android phones further spurred the adoption of smartphones. According to the figure, more than one-third of the Korean population adopted the technology within one and a half years after the release of the iPhone. This implies that smartphones were not an effective information channel until the iPhone was released.[6] Therefore, we treat the timing of the iPhone release as the beginning of the impact of smartphones on the gasoline market.

In the Korean gasoline market, smartphones contributed to a significant reduction in search costs for consumers because they are portable and immediately distribute reliable price data to consumers. First, the portability of smartphones enables consumers to search gasoline prices while driving, which is a novel feature added in this market due to the introduction of smartphones. Clearly, consumers can easily check gasoline prices on the Internet before driving; however, consumers generally only begin to search prices when they are on the road and low on gas. In this situation, smartphones are very useful because they provide price information whenever consumers need it. Second, smartphones functioned as a channel through which all information from OPINET was distributed. The optimal delivery mechanism for this information was through smartphone applications (hereafter, apps). Currently there are numerous gasoline price search apps that provide consumers with the prices of all stations in their vicinity even with GPS capabilities.[7] These apps are easy to download from the app store at no or little cost and offer a user-friendly interface. Another possible channel to distribute the price information was through a built-in web browser. Even before the apps were developed, the web browser allowed smartphone users to easily access the website. Because, as discussed above, consumers rapidly adopted OPINET, we expect the effect of smartphones on the market to be immediate and increasing in the number of smartphone users. In this respect, smartphone users are willing and able to search more

of smartphones on the gasoline market was prompt.

[6]The history of smartphones is longer than we would expect. Although the iPhone is not the first smartphone, it functioned as a catalyst for growth in the smartphone industry. Thus it is not an overstatement that the effect of smartphones began with the introduction of the iPhone.

[7]Nearly all apps use information on prices and station characteristics that is directly obtained from OPINET. Thus, their information is also precise and reliable. Furthermore, OPINET has provided a complimentary smartphone application since May 26, 2010.

often. As a result, information becomes more symmetric in this market as consumers search more.

1.3 Theoretical model and predictions

In this section, we derive testable theoretical predictions from the clearinghouse model developed by Chandra and Tappata (2011), which describes the implications of Varian's (1980) model of sales. In their model, consumers are categorized into two groups depending on their search costs: 'informed' consumers and 'uninformed' consumers. 'Informed' consumers, who have low search costs, obtain all price information by searching and only purchase from the lowest-priced seller. 'Uninformed' consumers never search because their search costs are sufficiently high and, instead, purchase from the first seller they encounter. Given the identical costs of sellers, the equilibrium reflects a mixed-strategy Nash pricing equilibrium, which results in price dispersion. Details are provided below.

In their model, n firms have the identical unit cost c and compete on price in a homogeneous goods market. There is a unit mass of consumers who have unit demand for the product with a maximum willingness to pay of $v > c$. A fraction $\lambda \in (0, 1)$ of consumers has zero search cost and is always informed of all prices that firms charge. The remaining consumers have positive search costs s, drawn from a continuous distribution $G(s)$ on the support $s \in [0, \bar{s}]$. Of these, certain consumers are informed of all market prices through searching in the expense of search costs while others are uninformed because of sufficiently high search costs. The proportion of informed consumers determines search intensity μ in this market.

Varian (1980) proved that for any $\mu \in (0, 1)$, there is no pure strategy equilibrium but a unique mixed-strategy Nash pricing equilibrium exists, and the equilibrium price distribution is given by:

$$F(p) = 1 - \left[\frac{1-\mu}{\mu n}\frac{v-p}{p-c}\right]^{\frac{1}{n-1}} \tag{1.1}$$

where $p \in [p^*, v]$ and the lowest price yielding positive profit is $p^* = \frac{cn\mu+(1-\mu)v}{1+(n-1)\mu}$. It is straightforward to demonstrate that the proportion of informed consumers is directly related to the degree of competition. At one extreme, when the proportions approaches 1 ($\mu \to 1$), the price domain increases ($p^* \to c$) and, in the limit, the entire distribution collapses to the marginal cost (competitive outcome); in contrast, the price domain collapses to $p = v$ (monopoly) at the other extreme ($\mu \to 0$), and each firm becomes a monopolist over $1/n$ consumers.

The expected benefit of searching associated with equation (1.1) now becomes:

$$E\left[p - p_{\min}\right] = \int_{p^*}^{v} p\left[1 - n(1 - F(p))^{n-1}\right] dF(p) \tag{1.2}$$

where $p_{\min} = \min(p_1, p_2, ..., p_n)$ and p_i is the price of firm $i = 1, ..., n$. As shown in Chandra and Tappata (2011), the benefit is a non-monotonic concave function of search intensity, which takes value zero at two extremes ($\mu = 0$ and $\mu = 1$).[8] More important, equation (1.2) can be interpreted as a measure of price dispersion in this model.[9] Finally, the equilibrium level of search intensity is determined by comparing the expected benefit of searching and the marginal consumer's search cost. Define the search cost of an indifferent consumer as s^* such that $E\left[p - p_{\min}\right] = s^*$. Then, the optimal search intensity becomes $\mu^* = \lambda + G(s^*)(1 - \lambda)$, which in turn determines equilibrium price dispersion.

We now demonstrate the equilibrium relationships between search intensity and price dispersion and margins. Figure 1.2 plots the expected benefit of searching (a concave curve) and the search costs of the marginal consumer (upward-sloping curves) over the proportion of informed consumers.[10] The equilibrium levels of search intensity and price dispersion are determined at the intersection of the two curves. Here, we can represent a decrease in search costs as shifts or rotations of $G^{-1}(s)$ to the right (e.g., the movement from $G_H^{-1}(s)$

[8]Chandra and Tappata (2011) and Pennerstorfer *et al.* (2014) proved that the function is strictly concave.

[9]Chandra and Tappata (2011) compare this dispersion measure with the traditional measures of price dispersion, such as the sample range and the standard deviation, and demonstrate that all measures resemble one another.

[10]The figure is nearly identical to Figure 8 in Chandra and Tappata (2011).

to $G_L^{-1}(s)$; H and L refer to high and low search costs, respectively). Then, the figure clearly demonstrates that price dispersion increases (Scenario 1) or decreases (Scenario 2) as search intensity increases. By defining $\hat{\mu}$ as the search intensity that maximizes the expected benefit of searching, we can formally state that as search intensity increases, price dispersion increases if $\mu^* < \hat{\mu}$ and decreases if $\mu^* > \hat{\mu}$. Conversely, the model predicts that an increase in search intensity makes the market more competitive, i.e., the price distribution collapses to the marginal cost, implying that margins or markups, on average, decrease.

1.3.1 Testable predictions

The theoretical model also provides similar predictions regarding price dispersion between markets (in our context, cities/districts) and average margins. Suppose that there are K identical markets as described above. Then, given the proportion of informed consumers, $\mu \in (0,1)$, the average price in each market $k = 1, ..., K$ is calculated by the geometric sum of the realized prices of stations drawn from the price distribution given by equation (1.1). Although the expected values of average prices are identical in every market, the variance of average prices across markets (price dispersion between markets) is not zero but depends on the equilibrium price distribution of equation (1.1) or, more specifically, the proportion of informed consumers, μ. Note that over the horizon of price supports, $p \in [p^*, v]$, the distribution is left-skewed if $\mu \to 1$ and is right-skewed if $\mu \to 0$, and in both cases, collapses to each extreme in the limit; when the proportion takes intermediate values, the price distribution is more or less balanced. This implies that price dispersion between markets is also a concave-shaped function of the proportion of informed consumers, which resembles the dynamics of price dispersion within a market as described by equation (1.2).[11] Obviously, we expect that average price-cost margins decline as the search by informed

[11]This discussion indicates that price variations between stations are closely related to those between cities/districts. In appendix A.1, we assess this by collecting *ex-post* supplementary price data for all operating stations in Seoul for a 30-day period, April 10 to May 9, 2013. The results show that district-level price dispersion (our dispersion measure) is highly correlated with station-level price dispersion and provide a possible justification for using average prices to infer stations' behaviors.

consumers is reinforced, as all stations in each market are more likely to set their prices close to the marginal cost (competitive outcome).

Yet, these predictions might be unclear when each market has different marginal costs that differ substantially across markets. However, this concern is minimized in our research design because wholesale gasoline prices, which account for most of the variable costs, are generally uniform across stations and cities in Korea. Therefore, when information asymmetry is removed from the markets (especially when $\mu \to 1$), average prices become closer across markets, as stations within a market set their prices near their marginal costs, which are fairly homogeneous across stations and cities. As a result, price dispersion across markets will decrease as the proportion of informed consumers approaches 1.

Finally, we now derive testable theoretical predictions for our empirical analysis. In our research setting, the introduction of smartphones exogenously reduces consumers' search costs, or increases the number of informed consumers, thereby increasing search intensity. Accordingly, one testable prediction we can draw from the model is that average margins decrease after the release of smartphones. However, the prediction regarding the price dispersion associated with the introduction of the smartphone is ambiguous. Our intuition would say that the use of smartphones moves the proportion of informed consumers toward 1, leading to the competitive outcome. Therefore, Scenario 2 (dispersion decreases) is more plausible in this market, judging from the fact that the technology was introduced after OPINET was launched and widely used by consumers. For a clear check, we conduct an empirical analysis similar to that of Chandra and Tappata (2011) to pin down the location of the current equilibrium. According to Figure 1.2, price dispersion for consumers with high search costs ($G_H^{-1}(s)$) is lower than that for consumers with low search costs ($G_L^{-1}(s)$) in Scenario 1 but is higher in Scenario 2. In our empirical analysis, we therefore explore the heterogeneous effect of consumers' search costs on price dispersion to determine the current status of the equilibrium in this market.

1.4 Data and identification strategy

1.4.1 Data and descriptive statistics

The data are gathered from several sources, and the sample period spans from April 15, 2008 to December 31, 2011. We collect daily average gasoline prices by city (232 cities) and weekly average after-tax wholesale prices from OPINET.[12] Because of the reliable data collection process through the credit card payment system, measurement errors in prices are expected to be minimal. The second primary data source is the Korea Gas Station Association, from which we obtain station information such as the number of gas stations, the number of vertically integrated stations by brand, and the number of exits and entries at a province/metropolitan city level.[13] Monthly population by age and gender and the number of automobiles are collected from the Ministry of Knowledge Economy and Statistics Korea, respectively.[14] Unfortunately, we were unable to obtain data on region-specific smartphone adoption rates. Instead, this paper uses an indicator variable that equals one after the introduction of the iPhone.

To describe dynamic changes in price dispersion, we first consider two unconditional dispersion measures applied in other studies (e.g., Jensen, 2007; Aker, 2010): (1) the coefficient of variation (the standard deviation divided by the mean in a given week) and (2) max-min price spreads (the difference between the highest and the lowest prices in a given week). Figure 1.3 presents box-plots of these measures by month. As the figure indicates, the degree of price dispersion was high and volatile before the iPhone's release; however, there is a striking reduction in price dispersion and the measures of dispersion become less dispersed

[12] Because OPINET only provides historical price data in the form of city averages, we collect daily average price data by city. Further, the after-tax wholesale price is calculated as nationwide average prices at which intermediate sellers and refiners sell to individual retail gas stations.

[13] Exits and entries are only recorded when stations newly register or cancel their registration.

[14] There are two main data sources for the Korean population. One is the Korean census, which is administered every 5 years. The other is the resident registration data, which are calculated each month. Regarding data credibility, the census is preferable to the resident registration data. Nonetheless, the latter data are used because we believe that the monthly time variation can account for the periodical demand factors.

thereafter. In other words, the figure clearly demonstrates the extent to which the changes in price dispersion were sudden and large with the timing that corresponds closely to the date when the iPhone was first introduced in Korea.

Further supporting evidence can be found in Table 1.1, which presents descriptive statistics for the average price-cost margins (the difference between retail and wholesale prices) and the two dispersion measures before and after the introduction of smartphones. The results demonstrate that both the mean and standard deviation of the margins and the two dispersion measures decrease considerably after the iPhone becomes available. In contrast to the small changes in margins, there are substantial decreases in the coefficient of variation (a 34.7 percent reduction) and the max-min spread (a 38.4 percent reduction). The last column of the table reports the differences in the means, which are significant at the 1 percent level.

1.4.2 Estimation model and identification strategy

Similar to Barron, Taylor, and Umbeck (2004) and Lewis (2008), this paper considers a heteroskedastic regression model of gasoline prices. Most important, measuring price dispersion requires us to control for price differences resulting from heterogeneity across markets. To do so, we include city and day fixed effects in the estimation model to account for both unobserved and observed characteristics on price differences. The city fixed effects identify any persistent price difference between cities due to different market environments, and the day fixed effects capture changes in the average price level over time, which are primarily driven by wholesale price movements. Therefore, we begin by considering the following price equation to elicit a measure of price dispersion:

$$p_{ct} = \alpha_c + \gamma_t + u_{ct} \tag{1.3}$$

where p_{ct} is the average gasoline price in city/district c on day t and α_c and γ_t are city and day fixed effects, respectively. Each residual, $\hat{u}_{ct}$, indicates whether the gasoline price of a city is above or below its expected level. Therefore, we use the estimated variance of the residuals as a measure of price dispersion. By using this dispersion measure, we essentially explore day-to-day temporal variations in city average prices.[15]

Although less than ideal, our dispersion measure using average prices can be employed to indirectly infer stations' behavior on the basis of our theoretical model. The model predicts that as information asymmetry is removed from the markets ($\mu \to 1$), all stations within a market are likely to set their prices close to their marginal costs, and thus, average prices across markets also become closer to the marginal costs. This implies that given similar marginal costs across markets, price dispersion between stations moves in the same direction as price dispersion between markets as the search intensity μ increases. This prediction is also supported by the fact that wholesale prices, representing most of variable costs, are fairly homogeneous across stations and cities in Korea. In this sense, we use our dispersion measure to indirectly estimate the changes in price dispersion between stations caused by the introduction of smartphones.

To exploit station characteristics at a province/metropolitan city level, the measure of price dispersion is weighted using the number of stations.[16] We assign greater weight to price dispersion if a city/district has a relatively large number of gas stations as a share of the total number in a province/metropolitan city.[17] The weighted dispersion measure at the province/metropolitan city level is calculated by:

$$\hat{u}_{it}^2 = \sum_{c=1}^{n_i} \omega_c \hat{u}_{ct}^2 \quad where \quad \omega_c = \frac{\#(stations\ in\ c)}{\sum_{c=1}^{n_i} \#(stations\ in\ c)} \tag{1.4}$$

[15]It is worth noting that the main reason for price dispersion in the Varian (1980) model lies in "hit-and-run" pricing strategies, which keep consumers guessing stations' prices over time. In this sense, our dispersion measure that explores temporal variation is consistent with the theoretical model on which we rely.

[16]The number of stations is gathered from OPINET at one spot day, January 5, 2012. It relies on the underlying assumption that the share of stations in a city within a province does not vary substantially over time.

[17]Korea is composed of 9 provinces and 7 metropolitan cities. Each province consists of several cities, and each metropolitan city consists of municipal districts. In terms of population, cities and districts can be regarded as comparable classes.

where $\hat{u}_{ct}$ is the residual from equation (1.3) in city c $(= 1, ..., n_i)$ on day t and $\hat{u}_{it}^2$ is the measure of price dispersion in province i on day t. Finally, the following estimation model is considered to analyze the effect of smartphones on price dispersion:

$$\ln\left(\hat{u}_{it}^2\right) = \alpha_i + \beta_1 S_t + \beta_2 \tau_t + \beta_3 S_t \times \tau_t + X_{it}\gamma + \varepsilon_{it} \tag{1.5}$$

where S_t is an indicator variable that equals one after the introduction of the iPhone, τ_t is the linear time trend, which has zero value at the time of the iPhone's release, α_i are province fixed effects, and X_{it} are monthly or weekly independent variables including after-tax wholesale gasoline price, population of individuals aged 25-65, the proportion of females, number of sedans, number of entries and exits, proportion of vertically integrated stations and pseudo-HHI.[18] ε_{it} is the error term.

Identification challenges and the selection of sample periods

A key concern in the estimation of equation (1.5) is that the estimated measure of price dispersion could be overestimated due to a failure to control for all unobserved components in the price equation. Thus, addressing omitted variable bias becomes crucial in our regression. To alleviate this problem, we include province fixed effects to account for province-specific unobserved heterogeneity. In addition, observed characteristics of both demand and supply are added to the estimation equation to explain the effect of observed market environments on price dispersion.

Clearly, the inclusion of both province fixed effects and observed characteristics cannot completely eliminate omitted variable bias due to the inability to control for all unobserved variables that change over time. A typical approach controlling for unobserved time-specific shocks or characteristics is to include time fixed effects in the estimation. Unfortunately, this strategy is not desirable in our research setting: because the introduction of smartphones was

[18] Only the after-tax wholesale gasoline price is weekly and others are monthly. The pseudo-HHI (Herfindahl-Hirschman Index) is calculated as the sum of the squared market share of each brand, where market share is calculated using the number of stations of each brand instead of quantity sold.

simultaneous country wide and their adoption took place gradually rather than all at once, time fixed effects will subsume not only time-specific macroeconomic shocks but also the common effects of smartphones. However, the latter effect is unintended and unfavorable. More important, it hampers identifying the effects of smartphones in the data.

To mitigate these identification issues, this paper adopts a simple and direct approach. Note that the key point regarding the identification is to design the market environments to be as close as possible before and after the introduction of smartphones so that the differential changes exclusively stem from the use of smartphones. Now this just becomes a selection problem. How much time before (or after) smartphones were introduced should be considered a "good" control (or treated) group? To determine this, we directly identify macroeconomic shocks by statistically detecting structural breaks using the time series method developed by Bai and Perron (1998, 2003) and restrict our attention to the period under the same regime while trying not to include time fixed effects in the estimation. Specifically, we use average wholesale prices as a representative cost variable to detect macroeconomic cost shocks that are primarily driven by global incidents. This identification strategy suggests a more rigorous criterion for selecting sample periods to control for the effect of macroeconomic shocks (in this market, the U.S. financial crisis and the pro-democratic movements in North Africa and the Middle East) rather than arbitrarily selecting the periods of interest.

Several aspects of this market make the proposed identification strategy appropriate. First, the channels through which macroeconomic cost shocks occur should be simple because few inputs are required for gasoline production, e.g., crude oil. Furthermore, it should be noted that Korea depends entirely on crude oil imports, implying that there are no alternatives to buffer worldwide macroeconomic cost shocks originating from exporting countries such as members of OPEC. As a result, exogenous global cost shocks are spontaneously reflected in the retail prices not only by directly affecting the input price but also by altering the expectations of market participants. Second, demand-driven macroeconomic shocks, which might make the direct identification of macroeconomic shocks highly complex, are expected to be minor in the gasoline market. One obvious reason is that demand shocks rarely occur in that market, and any substantial changes in government policies affecting consumers' behaviors were not observed during the period of interest. Even if there were an unobserved demand shock, it might be able to affect the first moment of price but cannot significantly affect the second moment because demand for gasoline is known to be unresponsive. Indeed, we include the observed demand- and supply-related characteristics in the estimation to account for observed heterogeneity across time and regions.

1.5 Empirical results: price-setting behavior

1.5.1 Identifying the macroeconomic cost shocks

We attempt to identify the macroeconomic cost shocks in a rigorous manner and discuss the sources of the shocks. Average wholesale prices are adopted as an approximation of the cost structure of retail gas stations because: (1) wholesale prices explain most of the retailers' variable costs and (2) cost shocks are directly reflected in the wholesale prices due to the industry's simple distribution structure.[19] Using the series, we apply Bai and Perron's (1998, 2003) method (hereafter, BP) to statistically identify possible structural breaks and the macroeconomic cost shocks. The basic outcomes are summarized in Figure 1.4. More detailed statistics and discussions concerning the method are presented in appendix A.2.

Figure 1.4 plots the average wholesale gasoline prices with the detected break points. The horizontal axis represents the number of weeks, which equals zero if it is the week of the iPhone's release, the first week of December. We identify four structural breaks that separate our period of interest into five segments, which we label I-V on the graph. Surprisingly, the first break occurred three weeks after Lehman Brothers Holdings Inc.'s bankruptcy on September 15, 2008, and the fourth break coincides with the inception of the pro-democratic movement in North Africa and the Middle East. The second break can be interpreted as the beginning of Korea's economic recovery from the U.S. financial crisis.

In contrast, the reason for the third break is not immediately clear. As a matter of fact,

[19] There are at most three steps: refiners, local distributors and retail gas stations.

it is difficult to determine whether there is a break between regime III and IV. One possible explanation for this break is the simple underlying estimation model, a constant regressor model. Because the basic process of the BP method is to minimize the sum of squared residuals with breaks, a constant regressor model might overestimate the number of breaks because it ignores other covariates that could affect the wholesale gasoline price. The other possible explanation is the introduction of smartphones. Factoring in the market interaction between retailers and refiners or distributors, it is reasonable to argue that the third break is due to the use of smartphones. Moreover, this argument is also bolstered by the observation that the break occurs one month after the iPhone's release and the 95 percent confidence intervals of the third break include the timing of the introduction of the iPhone.[20]

In the following empirical analysis, we posit that no macroeconomic cost shocks were present in regimes III and IV and that the two regimes share the same economic environment. The only difference is that regime IV is after the release of the iPhone. Therefore, our period of interest spans from May 21, 2009 to December 12, 2010, which corresponds to the range of $-190 \leq \tau_t \leq 380$.[21]

1.5.2 Price dispersion and margin

Price dispersion

We first apply a local linear regression to graphically depict our estimation specification. The results are displayed in Figure 1.5. The horizontal axis represents the number of days, which takes a value of zero at the time of the iPhone's introduction. Each point is an average of the log of squared residuals from equation (1.4) for each 5-day interval. We divide the

[20]In the following analysis, we use the timing of the smartphone's introduction instead of the third break point to investigate the impact of smartphones on this gasoline market. However, the main results remain the same even when we use the third break point indicated by the BP method to refer to the beginning of the smartphone effect.

[21]The sample periods of interest are chosen between the left end and the right end of 95 percent confidence intervals of the second and the fourth breaks. However, our analysis is not sensitive to the choice of sample periods within the 95 percent confidence intervals of the break points.

pre- and post-iPhone time periods with a dashed vertical line. In addition to local average points, Panel A incorporates a linear fit while Panel B applies a more flexible quadratic fit.

Figure 1.5 summarizes one of the key results of this paper. It demonstrates that the introduction of smartphones is associated with a significant and gradual reduction in gasoline price dispersion across markets. Additionally, it indicates that at approximately 250 days after the introduction of smartphones, price dispersion ceases to change and appears to converge to a new level. A similar analysis was conducted using the entire sample period and is summarized in Figure 1.6. In that figure, each point is obtained in the same way and separate quadratic fits are applied in each regime corresponding to Figure 1.4. The graph clearly illustrates that two global shocks, the U.S. financial crisis and the pro-democratic movement in North Africa and the Middle East, are responsible for extensively inflating the level of price dispersion. This implies that improper controls for macroeconomic cost shocks would provide misleading conclusions concerning the effect of smartphones on this market. Our proposed identification strategy corrects for these shocks.

Table 1.2 presents the regression results of equation (1.5), focusing on the selected sample period. Columns (1) - (3) use the log of weighted squared residuals described by equation (1.4) as dependent variables, while columns (4) and (5) consider the log of squared residuals directly obtained from equation (1.3). The results in columns (1) and (4) corresponding to panel A of Figure 1.5 report significantly negative coefficients on both the iPhone and the interaction term with a linear time trend, indicating that the introduction of smartphones contributed to gradually reducing price dispersion. On the basis of the estimations, price dispersion with smartphone coverage is on average 33.4 and 33.6 percent lower than without it. In Column (2), which corresponds to panel B of Figure 1.5, we allow for a more flexible quadratic trend. The results confirm that the decreasing trend is indeed gradual and report that the reduction in price dispersion is approximately 39.9 percent at the minimum of the trend.

For robustness checks, we also take into account how smartphone penetration affects the price dispersion in this market. To obtain the smartphone penetration ratio, denoted by $SmartPen$, we first calculate the proportion of smartphone users among mobile phone users in each month and then linearly interpolate the monthly observations. Columns (3) and (5) of Table 1.2 indicate that the coefficients on $SmartPen$ are significantly negative, which confirms that the reduction in price dispersion is associated with consumers' use of smartphones.

Finally, we examine the equilibrium relationship between price dispersion and some key variables: wholesale price and the number of entries and exits. In the search model developed by Chandra and Tappata (2011), they characterize that price dispersion is negatively related to marginal costs but positively related to the number of firms in equilibrium. Our estimations in Table 1.2 provide results consistent with these predictions. The coefficients on wholesale prices, representing marginal costs, are all negative but insignificant in two specifications. The coefficients on the number of entries (increases in the number of firms) are all significantly positive, whereas those on the number of exits (decreases in the number of firms) are all significantly negative. These results support that the market behaviors observed in this study are consistent with the consumer search model described in Section 1.3.

Dynamic effect of smartphones

Although we have attempted to control for macroeconomic cost shocks, there is still an omitted variable problem because of unobserved variables that vary with time and region. To address this issue, we employ a dynamic panel model. One advantage of the model is that we can control for omitted variables in the sense that the lags of the dependent variable are the best proxies for possible unobserved variables. In other words, treating the lagged dependent variables as predetermined enables us to control for the majority of serially correlated unobserved variables. In addition, the model estimates the dynamic adjustment of the smartphone effect over time and allows us to calculate the ultimate long-run effect of smartphones on the market. Following the convention for estimating the model, the

Arellano-Bond estimator is applied in the analysis.[22]

The results of the model with lagged dependent variables are presented in Table 1.3. Controlling for all other covariates and regional fixed effects, the iPhone coefficients remain negative and significant at the 10 percent level (and are close to the 5 percent level), representing the initial impact of introduction of smartphones.[23] Furthermore, these results are robust to the inclusion of additional lags in the estimation. The long-run treatment effects are calculated as $\beta_1/(1-\rho^*)$, where $\rho^* = \sum_i \rho_i$ and ρs are the coefficients of lagged dependent variables. The point estimates obtained using this formula indicate that the introduction of smartphones eventually contributed to a 33.5 to 34.9 percent reduction in the price dispersion in the market.

Arellano and Bond (1991) pointed out that the estimator performs poorly in the presence of serially correlated errors in levels and proposed a test for autocorrelation in the first-differenced errors. When there is no serial correlation in errors in levels, then the first-differenced errors are only first-order serially correlated but not at higher orders. The results in Table 1.3 confirm this.

Margin and markup

To assess the profitability of stations, we estimate analogous specifications to equation (1.5) by replacing the dependent variable with city average price-cost margins and markups (price-cost margins over price). The results of Table 1.4 clearly demonstrate that city average margins and markups decrease with statistical significance after smartphones were released. According to Column (1), the average margin declines by 7.67 won per liter (approximately 2.64 cents per gallon). Based on 2010 gasoline consumption, we estimate that Korean consumers received aggregate benefits of approximately 78.5 million dollars per year from the

[22]Because the data span a long time period, too many instrumental variables should be used according to Arellano and Bond (1991). Therefore, we allow for the choice of instrumental variables to be up only to 3 lags in the analysis.

[23]The p-values of the coefficients are 0.067, 0.065, and 0.071, respectively. Moreover, all of them are significant at the 1 percent level when the standard errors are not adjusted.

margin reduction. These savings imply enormous consumer gains if they are directly transferred to consumers.

Although the model in Section 1.3 ignores the possibility of collusion, a more transparent market environment induced by the provision of smartphones would provide stations with certain incentives to coordinate. Assuming that collusion is successful within the framework of our theoretical model, all stations will coordinate on the monopoly price v, which in turn results in a decrease in price dispersion and an increase in margins. However, our results in Table 1.4 prove that such coordination is highly unlikely because average margins or markups decrease after the introduction of smartphones. Therefore, we can derive the conclusion that collusive behavior among stations cannot be a possible explanation for the substantial decrease in price dispersion in this market.

In addition, Table 1.4 demonstrates that wholesale prices are negatively and significantly related to margins or markups, implying asymmetric price adjustment to cost changes. This is particularly in line with the past studies on the "rockets and feathers" phenomenon in the retail gasoline market (Borenstien, Cameron, Gilbert, 1997; Deltas, 2008; Verlinda, 2008; Lewis, 2011).[24] The results also show that the coefficients on the number of exits are positive and statistically significant at the 1 percent level whereas those on the number of entries are all insignificant. This indicates that in this market, margins or markups are not significantly affected by new entries, whereas a decrease in the number of stations substantially improves stations' margins or markups, meaning that less competition increases the profitability of stations.

1.5.3 Heterogeneous effects of smartphones

Our previous results demonstrate that the introduction of smartphones is associated with decreases in price dispersion and average margins. These results imply that the current

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[24] These studies investigate a commonly observed phenomenon that prices respond more rapidly to cost increases than to cost decreases, which implies a negative relationship between margins (or markups) and costs.

status of the equilibrium relationship between price dispersion and search intensity follows Scenario 2 in Figure 1.2 (i.e., dispersion decreases with search intensity). To support this, we further explore the heterogeneity of the treatment effect of smartphones on price dispersion to address the following arguments: if Scenario 2 is true and the decrease in price dispersion is primarily driven by smartphones, (1) price dispersion should decline more rapidly in urban areas (low search costs) than in rural areas (high search costs), as the adoption rate of smartphones is expected to be substantially faster in urban areas, and (2) the reduction in price dispersion will be greater when demand is high and the market is less rigid. The first argument is particularly useful because it tests whether price dispersion for consumers with low search costs is lower or higher than its counterpart and helps us pin down the current status of the equilibrium relationship between price dispersion and search intensity.

While analyzing the former argument, we encountered difficulties in applying the triple difference method to estimate the adjustment speed of price dispersion because the decreasing trend was not linear, as depicted in panel B of Figure 1.5. Accordingly, estimation using the whole selected sample (i.e., $-190 \leq \tau_t \leq 380$) would yield spurious results. Thus, we consider shorter treatment periods during which price dispersion actively declines. In the first two columns of Table 1.5, we present the triple difference results restricting the treatment period to be either 200 days or 250 days prior after the iPhone's introduction.

First, the negative coefficients on metropolitan city interacted with iPhone demonstrate that after the release of smartphones, price dispersion in metropolitan cities is lower than other areas. This implies that price dispersion is lower in a market in which consumers' search costs are reduced relatively more than in other areas because of the more rapid adoption of smartphones. Second, the triple interaction terms are negative and statistically significant, indicating that the decreasing trend of price dispersion after the beginning of smartphone use is more negatively sloped in metropolitan cities than in other areas, i.e., price dispersion decreased much more rapidly in metropolitan cities. From these results, we can confirm that the current equilibrium represents Scenario 2.

The last three columns of Table 1.5 report the results of interacting iPhone with population and/or the proportion of vertically integrated stations. Here, population and the proportion of vertically integrated stations are selected as the representative variables for demand and market rigidity, respectively. Negative coefficients on population interacted with iPhone illustrate that high demand affects price dispersion more negatively after the arrival of smartphones. The positive coefficient on the interaction term between the proportion of vertically integrated stations and iPhone confirms that price dispersion is less affected by smartphones when the market is rigid.

1.6 The consequence: entry and exit behavior

We have demonstrated that the introduction of smartphones reinforces competition among stations, thereby causing reductions in both price dispersion and average price-cost margins. As a consequence, the improved competition should disincentivize existing stations and potential entrants: certain inefficient stations suffer severely from low profitability and, simultaneously, certain potential entrants encounter unfavorable market environments upon entry. This intuitive prediction directs our attention to stations' entry/exit decisions, which are often overlooked in this literature. In so doing, we provide new findings on entry/exit behaviors that allow us to understand the effect of smartphones in greater depth.

To estimate stations' entry/exit behaviors, we apply an ordered Probit model based on the structural model of Berry and Reiss (2007).[25] In market (province/metropolitan city) i and time (month) t, we consider the following estimation equation:

$$\Pr\left(y_{it} = j\right) = V_{it}\left(X_{it}, N_{it}, S_t\right) - F_{it}, \qquad j = 0, 1, ..., J \tag{1.6}$$

where y_{it} is the number of either entries or exits with a maximum value of eight ($J = 8$), $V_{it}(\cdot)$ represents a station's variable profit, and F_{it} is a fixed cost. The vector X_{it} contains demand and cost variables that affect variable profits, and S_t is the indicator variable for

[25] Their underlying model is a two-period oligopoly model in which potential entrants first decide whether to enter and then choose how much to produce. It also assumes that each station has complete information about others' profits, and the researcher does not observe stations' fixed costs.

smartphones as before. The inclusion of the number of firms, N_{it}, into the variable profit function is important in this literature (e.g., Bresnahan and Reiss, 1991; Berry, 1992; Berry and Waldfogel, 1999) because it allows researchers to draw important inferences concerning strategic interactions and recover unobserved variable profits. When we include the variable, however, an endogeneity problem arises due to the simultaneous determination of the number of stations and entries or exits. Therefore, we address this issue by using proper instrumental variables as proposed in the literature.

Following Berry (1992), the variable profit function takes a parametric form of:

$$V_{it}\left(X_{it}, N_{it}, S_t\right) = \alpha S_t + X_{it}\beta - \delta \ln N_{it} \tag{1.7}$$

where the expression $-\delta \ln\left(N_{it}\right)$ causes the variable profit to decline at a decreasing rate and allows us to test whether the number of stations matters.

A conventional cross-sectional analysis often assumes that F_{it} itself is independently distributed across markets. However, this independence assumption regarding the distribution of unobservables is overly unrealistic because it disregards the presence of station heterogeneity (in fixed costs).[26] In this paper, we simply exploit the panel structure of the data to include station heterogeneity in the estimation model. Thus, the fixed cost is now specified as:

$$F_{it} = \xi_i + \xi_s + \epsilon_{it} \tag{1.8}$$

where ξ_i is the regional fixed costs, ξ_s is the seasonal time fixed costs, and ε_{it} is the fixed costs unobserved by the researcher and assumed to be independently distributed across region i and time t according to the standard normal distribution.

Additional data, which span from June 2007 to December 2011, are gathered, and only the price variables are now less precise.[27] One advantage of expanding the sample period is

[26]Recent studies (e.g., Bresnahan and Reiss, 1990; Berry, 1992; Mazzeo, 2002; Seim, 2006) have devoted considerable effort to including firms' heterogeneity into the model and proposed several means of alleviating the strong distributional assumption on fixed costs.

[27]OPINET provides monthly after-tax wholesale gasoline price and weekly average gasoline price on a

that it enables us to directly compare the effects of OPINET and smartphones on the entry and exit behaviors of stations. To describe the dynamics of entry and exit in the gasoline market, we present monthly aggregate entry and exit trends in Figure 1.7. The solid and dotted lines in the figure refer to entry and exit, respectively. The left vertical dotted line corresponds to the date when the OPINET service was launched and the right one to the date when the iPhone was first released in Korea.

The graph clearly demonstrates that immediately after the release of smartphones, the number of entries declines dramatically while the number of exits increases slightly but not significantly. The results are consistent with our prediction: the existence of a large entry cost in the gasoline market should immediately discourage potential entrants because of the reduced future profitability as a result of competition; however, existing stations would not respond to the increased competition as rapidly because the costs of exits are also high, primarily due to business-specific, non-transferable fixed assets such as gas pumps and tanks. Especially when entries are discouraged, these exit costs make selling a gas station or changing the business substantially more difficult.

An interesting observation from the figure is that entry and exit decisions appear to be unresponsive to the introduction of OPINET. Nonetheless, this result does not refute our argument concerning the role of information in this market.[28] Note that the timing of OPINET's launch was strategically announced to affect the market in a specific manner. As a result, people had sufficient time to adjust their behaviors, and thereby the timing of its effect on entry/exit decisions was spread so broadly that it is difficult to identify in the aggregate data. In contrast, although the timing of the iPhone's introduction was announced, the effect of smartphones on the gasoline market was at least *ex-ante* unexpected and unintentional. Fortunately, this exogeneity enables us to identify the effect of smartphones on entry/exit

province/metropolitan city level since June 2007. Thus, the mean of average price-cost margins, one of the explanatory variables, is calculated as the monthly mean of the differences between the two series of prices.

[28]Kim and Kim (2010) present evidence that the introduction of OPINET contributes to the improvement of competition.

decisions from the data.

Table 1.6 presents the results concerning entry and exit probability in panels A and B, respectively. Because an endogeneity problem arises in this estimation, as emphasized above, the logarithm of the number of operating stations is instrumented by market size and the mean and median of average prices in other markets in columns (3) and (4).[29] As with any nonlinear framework, the coefficients from Table 1.6 do not represent the marginal effects on entry probability. Instead, they indicate the change in the value of the latent variable - profit - relative to the option of remaining outside the market.

In accordance with our prediction concerning entry, the negative and significant coefficients on the iPhone variable in Panel A indicate that the introduction of smartphone services is associated with a reduction in profits, and thereby the entry probability declines. An interesting finding from the entry probability is that the reference variable for strategic interaction (i.e., the logarithm of the number of operating stations) becomes highly significant after using instruments, implying that strategic interaction plays an important role in entry decisions.

Analogous results for exit probability are presented in Panel B. Note that the interpretation of the coefficients is exactly the opposite of that in Panel A. The coefficients on iPhone are positive and marginally significant at the 5 percent level but only after IVs are used, indicating that the smartphones contributed to the decline in profits and thus increased the exit probability. However, the results show that the coefficients on the number of stations are too noisy to derive any inference of strategic interaction on the exit decision. To address weak IV problems in our estimation, we also present the first-stage F-statistics of the IVs in Table 1.6.[30] The statistics present strong evidence against the null hypothesis that the

[29]The most compelling instruments for the number of stations would be exogenous variables that affect the number of stations but not supply or demand. Berry and Reiss (2007) pointed out that market size can be used as an instrumental variable for the number of firms in the specific setting of linear demand and constant marginal costs. Indeed, Berry and Waldfogel (1999) employ market size as an instrumental variable. In addition to market size, we consider Hausman-type instruments (Hausman, 1997) using prices in other markets. In this paper, market size is calculated using the number of stations.

[30]The first-stage regression results are presented in Table 1.8

selected IVs are weak.

1.7 Concluding remarks

This paper studies the impact of smartphones on competition among stations in the Korean retail gasoline market by treating their introduction as a natural experiment. In this market, smartphones have provided consumers with direct access to gasoline price information from a pre-existing information channel, OPINET. Consequently, the access to information made possible by smartphones contributed to a substantial decrease in consumers' search costs and thereby improved competition among stations. In accordance with the relevant theory, we found that the adoption of smartphones is associated with dramatic decreases in both price dispersion and average price-cost margins. The estimates report a 33.5 to 34.9 percent reduction in price dispersion and a decrease in the average price-cost margin of 7.67 won per liter, corresponding to 2.64 cents per gallon. Based on 2010 gasoline consumption in Korea, we calculate approximately 78.5 million dollars in annual savings from the reduction in average price-cost margins, indicating significant consumer gains. In addition, this paper found new evidence indicating that the improvement in competition resulting from the introduction of smartphones is associated with a sudden decline in entries and a slow increase in exits.

Overall, the results and analysis shed light on the role of information in the efficiency of markets; information provision makes markets function efficiently, and markets improve welfare. Specifically, we emphasize the importance of information in a well-developed market system. It is also worth noting that gains from smartphone use are permanent rather than one-time gains because this change in the market is permanent. In addition, this paper emphasizes the positive externalities of IT innovation, in that information technology indirectly contributes to improving economic welfare by facilitating the functioning of markets. These findings are of particular relevance for policies and investment decisions in the IT industry.

Finally, our results can be broadly applied to various types of markets in which information plays an important role in the functionality of markets. Furthermore, because the release of smartphones is exogenous to many markets, it makes for a suitable instrumental variable in other relevant research designs. Similar applications considering the introduction of smartphones to a wide range of markets would contribute to enriching the literature.

1.8 Tables and figures

Table 1.1: Margin, coefficient of variation, and max-min spread

	Before smartphones			After smartphones			
	Obs	Mean (μ_0)	SD	Obs	Mean (μ_1)	SD	$\mu_0 - \mu_1$
Margin (won)	132,860	121.418	55.376	176,111	119.741	46.98	1.677***
Coeff. of variation (%)	19,707	0.636	0.768	25,130	0.221	0.232	0.416***
Max-min spread (won)	19,708	26.476	33.103	25,130	10.172	10.498	16.303***

*, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 1.2: Regression results on price dispersion

	Dependent variable: log of squared residuals				
	Weighted			Unweighted	
	(1)	(2)	(3)	(4)	(5)
iPhone	-0.3121***	-0.0644		-0.3912***	
	(0.0518)	(0.0628)		(0.0364)	
$\tau_t \times$ iPhone	-0.0015***	-0.0020		-0.0007**	
	(0.0005)	(0.0018)		(0.0003)	
τ_t	0.0010**	-0.0020		0.0006*	
	(0.0004)	(0.0015)		(0.0003)	
$\tau_t^2 \times$ iPhone		$2.6 \times 10^{-5***}$			
		(8.5×10^{-6})			
τ_t^2		$-1.7 \times 10^{-5*}$			
		(8.5×10^{-6})			
SmartPen			-0.0145***		-0.0055**
			(0.0045)		(0.0028)
Wholesale price	-0.7591	-0.6552	-1.2682**	-1.3681***	-2.0553***
(in thousands)	(0.4998)	(0.5216)	(0.5065)	(0.2679)	(0.2596)
Number of entries	0.0063**	0.0060**	0.0069**	0.0136***	0.0154***
	(0.0030)	(0.0029)	(0.0030)	(0.0038)	(0.0039)
Number of exits	-0.0477***	-0.0416***	-0.0475**	-0.0286***	-0.0242***
	(0.0056)	(0.0051)	(0.0057)	(0.0059)	(0.0058)
Other covariates	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
City FE	No	No	No	Yes	Yes
Observations	9,132	9,132	9,132	132,103	132,103
R^2	0.3154	0.3220	0.3069	0.1421	0.1402

Notes: Standard errors are clustered by date or by date and province (column (4) and (5)). Other covariates include a constant, population of individuals aged 25-65 (in millions), proportion of females, number of sedans (in millions), number of operating stations, proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively

Table 1.3: Dynamic panel regression on price dispersion

	Dependent variable: log of est. price dispersion		
	(1)	(2)	(3)
iPhone (β)	-0.0657*	-0.0658*	-0.0657*
	(0.0359)	(0.0357)	(0.0364)
Dependent variable lag 1 (ρ_1)	0.8448***	0.8695***	0.8676***
	(0.0509)	(0.0703)	(0.0691)
Dependent variable lag 2 (ρ_2)		-0.0309	-0.0052
		(0.0305)	(0.0329)
Dependent variable lag 3 (ρ_3)			-0.0656***
			(0.0123)
Dependent variable lag 4 (ρ_4)			0.0500***
			(0.0100)
Other covariates	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes
Long run effect of iPhone	-0.4233***	-0.4076***	-0.4287**
	(0.1579)	(0.1542)	(0.1676)
Arellano-Bond test for autocorrelation			
order 1	-1.7006*	-1.7951*	-1.7984*
order 2	0.8682	1.5555	1.3976
order 3	-1.5805	-1.5845	-1.7268
Observations	9128	9126	9122
Wald χ^2	8299.32	17241.66	73106.59

Notes: Robust standard errors are presented in the parentheses. Other covariates include after-tax wholesale gasoline price, population of individuals aged 25-65 (in millions), proportion of females, number of sedans (in millions), number of operating stations, number of entries and exits, proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 1.4: Margins and markups

	Dependent variable	
	City average price-cost margin	City average markup (%)
	(1)	(2)
iPhone	-7.6674***	-0.4348***
	(0.7034)	(0.0394)
Wholesale price	-0.4403***	-0.0282***
	(0.0077)	(0.0004)
Number of entries	0.1156	0.0048
	(0.1450)	(0.0082)
Number of exits	1.7658***	0.0999***
	(0.2083)	(0.0117)
Other Covariates	Yes	Yes
Common linear trend (τ_t)	Yes	Yes
City FE	Yes	Yes
Observations	132,103	132,103
R^2	0.7807	0.7641

Notes:Notes: Standard errors are clustered by date and province. Other covariates include a constant, population of individuals aged 25-65 (in millions), proportion of females, number of sedans (in millions), number of operating stations, proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively

Table 1.5: Heterogeneous effect of smartphones

	Dependent variable: log of squared residuals (weighted)				
	$\tau_t \leq 200$	$\tau_t \leq 250$		$-190 \leq \tau_t \leq 380$	
	(1)	(2)	(3)	(4)	(5)
iPhone	-0.1637**	-0.1191*	-0.2530***	-0.4496***	-0.4703***
	(0.0706)	(0.0658)	(0.0547)	(0.0552)	(0.0554)
$\tau_t\times$ iPhone	-0.0009	-0.0025***	-0.0017***	-0.0013*	-0.0014***
	(0.0008)	(0.0006)	(0.0005)	(0.0005)	(0.0005)
Metropolitan city	-0.2963***	-0.2407***			
$\times$ iPhone	(0.0578)	(0.0534)			
$\tau_t\times$ iPhone	-0.0008**	-0.0005**			
$\times$ metropolitan city	(0.0004)	(0.0002)			
Population aged 25-65			-0.0453***		-0.0831***
$\times$ iPhone			(0.0105)		(0.0150)
Prop. of vert. integ station				0.6852***	1.3295***
$\times$ iPhone				(0.1736)	(0.2471)
Other Covariates	Yes	Yes	Yes	Yes	Yes
Common linear trend (τ_t)	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Observations	6,256	7,056	9,132	9,132	9,132
R^2	0.2845	0.2998	0.3164	0.3162	0.3188

Notes: Standard errors are clustered by date. Other covariates include a constant, after-tax wholesale gasoline price, population of individuals aged 25-65 (in millions), proportion of females, number of sedans (in millions), number of operating stations, number of entries and exits, proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 1.6: The probability of entry and exit

	Ordered Probit		Ordered Probit with IVs	
	(1)	(2)	(3)	(4)
Panel A: The probability of entry				
opinet	0.0210	0.0580	0.1918	0.2281
	(0.1285)	(0.1310)	(0.1398)	(0.1425)
iPhone	-0.4847***	-0.5053***	-0.3693***	-0.3975***
	(0.1199)	(0.1222)	(0.1251)	(0.1270)
Log of number of operating stations	-2.4869	-2.7347	-7.3892***	-7.5242***
	(1.8413)	(1.8470)	(2.4556)	(2.4591)
Other covariates	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes
Seasonal FE (quarter)	No	Yes	No	Yes
Observations	880	880	880	880
first statge F-stat of IVs	N/A	N/A	454.71***	456.49***
LR χ^2	571.73	574.33	579.13	581.68
Panel B: The probability of exit				
opinet	-0.0119	-0.0594	0.0635	0.0240
	(0.1544)	(0.1575)	(0.1616)	(0.1645)
iPhone	0.2257*	0.2576*	0.2775**	0.3113**
	(0.1331)	(0.1352)	(0.1374)	(0.1389)
Log of number of operating stations	-0.1094	0.1349	-2.1069	-2.0341
	(1.9507)	(1.9582)	(2.2688)	(2.2702)
other covariates	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes
Seasonal FE (quarter)	No	Yes	No	Yes
Observations	880	880	880	880
first statge F-stat of IV	N/A	N/A	454.71***	456.49***
LR χ^2	288.25	291.10	289.11	291.90

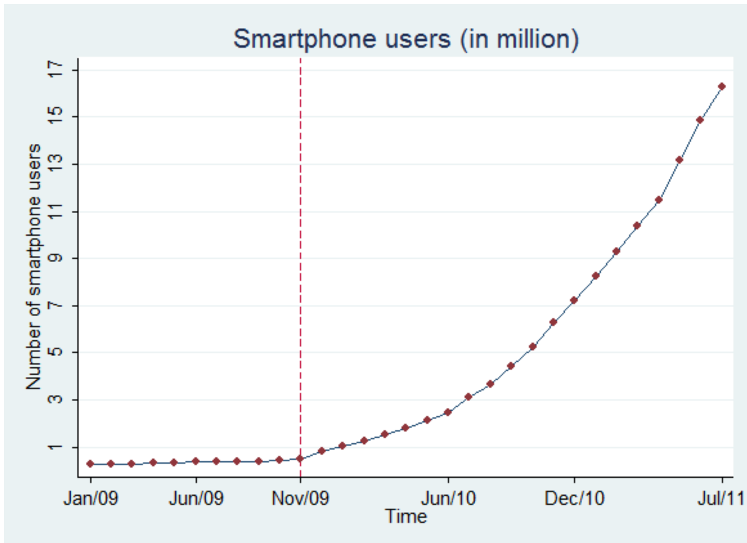
Notes: Other covariates include mean of average price-cost margins per liter, after-tax wholesale gasoline price, change in population of individuals aged 25-65 (in millions), proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 1.7: Estimates of the first-stage regression

	Dependent variable Log of number of stations (1)	(2)
Market size	12.4563***	12.4687***
	(0.3438)	(0.3429)
Mean price of other markets	-0.0005***	-0.0005***
	(0.0001)	(0.0001)
Median price of other markets	0.0006***	0.0005***
	(0.0001)	(0.0001)
opinet	0.0353***	0.0359***
	(0.0014)	(0.0014)
iPhone	0.0258***	0.025***
	(0.0013)	(0.0014)
other covariates	Yes	Yes
Regional FE	Yes	Yes
Seasonal FE (quarter)	No	Yes
Observations	880	880
F-stat of IVs	454.71***	456.49***
R^2	0.9996	0.9996

Notes: Other covariates include a constant, mean of average price-cost margins per liter, after-tax wholesale gasoline price, change in population of individuals aged 25-65 (in millions), proportion of vertically-integrated stations, and pseudo-HHI. And *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Figure 1.1: Number of smartphone users over time



Sources: The Korea Information Society Development Institute (KISDI).

Figure 1.2: Equilibrium price dispersion and consumer search intensity

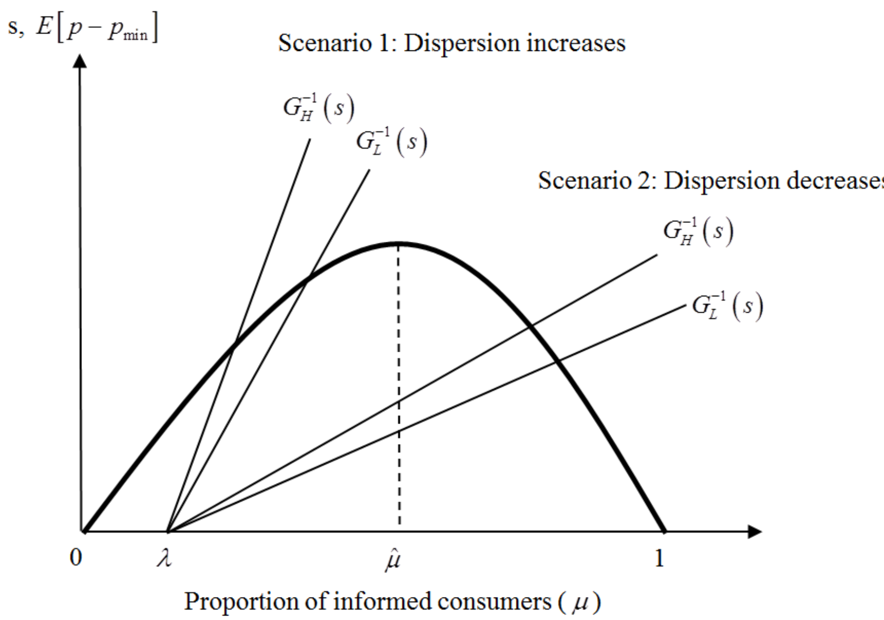
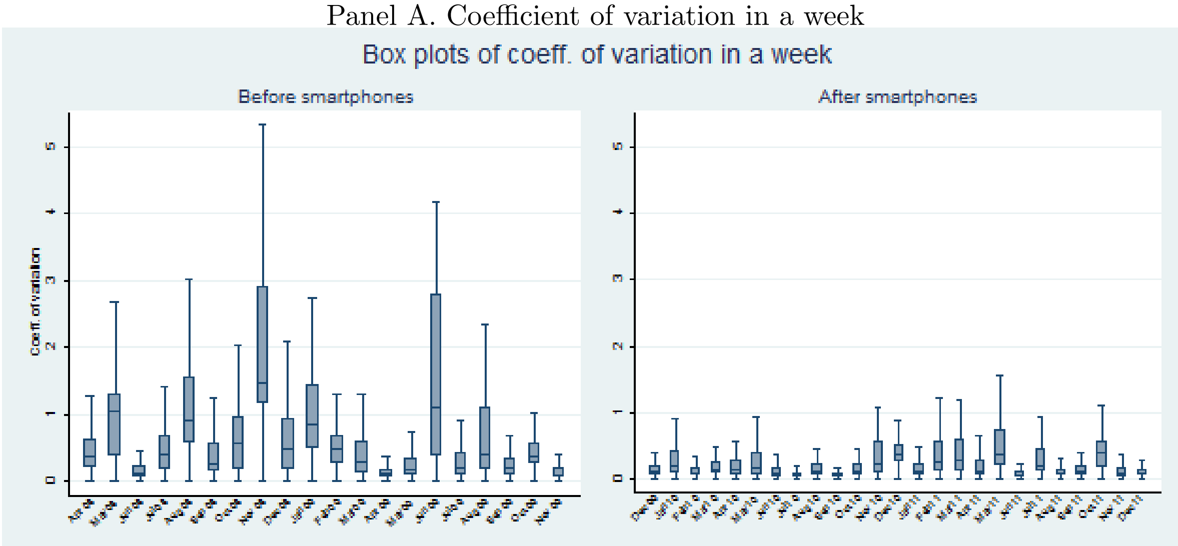


Figure 1.3: Box plots of some measures of price dispersion

Panel A. Coefficient of variation in a week



Panel B. Max-min spread in a week

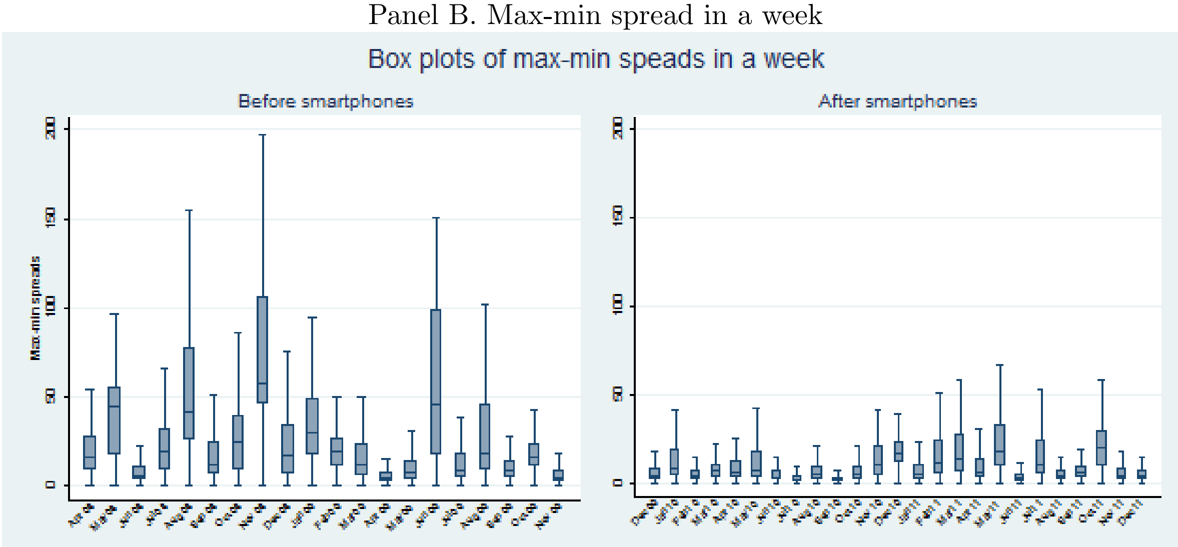


Figure 1.4: Average wholesale gasoline prices with structural breaks

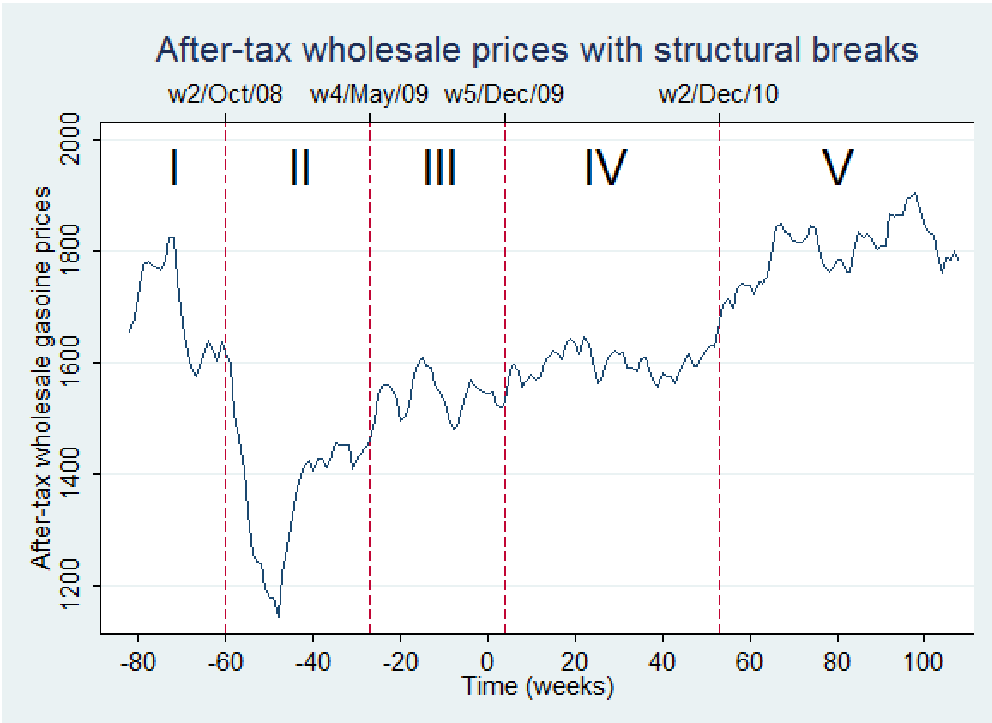
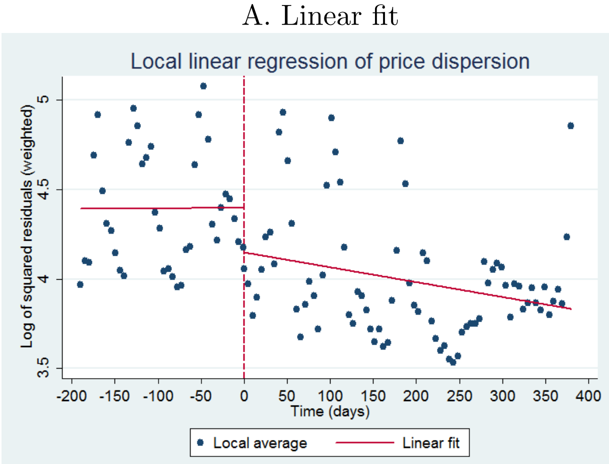


Figure 1.5: Local linear regression of price dispersion

A. Linear fit



B. Quadratic fit

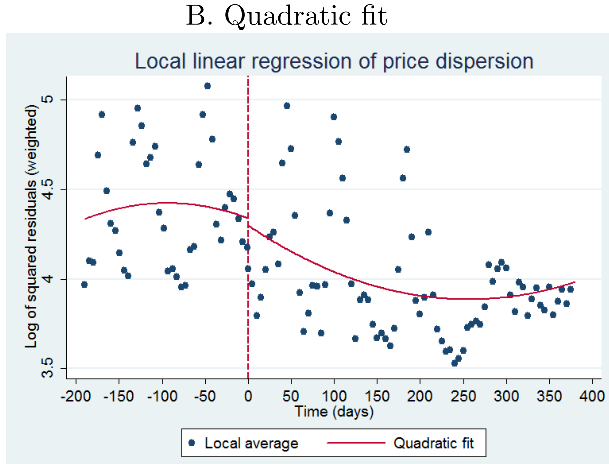


Figure 1.6: Local linear regression of price dispersion (entire sample)

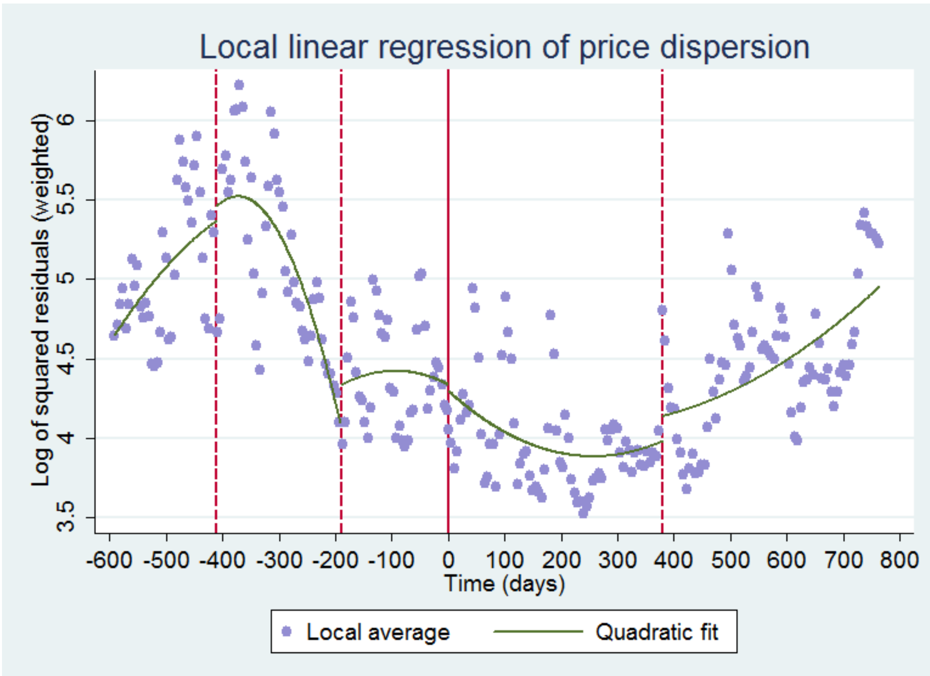
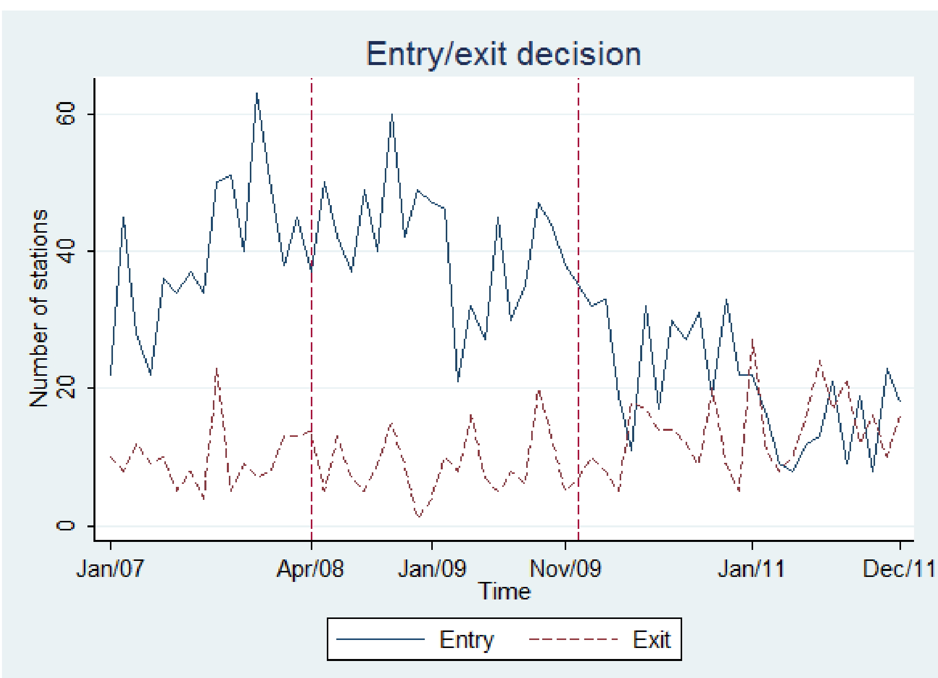


Figure 1.7: Trend of entry/exit decisions



Chapter 2

ASYMMETRIC PRICING DYNAMICS WITH MARKET POWER: INVESTIGATING ISLAND DATA OF THE RETAIL GASOLINE MARKET[1]

2.1 Introduction

Gasoline prices respond more quickly to cost increases than to cost decreases. This phenomenon, known as asymmetric pricing or "rockets and feathers," commonly occurs in a variety of industries and, as such, has been examined in many studies.[2] In this paper, we examine the link between asymmetric pricing and market power and, by investigating sticky pricing behaviors by gas stations, present new empirical evidence that tacit collusion is the main driving force behind such a link.

The literature offers two strands of theoretical models to explain the rockets-and-feathers phenomenon: consumer search and tacit collusion.[3] Rather than exclusively advocating one model over the other, we assume that both models are relevant for understanding the pricing dynamics in the real world but have different degrees of relevancy depending on the circumstances with regard to market power. Specifically, our unique island data, which we collect from the Oil Price Information Network (OPINET), an Internet website for gasoline price search in Korea, provide an interesting research setting because markets are geographically separated (isolated islands, bridged islands, and the mainland). In this paper, geographical separation serves as a reliable measure of market power because it restricts spatial competition among gas stations. More important, this geographical separation enables us to

[1] Coauthored with Daeyong Lee, Peking HSBC Business School, Shenzhen, China

[2] For example, Peltzman (2000) examines a wide range of industry and observes this pattern in two out of three markets.

[3] Section 2.2 provides a detailed discussion on both models.

highlight the implications of tacit collusion on the isolated islands, while illustrating that the consumer search model is more relevant on the mainland.

The graphs in Figure 2.1 trigger our research question of how market power affects asymmetric pricing dynamics. We chose two stations, one from the mainland (left panel, low market power) and one from an isolated island (right panel, high market power), and plot their retail and wholesale prices. They display strikingly different pricing strategies; whereas retail price movements on the mainland trace cost fluctuations with a slower speed of price adjustments to cost decreases, those on the isolated island do not closely follow the cost fluctuations but are mostly sticky. The asymmetric pricing behavior shown on the left-hand side of the figure has been well-supported by prior studies based on the consumer search model (e.g., Lewis, 2011). In contrast, the sticky pricing on the right-hand side is a newly observed pattern that cannot be explained by the consumer search model. To account for this, we hypothesize a certain type of tacit collusion in which stations tacitly coordinate with one another by maintaining their past prices as a focal point (Borenstein, Cameron, and Gilbert, 1997), and as such, we propose a relationship between sticky pricing behaviors and market power. In doing so, we can examine the role of tacit collusion in explaining the link between market power and asymmetric pricing dynamics.

This paper demonstrates how the link between market power and asymmetric pricing is formed by tacit collusion, to shed light on the role of sellers in explaining asymmetric pricing. First, our empirical analysis confirms that gasoline prices respond asymmetrically to cost changes and that market power and price-response asymmetry are positively related. Second, we provide direct evidence of tacit collusion by examining the probability of price stickiness across market power. Consistent with the collusion model, our results show that the probability of price stickiness is positively correlated with market power and responds asymmetrically to cost changes. In particular, we find that stations with high market power are more likely to stick with their past prices in response to cost decreases during high-margin periods.

By focusing on the mainland sample, we also examine the effect of station heterogeneity on asymmetric pricing to obtain further evidence of tacit collusion even in a relatively competitive environment.[4] We find that low-cost stations respond to cost decreases more rapidly and frequently than high-cost stations because deviation profits for low-cost stations more easily outweigh the benefits from coordinating than those for high-cost stations, and thus behave like a collusion breaker in this market. In general, these findings confirm that sellers do play an important role in explaining asymmetric pricing. Finally, we find a negative effect of market power on the relationship between margins and price dispersion, which indicates that tacit collusion is the main channel through which market power affects asymmetric pricing.

This study contributes to the literature in three ways. First, we emphasize the role of sellers in explaining asymmetric pricing dynamics. Previous studies investigating asymmetric pricing (Karrenbrock, 1991; Borenstein, Cameron, and Gilbert, 1997; Johnson, 2002; Lewis, 2011) have largely focused on the effects of consumer search on asymmetric pricing. In contrast, relatively less attention has been paid to how sellers help form the observed asymmetric pricing pattern. Eckert (2002) and Noel (2007a, 2007b) demonstrate that imperfect competition among sellers can explain a special asymmetric pricing pattern in the Canadian gasoline market, based on the Edgeworth cycle model. However, their results are not generalizable enough to explain the asymmetric pricing dynamics of our interest because the Edgeworth cycle pattern is independent of cost changes. In our study, we focus on the phenomenon that retail prices respond asymmetrically to cost changes. By highlighting sellers' market power, we find that tacit collusion by sellers plays a significant role in explaining sticky pricing strategy and, in turn, affects asymmetric pricing to cost changes. These empirical findings could not be explained by previous studies based on consumer search models.

Second, to our best knowledge, this study is the first to explicitly investigate the sticky pricing strategy on tacit collusion regarding the rockets-and-feathers phenomenon. By doing

[4] Although consumer search plays the most important role in asymmetric pricing behaviors on the mainland, we cannot disregard the notion that tacit collusion may have influential effects on asymmetric pricing in a *localized* market.

so, the study can provide direct evidence of tacit collusion that leads to the positive relationship between market power and asymmetric pricing. Most closely related to our study, Deltas (2008) and Verlinda (2008) empirically show that price-response asymmetry is positively correlated with market power. Using a panel data set on the state level, Deltas (2008) shows that states with high margins exhibit greater degrees of response asymmetry than states with low margins. Verlinda (2008) introduces product differentiation as a market power measure and finds that station attributes, such as brands and proximity to rival stations, explain the variation in the degree of asymmetric price adjustment. Though successful in showing the positive link, they were unable to explain why such a link is formulated, in part because of data limitations. Conversely, this paper investigates the variation in sticky pricing strategy across market power to uncover the role of tacit collusion in explaining asymmetric pricing dynamics.

Third, we propose geographical separation as a reliable measure of market power by exploiting a novel data set. Several studies (Karrenbrock, 1991; Duffy-Deno, 1996; Borenstein, Cameron, and Gilbert, 1997; Johnson, 2002; Deltas, 2008) using aggregate data on gasoline prices at a regional level experience difficulty in measuring market power, which likely occurs at a local or station level. In contrast, our data features contain detailed geographical information on a station level, enabling us to provide a precise measure of market structure that reflects the natural segmentation of local markets according to market power.

The rest of this paper proceeds as follows: Section 2.2 explains two main theoretical models regarding asymmetric pricing dynamics—namely, consumer search and tacit collusion—and provides a link between them and their theoretical predictions. Section 2.3 describes the data gathered from OPINET and presents descriptive statistics. Section 2.4 discusses the econometric models, and Section 2.5 provides the empirical analyses and results offering support for our theoretical predictions. In Section 2.6, we discuss other concerns with our main results. Section 2.7 concludes.

2.2 Theoretical predictions: consumer search versus tacit collusion

Regarding asymmetric gasoline pricing dynamics, there are two main strands in the literature as identified in the seminal article by Borenstein, Cameron, and Gilbert (1997): (1) the consumer search model and (2) the focal point tacit collusion model. First, the consumer search model (Yang and Ye, 2008; Tappata, 2009; Lewis, 2011) suggests that asymmetric consumer search for retail prices creates response asymmetry. Tappata (2009) and Yang and Ye (2008) develop dynamic search models in which "rational" consumers search for prices under imperfect information about production costs.[5] Under persistent cost realizations, consumers expect high costs in the next period if current costs are high, so their search intensity decreases. As a result, stations have less incentive to lower their prices with unexpected negative cost shocks. Conversely, consumer search intensifies with low costs, and thus stations respond to positive cost shocks immediately. The variability of search intensity associated with cost changes forms the price-response asymmetry.

Lewis (2011) develops a reference search model in which consumers form "adaptive" expectations about price distributions based on observations during the last period's purchases (i.e., a reference price for search). The model also predicts that consumer search intensity increases if prices are above the reference price (positive cost shocks), and vice versa. Consequently, more search in response to positive cost shocks forces stations to adjust their prices quickly, which leads to lower margins and less price dispersion. In addition, slow price adjustment with negative cost shocks resulting from reduced search intensity contributes to higher margins and greater price dispersion. In this sense, the consumer search model naturally derives an additional prediction of a positive relationship between margins and price dispersion.

In addition, Lewis's (2011) model suggests that the asymmetric consumer search in re-

[5] Both models rely on a nonsequential search model similar to Varian (1980) and Burdett and Judd (1983), in which costs evolve over time following a Markov process and this process is known by consumers. In these models, consumers react asymmetrically to cost changes in their search because they either observe the cost draws with uncertainty (Tappata, 2009) or asymmetrically learn them from past price observations (Yang and Ye, 2008).

sponse to price changes creates a unique relationship between margins and the extent of price responses to cost changes. If costs are reduced below consumers' reference prices, stations attempt to lower prices only enough to make consumers stop searching and thus carry high margins. Accordingly, cost fluctuations have a relatively weaker effect on retail prices during high-margin periods than during low-margin periods.

A second strand that explains asymmetric gasoline pricing dynamics relies on a model of focal point tacit collusion. Borenstein, Cameron, and Gilbert (1997) initially hypothesized that past prices would serve as a focal point at which gas stations coordinate, based on the "trigger price" model of Green and Porter (1984) in which coordination is sustainable if and only if the market price is above a threshold level. In this model, sustainability of collusion is closely related to margin changes resulting from cost fluctuations. When a significant positive cost shock occurs, stations would no longer collude and promptly raise prices because, otherwise, retail margins would become negative. In contrast, collusion is easier to sustain with cost declines because maintaining past prices benefits the margins. In this respect, focal point tacit collusion can explain asymmetric pricing behaviors of stations.

If this type of collusion is successful in a market, we should observe a certain price pattern: prices become mostly sticky with a few discrete price changes, and price breaks occur more frequently when costs are rising. This pattern implies that station's decisions on whether to alter their prices are relatively unresponsive to cost changes. Nonetheless, cost changes would occasionally influence pricing decisions by affecting margins or the sustainability of collusion. For example, when margins are low, cost increases further reduce the margins and thus jeopardize the coordination. In contrast, negative cost shocks during high-margin periods make it easier for stations to collude until deviation profits outweigh the benefits from coordinating. Therefore, we can predict that prices are stickier with negative cost shocks when margins are high, that prices are less sticky with positive cost shocks when margins are low, or both. Because stations are more likely to maintain their past prices with greater margins, we can further predict a negative relationship between margins and price dispersion.

With regard to the dynamic deviation process from the coordination, station heterogeneity in costs can lead to different predictions as well. As wholesale prices are falling, stations with high costs should still be willing to collude at their past prices, whereas stations with low costs are likely to break from the collusion and set prices more competitively. Therefore, we expect low-cost stations to adjust their prices more quickly to cost declines and change prices at least as often as high-cost stations do. In contrast, cost increases should disincentivize high-cost stations from keeping the coordination and thus make them adjust prices to cost changes faster than low-cost stations. Considering that low-cost stations have more flexibility to change their prices, we also expect more frequent price changes by low-cost stations in response to cost increases.

Though intuitively appealing, as already noted by Lewis (2011), no rigorous model of focal point collusion theory has yet been developed in the literature to explain why past prices can serve as a stable focal point. Provided that stations make use of a focal point to resolve coordination problems, monopoly prices might be a natural focal point at first glance.[6] Rather than developing a model, we discuss specific market characteristics that possibly help explain why past price outperforms monopoly prices and can serve as more appropriate focal points in this gasoline market.

First, differentiated features of the gasoline market cause difficulty for stations in arriving at a consensus on a particular monopoly price as a focal point without communication (or even with communication). Gasoline stations are spatially differentiated, and their attributes such as convenience store and car wash also differentiate them from others. Furthermore, different brand stations face changing wholesale prices over time. These market characteristics predict multiple monopoly prices across stations that fluctuate over time and make it

[6]In a general supergame setting, the "Folk theorem" asserts that for sufficiently low discount rates, nearly any set of payoffs can sustain collusive outcomes, indicating the existence of multiple Nash equilibria with prices above competitive levels. However, it is not obvious how a focal point occurs as a form of coordination when firms cannot communicate. Nonetheless, it is worth mentioning Schelling's (1960) notion that in the presence of multiple equilibria, agents can quite often recognize a focal point and use it to coordinate.

impossible for stations to coordinate on a particular monopoly price as a focal point.[7] Second, a price war could easily be triggered because gasoline itself is nearly homogeneous, even though stations are differentiated and their advertised prices are easily observable by both competitors and consumers. In this environment, a small price decrease can attract many consumers in a localized market, which resembles the Bertrand competition. Consequently, changing prices would be a signal of a price war to nearby competitors and thus deteriorate the stability of the coordination.[8] For these two reasons, we consider past prices a more sustainable focal point in the retail gasoline market than monopoly prices, which fluctuate with cost changes.

The theoretical models we use to link marker power to price-response asymmetry largely rely on supergame models of tacit collusion (Rotemberg and Saloner, 1986; Haltiwanger and Harrington, 1991; Borenstein and Shepard, 1996). Rotemberg and Saloner (1986) provide a model of tacit collusion that leads to price wars under *i.i.d.* demand shocks, whereas Haltiwanger and Harrington (1991) derive the same implication under a more realistic assumption of cyclical demand shocks. Borenstein and Shepard (1996) reinterpret these models in terms of dynamic cost changes rather than demand shocks and illustrate that current collusive margins increase with expected cost declines, and vice versa. This implies that sustainability of collusion is inversely related to the direction of cost changes, thus indicating asymmetric price response to cost changes. All these models indicate that the discount factor is an increasing function of the number of firms; from this, we can infer that the collusive outcomes are more sustainable with the market power represented by fewer firms.[9] Consequently, provided that tacitly collusive behaviors form the price-response asymmetry, we are more likely to observe the response asymmetry in a market with fewer firms (i.e., more market power). In this

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[7]It is straightforward to derive from a framework of a repeated Bertrand-style competition game (e.g., Slade, 1989) that heterogeneous firms under a differentiated market have different monopoly prices.

[8]Slade (1992) shows evidence of price war behaviors in the retail gasoline market, which is consistent with a kinked demand model of tacit collusion.

[9]For example, Haltiwanger and Harrington (1991) show that collusion is sustainable if the common discount factor δ is such that $\delta \geq \bar{\delta} = (n-1)/n$, where n is the number of firms. Here, $\bar{\delta}$ is increasing in n, implying the difficulty of sustaining collusion with a higher number of firms or lower market power.

sense, tacit collusion can play an important role in the channel through which market power affects the price-response asymmetry.

By combining both consumer search and tacit collusion models, we can draw several predictions that illustrate the effect of market power on asymmetric pricing dynamics.[10] In doing so, it is worth noting that tacit collusion causes asymmetric pricing regardless of consumer search. In line with this notion, we predict that market power has a positive effect on the asymmetry by facilitating collusion among stations. In contrast, we expect the magnitude of responsiveness to cost changes to decline with market power because stations under collusion are relatively unresponsive to cost changes. In addition, recall that both models have the opposite predictions on the relationship between margins and price dispersion. As a consequence, price dispersion should be more negatively related to margins as market power increases. We summarize all these theoretical predictions in Table 2.1 and test them in Section 2.5.

2.3 Data and descriptive statistics

An investigation on price-response asymmetry and market power requires a disaggregate high-frequency panel data set of retail gasoline prices and costs to derive meaningful implications on stations' behaviors. Especially the acquisition of such data sets is essential to examine the effect of market power on price-response asymmetry. To meet this criterion, we constructed a unique panel data set by focusing on the Korean retail gasoline market in which gasoline stations are geographically separated.

In Korea, a government-sponsored website, OPINET, provides real-time gasoline price information as well as detailed characteristics of all stations in the country.[11] We collected

[10]It is difficult to determine how two driving forces, tacit collusion and consumer search, jointly affect asymmetric pricing in a unified framework. In turn, it is not easy to predict how market power has an effect on asymmetric pricing. Nonetheless, we derive the indication of market power effects by combining predictions of two models because it is reasonable to assume that tacit collusion is more or less independent of consumer search.

[11]OPINET, operated by the Korean National Oil Corporation, was introduced on April 15, 2008, to encourage consumer search behaviors by providing consumers with reliable gasoline price information. All

the real-time data of retail prices from the website every Wednesday between 11:00 A.M. and 3:00 P.M. from July 2012 to June 2013 (52 weeks). We also gathered station attributes of brands, addresses, and whether the station is self-service and/or has amenities such as convenience stores, car washes, and auto repair shops on the first week of each month or upon entry of a new station. Using the address information, we were able to calculate geographical distances between stations by collecting latitude and longitude information in a GPS unit. In addition, we use weekly average wholesale gasoline prices by brands, obtained from OPINET, as a measure of cost variables for retail stations.[12] Last, population by Eub/Myeon/Dong (the smallest administrative units in Korea; Dong hereinafter) and the number of automobiles by cities are collected each month from the Ministry of Knowledge Economy and Statistics Korea, respectively.

The data include all operating stations in 13 selected cities, parts of which are island areas containing at least one gas station, and these cities cover both rural and urban areas.[13] Figure 2.2 depicts a part of the map with the location of stations in our data set, clearly showing that stations are distinctly classified into three groups: stations on isolated islands (not connected with the mainland), bridged islands (connected with the mainland by bridges), and the mainland. The data identify 506 gas stations in total; of these stations, 31 are located on isolated islands, 196 on bridged islands, and 279 on the mainland. Note that stations engage in spatial competition in the typical retail gasoline market, and geographical separation of our data set can naturally restrict the competition. For example, stations on isolated islands are likely protected by geographical separation from competing with stations

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detailed information is complimentary, and the price information is accurate and reliable because OPINET uses a credit card payment system to collect the information. After a consumer purchases gasoline with a credit or debit card, information such as gasoline price per liter, the name of the station, and its address is electrically sent to financial network providers and stored in their database. Finally, OPINET updates the information from the databases every six hours.

[12] Wholesale prices are calculated as nationwide average prices at which intermediate sellers and refiners sell to individual retail gas stations.

[13] The 13 cities are Ansan-si, Yeosu-si, Tongyeong-si, Geoje-si, Gangwha-gun, Ongin-gun, Taean-gun, Sinan-gun, Jindo-gun, Wando-gun, Goheung-gun, Namhae-gun, and Ulleung-gun, all of which are located along the coast and most of whose jurisdiction have a group of small islands.

in other places and thus obtain considerable market power. Taking into account that the number of stations on an island would also determine market power, we further restrict our sample to isolated islands with a small number of stations.[14] We therefore use geographical separation as a good proxy variable for market power.

Our measure of market power has several advantages over other market power measures. Prior studies typically use markup or price-cost margins to measure a firm's market power. However, these measures might be practically undesirable in many research settings mainly because cost variables are inaccurately collected and measurement errors in the variables possibly cause researchers to derive false conclusion. Indeed, cost variables are sometimes unobservable and quite often are private information, and this is also true in the gasoline market. To overcome this limitation, some studies adopt indirect ways to obtain a reliable measure of market power rather than margins or markups. For example, Verlinda (2008) adopts the degree of product differentiation as a measure of market power. Though successful in explaining market power induced by product variety, the measure has some limitations in that it disregards heterogeneity of market segments. Especially in the gasoline market measuring market power by market segments is difficult because spatial competition hinders researchers from defining a local market segment. In this case, our measure, geographical separation, can overcome these limitations and serve as an appropriate measure of market power in the retail gasoline market.

To describe how marker power influences price-response asymmetry, we first plot average retail prices by island types and wholesale prices in Figure 2.3. As the figure shows, retail prices of all island types respond asymmetrically to wholesale prices (i.e., retail prices rise much faster with cost increases than they fall with cost decreases). This phenomenon is even more pronounced in retail prices of isolated islands, indicating that market power plays an important role in the price-response asymmetry. The plotted wholesale prices also illustrate that our sample period covers a set of various cost shocks, with two complete cycles of price

[14] Thus, we excluded Jeju island from the sample; the maximum number of stations on isolated islands is four in our data.

fluctuation.

Moreover, we tabulate descriptive statistics of proportion of price changes in Table 2.2, to infer the implications of collusive behaviors from price stickiness. Panel A calculates the proportion of a station's price changes over the periods during which previous cost shocks are either positive or negative, and panel B computes the same variables over low- and high-margin periods.[15] Overall, the statistics reveal that the proportion of price changes decreases with geographical separation (i.e., in order of the mainland, bridged islands, and isolated islands), indicating a positive relationship between market power and price stickiness. Table 2.2 also presents the mean differences of the variables in the last row of each panel. Positive differences indicate that a station changes its price more frequently with positive cost shocks or low margins for all island types. However, the t-test results indicate a somewhat different story about the results. Of note, the asymmetries in the frequency of price changes responding to both cost shocks and margins are statistically valid for the mainland and bridged islands at the 5% significance level; for the isolated islands, only the asymmetry in response to margins is significant at the 10% (but close to the 5%) level. This result implies that the pricing decision of a station on an isolated island is heavily dependent on margin changes but not directly on cost shocks, as consistently predicted by the focal point tacit collusion theory.

2.4 Econometric model

To econometrically model the dynamic process that describes the relationship between retail and wholesale gasoline prices, we apply the error correction model, as suggested by Borenstein, Cameron, and Gilbert (1997) and subsequently adopted by other related studies in the literature. The model has some advantages in that it accounts for the long-term relationship between retail and wholesale prices and the tendency to revert to that relationship.

[15] Here, we simply define low- (high-) margin periods as those during which price-cost margins are below (above) the mean.

Specifically, we consider the following regression equation:

$$\begin{aligned}\Delta p_{it} = &\sum_{j=1}^{J}\left[\left(\alpha_j^{+,m} + \alpha_j^{+,br}Bridge_i + \alpha_j^{+,is}Isolate_i\right)\Delta p_{i,t-j}^{+} + \left(\alpha_j^{-,m} + \alpha_j^{-,br}Bridge_i + \alpha_j^{-,is}Isolate_i\right)\Delta p_{i,t-j}^{-}\right]\\ &+ \sum_{k=0}^{K}\left[\left(\beta_k^{+,m} + \beta_k^{+,br}Bridge_i + \beta_k^{+,is}Isolate_i\right)\Delta c_{i,t-k}^{+} + \left(\beta_k^{-,m} + \beta_k^{-,br}Bridge_i + \beta_k^{-,is}Isolate_i\right)\Delta c_{i,t-k}^{-}\right]\\ &+ \theta\eta_{i,t-1} + X_{it}\gamma + \xi_i + \varepsilon_{it}\end{aligned} \tag{2.1}$$

where for the variable y_{it}, we denote $\Delta y_{it}^{+} = \max\left(y_{it} - y_{i,t-1}, 0\right)$ and $\Delta y_{it}^{-} = \min\left(y_{it} - y_{i,t-1}, 0\right)$ and p_{it} and c_{it} are retail and wholesale prices for a station i at time t, respectively. In addition, X_{it} includes population per station, the number of sedans per station, the number of stations within a 2-km radius, station brands, and whether a station is self-service and/or has facilities such as a car wash, a convenience store, and an auto repair. Finally, ξ_i are station fixed effects, and ε_{it} is assumed to be independent and identically distributed.

To allow for different speeds of price adjustment by island types, we interact changes in retail and wholesale prices and their lags with island indicator variables, $Bridge_i$ and $Isolate_i$, which equal 1 if a station is located on a bridged or an isolated island and 0 otherwise. The coefficients on the changes in retail and wholesale prices, α's and β's, represent the short-term dynamics of price adjustments. In addition, we include the error correction term, $\eta_{i,t-1} = p_{i,t-1} - \delta_i - \phi c_{i,t-1}$, in the estimation to account for the mean reversion effects on the price adjustment dynamics. In our setting, we regard the term as the deviation of prices from their long-term relationship to the costs. Therefore, the coefficient of the term, θ, represents the short-term correction in current prices that helps push retail prices back to the level implied by the long-term relationship, and we expect this sign to be negative because positive price deviations by more than the long-term equilibrium would cause downward pressure on the current prices until the long-term relationship is recovered.

For specific estimation of the econometric model, we adopt a two-step estimation procedure following Engel and Granger (1987).[16] First, to derive the long-term relationship

[16] Alternatively, we could estimate the econometric model on the basis of an all-in-one estimation after expanding the error correction term explicitly. Our empirical results are insensitive to whether the esti-

between retail and wholesale prices implied by the error correction term, we begin by estimating the following equation:

$$p_{it} = \delta_i + \phi c_{it} + \eta_{it}. \tag{2.2}$$

Here, the station fixed effects allow the long-term relationship to vary across stations by a constant. In the second stage, we replace the error correction term in equation (2.1) with the lagged residual, $\hat{\eta}_{it-1}$, from the first-stage regression.

Following Lewis (2011), we also consider possible nonlinearity of the estimation model depending on margins and apply a threshold autoregressive model (Enders and Granger, 1998). This can be done by separately estimating equation (2.1) for high- and low-margin periods. Now, note that the error correction term provides a natural way to identify low- and high-margin periods on the basis of the long-term relationship. Thus, "high-" margin periods are identified if $\eta_{i,t-1} > \lambda$ for a threshold value λ and "low-" margin periods otherwise. Here, we select the threshold value by minimizing the sum of squared residuals from the regression of equation (2.1).[17]

Because the regression of equation (2.1) includes lagged values of prices and the error correction term, it is difficult to demonstrate the extent of the response asymmetry from the coefficients of the estimation model. Therefore, we use the estimated coefficients to calculate the cumulative response function (CRF) and show the cumulative response of prices graphically. These CRFs describe the path of price responses when a single shock in wholesale prices occurs at time t. More specifically, prices at n period after a cost shock are affected directly by the past cost change (β_{k-n}) and indirectly by the past price changes (α_j's) and the error correction term. Part B.1 of the appendix provides details of the construction of CRFs.

An advantage of calculating CRFs is that we can easily compare the differences in price

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mation occurs in one stage or two stages. Considering possible econometric problems caused by spurious regression of nonstationary variables, however, we adopt the two-step regression rather than the all-in-one. See Engel and Granger (1987) for a discussion of the asymptotic efficiency of this two-step procedure.

[17] We obtain the threshold value, λ, by using a grid search between the maximum and the minimum of $\hat{\eta}_{it}$, and we allow the value to vary up to the second decimal place.

response with the positive and negative cost shocks and construct an asymmetry function of price response (A_{t+f}).

$$A_{t+f} = CRF^{+}_{t+f} - CRF^{-}_{t+f} \tag{2.3}$$

where CRF^{+}_{t+f} and CRF^{-}_{t+f} are the CRFs at f period after a positive and negative cost shock, respectively. Then, the asymmetry function, A_{t+f}, represents the predicted asymmetry level of price responses over time.

As the second set of regression, we analyze sticky pricing behaviors of stations by estimating the probability of price stickiness. Analogous to equation (2.1), we consider a simple estimation specification as follows:

$$\begin{aligned} \Pr\left(y_{i,t+1} = 1\right) = &\sum_{k=0}^{K} \left(\beta_k^{+,m} Mainland_i + \beta_k^{+,br} Bridge_i + \beta_k^{+,is} Isolate_i\right) \Delta c^{+}_{i,t-k} \\ &+ \sum_{k=0}^{K} \left(\beta_k^{-,m} Mainland_i + \beta_k^{-,br} Bridge_i + \beta_k^{-,is} Isolate_i\right) \left|\Delta c^{-}_{i,t-k}\right| \\ &+ X_{it}\gamma + \xi_i + \xi_s + \varepsilon_{it} \end{aligned} \tag{2.4}$$

where the dependent variable, $y_{i,t+1}$, is a binary variable that equals 1 if $\Delta p_{i,t+1} = 0$ and 0 otherwise. We define Δc^{+}_{it}, Δc^{-}_{it} and X_{it} as previously, ξ_i are station fixed effects, and ξ_s are seasonal fixed effects. The error, ε_{it}, is assumed to be independently distributed across station i and time t according to the standard normal distribution.

The specification relies on the economic intuition that stations' pricing decisions on whether to change their prices are affected by past cost changes and observed market and station characteristics. The interaction terms between changes in costs and island indicator variables would allow us to estimate the different effects of cost changes on pricing decision according to market power. For interpretation ease, we use three indicator variables in the interaction terms instead of two and take the absolute values on negative changes in costs.

2.5 Empirical analysis

2.5.1 Asymmetric price response to cost changes

We begin by investigating the asymmetric pricing dynamics and then analyzing how market power affects the dynamics. The estimated coefficients of equation (2.1) appear in Table 2.3, in which we include four lags of price and cost variables (roughly 1 month)—that is, $J = K = 4$.[18] According to specification (1) in the table, the results show that gas stations on the mainland raise their prices by 12.51 percentage points immediately and by 11.66 percentage points in the following week for a one unit cost increase. In contrast, they reduce gasoline prices by 3.57 percentage points immediately and by 9.20 percentage points in the following week for a one unit cost decrease. These contrasting price adjustments show the rockets-and-feathers phenomenon.

The estimates also show the different degrees of price-response asymmetry across market power. For example, when we measure the asymmetry level as the difference in price adjustments to positive and negative cost changes, a station located on the mainland raises its price by 12.51 percentage points or reduces it by 3.57 percentage points for a one unit cost change; thus, we measure the asymmetry level for the first week as 8.94 percentage points. In the same way, we can calculate the asymmetry level for the stations located on the isolated and bridged islands as 11.55 and 8.89, respectively. These results illustrate that stations located on the isolated islands have higher asymmetry level than stations on the mainland or bridged islands, implying a positive relationship between market power and price-response asymmetry.

To understand the overall asymmetric pricing behaviors from the estimated results in a more rigorous way, we calculate the implied CRFs by island types and present them in Figure 2.4. Specifically, panel A of Figure 2.4 clearly illustrates the price-response asymmetry and

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[18] Although additional lags continue to be significant, they have little effect on the estimates, while we lose substantial degrees of freedom. In addition, these lag lengths (1–2 months) are similar to those used in previous studies (e.g., Deltas, 2008; Lewis, 2011).

its relationship to market power. For example, when the cost increases by one unit, stations on isolated islands raise their gasoline prices within five weeks by roughly 50 percentage points and these increased prices remain stable after five weeks; however, they reduce their gasoline prices slowly for a one unit decrease in costs, and it takes more than 10 weeks to approach a new steady level of price. Likewise, we observe similar patterns for stations on the bridged islands or mainland.

One observation from panel A of Figure 2.4 is that the CRFs to a positive cost shock lie above those to a negative cost shock in all regions. This indicates that stations adjust their prices more quickly in response to an increase in the wholesale price than to a decrease, thereby creating the asymmetric pricing. In addition, these asymmetry levels vary with market power: the asymmetry level is the greatest for stations on isolated islands, followed by stations on the mainland and then bridged islands. This pattern of a positive relationship between asymmetric pricing and market power is confirmed in panel A of Figure 2.5, which depicts the cumulative differences between CRFs to positive and negative cost changes (i.e., the cumulative sum of the asymmetry function in equation (2.3)) corresponding to panel A in Figure 2.4. Finally, we find heterogeneity in the magnitude of price responsiveness across market power. As panel A of Figure 2.4 shows, the CRFs for stations on the isolated islands lie below the other two, which suggests that the responsiveness of prices to cost changes decreases with market power, consistent with our theoretical predictions.

At first glance, one of the empirical results might appear puzzling: that is, the asymmetry level on bridged islands is almost identical to or slightly lower than that on the mainland. This would contradict the theoretical prediction of a positive relationship between market power and asymmetric pricing, assuming higher market power of stations on bridged islands than on the mainland. A possible explanation for this comes from demand mobility. For example, if stations on a bridged island stick with their past prices with cost decreases while stations on the mainland reduce their prices, consumers on the island are likely to cross the bridge to buy fuel at a cheaper station on the mainland. As a result, stations on the bridged island would likely adjust their prices rapidly to prevent this exodus of demand, resulting in a reduction in the asymmetry level. In support of this argument, panel A of Figure 2.4 also shows that stations on bridged islands adjust prices to cost decreases as quickly as those on the mainland while stations on isolated islands take relatively longer to adjust prices, especially to cost decreases. Indeed, most of the cost and price variables interacted with the indicator variable of bridged islands in Table 2.3 are statistically insignificant, and their joint significance test cannot reject the null hypothesis that those variables are significantly different from zero. In this sense, we can conclude that the asymmetric pricing behaviors on bridged islands are not significantly different from those on the mainland.

Following Lewis (2011), we further investigate the nonlinearity of price adjustment according to margin size. As panel B of Figure 2.4 depicts, we calculate the CRFs on the basis of the estimated coefficients from specification (2) of Table 2.3.[19] In addition to the previously discussed results, the figure shows that stations respond to cost increases (decreases) more slowly (quickly) in the state of high margins than low margins. This is consistent with Lewis's (2011) model. When margins are high, stations adjust their price only enough to make consumers stop searching, resulting in a slower adjustment of prices; in contrast, when margins are low, stations respond quickly to cost increases because they would lose profits otherwise. In this respect, this model implies a negative relationship between margins and asymmetry levels. Indeed, panel B of Figure 2.5, which depicts the cumulative differences in the CRFs of panel B of Figure 2.4, shows that the asymmetry levels over high-margin periods are significantly lower than those over low-margin periods.

Note that the negative relationship between margins and price responsiveness predicted by consumer search is observationally equivalent to the outcome of the collusion model. According to the collusion model, stations are more likely to stick with their past prices during the periods when margins are high, and thus prices are less responsive to cost changes for high-margin periods. On this account, it is almost indistinguishable whether the margin

[19]The value of λ, which minimizes the sum of squared residuals in the estimation, is $\lambda = -26.52$ (wons per liter, corresponding to -9.12 cents per gallon), obtained by the grid search. This indicates that 26.7% of observed weeks is in low-margin states whereas 73.4% of weeks is in high-margin states.

effects on price responsiveness result from consumer search or stations' collusion. Nonetheless, the striking difference of CRFs over high- versus low-margin periods, especially on the mainland (a competitive environment in which collusion plays a minor role), leads us to believe that consumer search predicted by Lewis's (2011) model plays an important role in explaining this result.

2.5.2 Tacitly collusive behaviors

Sustainability of tacit collusion

As noted previously, the tacit collusion at a focal point predicts price stickiness because stations coordinate by maintaining their past prices. To demonstrate evidence of collusive behaviors, we investigate the sustainability of collusion by estimating the probability of price stickiness. The estimation uses the Probit model and includes the variables of changes in costs and their lags to determine how cost changes affect the sustainability of collusion. Table 2.4 reports the results, and each coefficient calculates the marginal effects.

Table 2.4 provides empirical evidence of tacit collusion and thus indicates that tacit collusion is the key that disentangles the observed positive correlation between market power and asymmetric pricing dynamics. As columns (1) and (2) show, a common aspect is that the coefficients on cost changes on isolated islands are statistically insignificant whereas those in other places are negative and statistically significant. This striking difference indicates that stations on the mainland and bridged islands are more likely to change their prices or break from the collusion in response to both positive and negative cost changes; in contrast, stations on isolated islands are generally unresponsive to any direction of cost changes and adhere to their past prices, thereby keeping the collusion. In addition, we apply a simple test for the asymmetric effect of cost changes on the probability of price stickiness. The F-statistics in the last panel of Table 2.4 confirm that stations on the mainland and bridged islands are more likely to maintain their past prices to negative cost changes than to positive ones.[20] Overall, these results indicate that market power can affect asymmetric pricing by facilitating the coordination at a focal point.

In addition, we investigate how the sustainability of collusion is affected by cost fluctuations according to margin size. Columns (3) and (4) in Table 2.4 provide the estimation results with the same specification depending on margins size.[21] Although stations with market power are generally unresponsive to cost changes, a certain cost change that significantly affects margins can have some influence on collusive behaviors. In other words, additional increases in costs during low-margin periods jeopardize the stability of the collusion, whereas cost reductions during high-margin periods reinforce the coordination. Notably, columns (3) and (4) show that the coefficients on $\left|c_t^-\right| \times isolated$ during high-margin periods are positive and statistically significant at the 1% level. This indicates that during periods when margins are high, stations on isolated islands are more likely to stick with their past prices for cost decreases, meaning that sustaining the coordination becomes easier when margins are high and costs fall. Moreover, though insignificant, the coefficients on $c_t^+ \times isolated$ for low-margin periods are negative and have relatively larger values than the same coefficients in columns (1) and (2), which implies that the tacit collusion is no longer sustainable when margins are low and costs increase. In contrast, stations on the mainland and bridged islands actively change their prices especially to cost decreases when margins are high and to cost increases when margins are low.

Collusion in a competitive environment

In the retail gasoline market, a station would have some local market power even in a generally competitive market in part because entry is geographically limited to some extent. As a result, we expect that the local market power will affect stations' pricing strategy in a

[20]In a simple joint F-test, we assess whether the sum of coefficients on positive cost changes is greater than the sum of coefficients on negative cost changes.

[21]For this estimation, we simply determine high-margin periods if the residuals from equation (2.2) are greater than zero and low-margin periods otherwise.

localized market by facilitating the coordination of stations. However, empirical evidence by previous studies is inconclusive. Many studies, including Borenstein, Cameron, and Gilbert's (1997) and Lewis's (2011), find no support for collusive behaviors, whereas some studies, such as Verlinda's (2008), provide empirical evidence that stations use their market power in a localized market, which affects the asymmetric pricing dynamics.

Here, we also seek empirical evidence of tacit collusion by focusing only on the mainland sample, in which we expect competition to be high. Specifically, our argument centers on the effect of firm heterogeneity on asymmetric pricing dynamics. Note that the consumer search model does not provide any explanation for why sellers' heterogeneity in costs affects the speed of price adjustment differently whereas the collusion theory does. Therefore, investigating the effect of firm heterogeneity on price adjustment can provide evidence of collusive behaviors even in a competitive environment. This approach is similar to Verlinda's (2008) study, which investigates the effect of product differentiation on asymmetric pricing adjustment. In this paper, we use self-service stations and unbranded stations as low-cost stations to approximate the cost structure of stations.[22]

First, we investigate the price-response asymmetry according to station heterogeneity in costs. Figure 2.6 depicts the CRFs of full-service versus self-service stations in panel A and the CRFs of branded versus unbranded stations in panel B.[23] According to the prediction of the collusion model, stations with low cost have less incentive to keep the coordination when wholesale prices are falling and, as a result, adjust their prices more quickly than nearby stations with high cost. Panel A of Figure 2.6 clearly shows that self-service stations tend to adjust prices more quickly to negative cost shocks than full-service stations, though both types of stations respond to positive cost shocks at a similar speed. This striking difference

[22]Self-service and unbranded stations account for 10.11% and 8.44% of the entire mainland sample, respectively. Therefore, this classification is appropriate to represent the small fraction of stations with relatively low operating costs.

[23]For the estimation, we consider a similar specification to equation (2.1). We use four lags of changes in prices and costs interacted with either self-service stations or unbranded stations instead of those interacted with island types. The estimation results appear in Table 2.8.

in price adjustments results in a higher asymmetry level for full-service than self-service stations. In contrast, panel B of Figure 2.6 shows no clear difference in price adjustments between branded and unbranded stations.

In addition, we examine the probability of price stickiness depending on firm heterogeneity and presented the results in Table 2.5. The negative coefficients on cost variables interacted with either self-service or unbranded dummy variables indicate that the probability of price stickiness for self-service and unbranded stations decreases in response to any direction of cost changes relatively more than their counterparts. Consequently, the table shows that both self-service and unbranded stations change their prices to positive cost shocks relatively more often whereas only unbranded stations are more likely to change prices to cost decreases than branded stations. Overall, stations with low operating costs respond to cost changes more frequently, indicating that low-cost stations are the main collusion breakers, provided that stations coordinate by maintaining their past prices. Ironically, the collusion-breaking behaviors resulting from firm heterogeneity in operating costs provide evidence of tacit collusion in this market. The results therefore imply that tacit collusion plays an important role in forming asymmetric pricing even in a competitive localized market.

2.5.3 Changes in price dispersion

As stressed, the two theoretical models that this paper relies on have opposite predictions on the relationship between price dispersion and margins. The consumer search model generally supports that price dispersion increases when margins rise (or prices fall) because fewer consumers choose to search when prices are lower than their expectations and the reduced search intensity causes wider price distribution. In contrast, the collusion model states that price dispersion declines or stays the same when margins grow as the coordination at a focal point is reinforced by the greater margins. This clear difference predicts the negative effect of market power on the relationship between price dispersion and margins and thus helps us disentangle the role of tacit collusion in explaining asymmetric pricing dynamics.

We test such predictions with a simple regression specification following Lewis (2011) and present the results in Table 2.6. We consider two kinds of price dispersion measures as dependent variables in the following analysis: a region-wide price dispersion and a local price dispersion. We calculate the region-wide dispersion as the standard deviation of the prices for all stations within the administrative unit, Dong. We measure the local price dispersion around a station by the standard deviation or the max-min spreads of the prices of competing stations within several boundaries—for example, 2-km or 5-km radius around the station.[24] The current change in the retail prices and the lagged margins interacted with island types serve as independent variables, and we construct them in the same format as their corresponding dependent variables. For example, we use average margins and average prices of stations within 2-km radius around a station in the estimation when analyzing the local price dispersion within the 2-km boundary. We also include the variable of average prices in the regression to control for temporary price dispersion caused by large overall price movements. The temporary price dispersion would occur in the transition of price adjustment simply because some stations move a little earlier than others in response to large overall price changes. Finally, we include the Dong or station fixed effects to control for station heterogeneity.

The results in Table 2.6 present robust evidence in support of the theoretical predictions. First, the coefficients on margins interacted with the mainland and bridged islands are all positive and highly significant at the 1% level for all specifications. This positive relationship provides evidence that consumer search plays a more important role in explaining the observed asymmetric pricing in a competitive environment than collusive behaviors. In contrast, the same coefficients for isolated islands are almost insignificant and become even negative in three columns of the table. More important, we find a clear pattern that the values of these coefficients decline as the markets are more isolated. All these results confirm that tacit collusion can explain the negative effect of market power on the relationship

[24]When creating the local variables around a station within several boundaries, we were careful to consider the geographical separation. For example, we calculate local price dispersion around a station on an isolated island within a 2-km radius as the standard deviation of prices of competing stations only on the island within 2-km radius.

between margins and price dispersion, and therefore they provide support for the argument that tacit collusion is the key channel through which market power affects the asymmetric pricing. Finally, the significant and positive coefficients on price changes indicate that large overall price movements for any direction contribute to increases in price dispersion. Thus, we verify that controlling for overall price movements is necessary to analyze the relationship between margins and price dispersion.

2.6 Alternative explanations

This paper relies heavily on two identification strategies: (1) we derive the sticky pricing strategy from a certain type of tacit collusion in which stations coordinate by maintaining their past prices as a focal point, and (2) we measure market power indirectly by classifying groups according to geographical separation. In this section, we discuss some alternative explanations over the main identification issues.

First, we reinforce our main arguments by demonstrating that the observed sticky pricing patterns result from the tacit collusion associated with market power, but not from inventory adjustment. To do so, we consider a simple pricing strategy based on inventory, in which a station changes its price only when most of the gasoline in a gas tank is sold and a new purchase is made. Then, this pricing strategy generates price stickiness and further predicts that the duration of sticky pricing will decrease with the demand for gasoline because the gasoline in the tank will be sold out faster with high demand. Yet this inventory story does not suggest any effects of margins on the duration of price stickiness. To test this alternative, we regress the duration (weeks) of sticky pricing of a station on margins and changes in prices. The construction of the independent variables is the same as in Table 2.6. Because the sales volume data are not available, we instead use the overall average price movements around a station as a proxy for changes in demand.[25] By the law of demand, an increase in overall average price leads to less demand for gasoline, and vice versa.

[25]In particular, this strategy is plausible because demand shocks rarely occur in the retail gasoline market.

The results in the first two columns of Table 2.7 provide inconsistent results with the inventory argument. The coefficients for changes in overall prices are significantly negative, indicating that changes in prices to any direction make the duration of sticky pricing shorter. Especially the negative coefficients on positive price changes imply that the duration of sticking with the past prices declines as demand decreases. This result contradicts the inventory story, which predicts that less demand slows down sales of gasoline in the tank and thus stations are likely to keep current prices based on the cost when they ordered (i.e., longer duration of sticky price). Moreover, the results show a consistent pattern that increases in margins have a negative effect on the duration on the mainland and bridged islands but a positive effect on isolated islands. This can be interpreted as stations with high market power (isolated islands) keeping the collusion longer during periods when margins are high whereas stations with low market power (mainland and bridged islands) change their prices or break from the collusion more often because competition among stations is easily stimulated by margin increases. All the results indicate that the alternative is unlikely and rather provide robust evidence of tacit collusion.

In addition, we further take into account a more rigorous inventory model developed by Aguirregabiria (1999), in which cyclical price behavior characterized by long periods without nominal price changes and short periods with very low price is explained by stock-out probability in the presence of fixed ordering costs. In this model, we focus on a rationale that explains price stickiness. As the amount of inventory declines with high demand, the stock-out probability increases, and expected sales become more inelastic with respect to markup (or price), which in turn disincentivizes stations from changing their prices. We also expect that this sticky pricing behavior in response to high demand (in our context, decreases in average retail prices) is more pronounced with *high fixed ordering costs*. Here, it is noteworthy that sticky pricing patterns predicted by the inventory model resemble the outcomes by tacit collusion; however, the collusion model does not predict variation in price stickiness depending on ordering costs.

To test this alternative, we investigate whether the duration of sticky pricing varies with ordering costs responding to demand changes. Because the ordering cost on isolated islands becomes especially high during the monsoon season (July and August) due to bad weather, we use a dummy variable for the rainy season as a proxy for high ordering costs and interact it with overall price changes. We also focus only on the isolated island sample in the regression because heavy rains would have little effect on transportation costs on the bridged islands and mainland. The results in the last two columns of Table 2.7 show that the coefficients on the interaction term between overall price change around a station and the rainy season dummy are statistically insignificant. This indicates that variations in ordering costs have no substantial effect on the duration on price stickiness with demand changes and provides little supports for the inventory model over our main results.

Finally, we advocate that geographical separation represents a measure of market power and leads to a greater level of response asymmetry. One concern with the geographical separation might be that gas stations on isolated islands face a low elasticity of demand due to government subsidy. If this is the case, more inelastic demand would lead to greater asymmetric pricing and price stickiness. Indeed, the central government in Korea gives gasoline tax-exemption benefits to people who work in primary industries using agricultural or fishing machinery. This tax-exemption policy should affect people not only on isolated islands but also in most rural areas, including bridged islands.[26] Thus, if our market power measure reflects the different effects of the government policy, we would expect to observe similar levels of price-response asymmetry on both bridged and isolated islands or greater price-response asymmetry on bridged islands than on the mainland, which is not consistent with our main results presented in Section 2.5.

2.7 Conclusion

This paper investigates the link between market power and asymmetric pricing and how the link is formulated by tacitly collusive behaviors. To connect market power with asymmetric

[26]Our data indicate that the proportions of stations located in rural places are 100%, 82.2%, and 43.4% on isolated islands, bridged islands, and the mainland, respectively.

pricing, we exploit a unique island data set and introduce geographical separation as a reliable measure of market power. To empirically test the dynamic process of retail and wholesale gasoline prices, we use the error correction model and confirm the existence of price-response asymmetry and its positive relationship to market power. Based on the focal point tacit collusion model, we investigate the probability of price stickiness across market power to provide direct evidence of tacit collusion. Our findings suggest that market power is strongly correlated with the degrees of price stickiness, which implies that tacit collusion is the key channel through which market power affects asymmetric pricing. We also obtain further evidence of tacit collusion in a localized market by examining the effect of station heterogeneity on asymmetric pricing. Last, we found a negative effect of market power on the relationship between margins and price dispersion.

Overall, this paper emphasizes the important role of sellers in explaining asymmetric pricing and derives meaningful implications from sticky pricing behaviors. Our analyses suggest that price stickiness a good indicator to uncover collusive behaviors in a market in which market power significantly affects the pricing decisions of market participants. This implication is general enough to apply to other markets with similar market environment characteristics and is of particular relevance to policy makers.

Future work on this subject might extend in various directions. First, the absence of a rigorous model for the focal point tacit collusion stimulates the need to fill the gap between empirical and theoretical models. In addition, it would be worthwhile to examine how government policy changes (e.g., suspension and reinstatement of gasoline sales tax) might affect asymmetric pricing dynamics across different market structures.

2.8 Tables and figures

Table 2.1: Theoretical prediction summary

	Consumer Search	Tacit Collusion	Market Power Effect
Asymmetric Pricing	Yes	Yes	Positive
Responsiveness to cost shocks	Responsive	Relatively unresponsive	Negative
when high margins	Less responsive	Stickier to neg. cost shocks	
when low margins	More responsive	Less sticky to pos. cost shocks	
Relationship between dispersion and margins	Positive	Negative	Negative
Pricing behaviors of low-cost stations		Rapid price adjustment and frequent price changes	

Table 2.2: Proportion of price changes (%)

	Mainland		Bridged		Isolated	
	Obs.	Mean (S.D.)	Obs.	Mean (S.D.)	Obs.	Mean (S.D.)
Panel A. Responsiveness to cost shocks						
$\Delta c_{t-1} \geq 0$	279	41.070 (15.219)	196	32.733 (12.656)	31	21.196 (15.540)
$\Delta c_{t-1} \leq 0$	278	38.667 (16.215)	196	28.645 (12.503)	31	18.936 (13.955)
$H_0 : diff \leq 0$		2.403**		4.089***		2.260
Panel B. Responsiveness to margins						
Low margin	277	43.915 (15.012)	196	34.893 (12.112)	31	23.355 (16.333)
High margin	279	36.258 (15.587)	196	26.727 (12.257)	31	17.159 (13.403)
$H_0 : diff \leq 0$		7.657***		8.166***		6.196*

Note: *, **, and ***refer to the 10%, 5% and 1% significance levels, respectively.

Table 2.3: Regression on asymmetric price adjustment

	(1) Baseline			(2) Regression Depending on Margin					
					High Margins			Low Margins	
	Mainland	Interaction Bridged	Interaction Islolated	Mainland	Interaction Bridged	Interaction Islolated	Mainland	Interaction Bridged	Interaction Islolated
Δc_t^+	0.1251***	-0.0203	-0.0611**	0.1018***	-0.0393***	-0.0772***	0.2652***	-0.0529	-0.0927
	(0.0080)	(0.0124)	(0.0266)	(0.0083)	(0.0131)	(0.0283)	(0.0247)	(0.0383)	(0.0728)
Δc_{t-1}^+	0.1166***	-0.0515***	-0.0074	0.0723***	-0.0675***	0.0292	0.3184***	-0.0015	-0.2111***
	(0.0082)	(0.0122)	(0.0260)	(0.0097)	(0.0149)	(0.0309)	(0.0219)	(0.0342)	(0.0604)
Δc_{t-2}^+	0.1448***	-0.0063	-0.0343	0.0856***	-0.0257*	-0.0221	0.3969***	0.0258	-0.1954***
	(0.0082)	(0.0121)	(0.0253)	(0.0094)	(0.0144)	(0.0305)	(0.0220)	(0.0333)	(0.0594)
Δc_{t-3}^+	0.1064***	0.0127	-0.0498*	0.0810***	0.0044	-0.1048***	0.3645***	-0.0231	-0.0815
	(0.0089)	(0.0132)	(0.0271)	(0.0095)	(0.0145)	(0.0306)	(0.0280)	(0.0431)	(0.0710)
Δc_{t-4}^+	0.0331***	0.0014	0.1067***	0.0318***	-0.0135	0.0965***	0.1196***	0.1359***	0.0170
	(0.0086)	(0.0134)	(0.0288)	(0.0087)	(0.0136)	(0.0302)	(0.0315)	(0.0491)	(0.0819)
Δc_t^-	0.0357***	-0.0198*	-0.0872***	0.0360***	-0.0155	-0.0814***	0.0377	-0.0346	-0.0894
	(0.0075)	(0.0113)	(0.0244)	(0.0076)	(0.0116)	(0.0256)	(0.0249)	(0.0381)	(0.0713)
Δc_{t-1}^-	0.0920***	-0.0360***	-0.1554***	0.0811***	-0.0431***	-0.1876***	0.0467	-0.1411**	-0.2109***
	(0.0083)	(0.0116)	(0.0243)	(0.0086)	(0.0118)	(0.0251)	(0.0368)	(0.0602)	(0.0930)
Δc_{t-2}^-	0.0969***	-0.0323***	-0.1023***	0.0902***	-0.0367***	-0.0887***	0.0249	0.0322	-0.2822***
	(0.0081)	(0.0117)	(0.0243)	(0.0084)	(0.0121)	(0.0251)	(0.0281)	(0.0467)	(0.0746)
Δc_{t-3}^-	0.0677***	-0.0060	-0.0175	0.0509***	-0.0139	0.0006	0.0531**	0.0998**	-0.1671***
	(0.0081)	(0.0120)	(0.0247)	(0.0086)	(0.0125)	(0.0256)	(0.0235)	(0.0412)	(0.0787)
Δc_{t-4}^-	0.0555***	0.0023	-0.1114***	0.0429***	0.0056	-0.1419***	0.0712***	-0.0359	-0.0611
	(0.0080)	(0.0120)	(0.0248)	(0.0087)	(0.0127)	(0.0266)	(0.0210)	(0.0345)	(0.0659)
Δp_{t-1}^+	0.0000	-0.0461**	0.0721**	0.0106	-0.0266	0.1034***	0.0495	-0.0845	0.0807
	(0.0131)	(0.0198)	(0.0314)	(0.0139)	(0.0217)	(0.0326)	(0.0380)	(0.0540)	(0.1113)
Δp_{t-2}^+	0.0989***	0.0065	-0.2217***	0.1110***	0.0171	-0.1822***	0.1383***	-0.0878	-0.2832***
	(0.0123)	(0.0187)	(0.0304)	(0.0126)	(0.0198)	(0.0317)	(0.0403)	(0.0556)	(0.0880)
Δp_{t-3}^+	0.1314***	-0.0049	0.0445	0.1293***	-0.0131	0.0068	0.2186***	-0.0591	0.3828***
	(0.0116)	(0.0177)	(0.0299)	(0.0117)	(0.0181)	(0.0305)	(0.0428)	(0.0586)	(0.0984)
Δp_{t-4}^+	0.1196***	0.0274	-0.0776***	0.1244***	0.0126	-0.0755***	0.0177	0.1795**	0.2910*
	(0.0113)	(0.0174)	(0.0299)	(0.0111)	(0.0173)	(0.0292)	(0.0509)	(0.0720)	(0.1668)
Δp_{t-1}^-	-0.0780***	-0.0138	0.0792**	-0.0674***	-0.0405*	0.0596*	-0.1501***	0.0263	0.1956***
	(0.0131)	(0.0196)	(0.0317)	(0.0142)	(0.0211)	(0.0357)	(0.0324)	(0.0495)	(0.0669)
Δp_{t-2}^-	0.0034	0.0290	-0.0205	0.0063	0.0163	-0.0211	-0.0757***	0.0362	0.0783
	(0.0129)	(0.0195)	(0.0319)	(0.0143)	(0.0214)	(0.0370)	(0.0288)	(0.0459)	(0.0620)
Δp_{t-3}^-	0.0607***	0.0349*	-0.0556*	0.0507***	0.0163	-0.0233	-0.0068	0.0389	-0.0224
	(0.0124)	(0.0190)	(0.0313)	(0.0145)	(0.0215)	(0.0358)	(0.0247)	(0.0414)	(0.0641)
Δp_{t-4}^-	0.1015***	-0.0102	-0.0889***	0.1098***	-0.0258	-0.0361	0.0195	-0.0136	-0.1062*
	(0.0118)	(0.0182)	(0.0299)	(0.0140)	(0.0212)	(0.0359)	(0.0223)	(0.0359)	(0.0564)
$\hat{\eta}_{i,t-1}$		-0.1647***			-0.1903***			-0.2309***	
		(0.0044)			(0.006)			(0.0191)	
Other covariates		Yes			Yes			Yes	
Station FE		Yes			Yes			Yes	
Observations		22,035			16,905			5,130	
R^2		0.3551			0.2738			0.4003	

Note: : Other covariates include a constant, brands, self-service, convenience store, auto repair, population per station, the number of sedans per station, and the number of stations within a 2-km radius. The standard errors are in the parentheses. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 2.4: Probability of price stickiness (Probit model)

	Dependent Variable: $1(\Delta p_{i,t+1} = 0)$					
	(1)	(2)	(3)		(4)	
			Low	High	Low	High
$\Delta c_t^{+}\times$ Mainland	-0.2436***	-0.2447***	-0.2005***	0.0023	-0.2045***	0.0044
	(0.0230)	(0.0230)	(0.0341)	(0.0435)	(0.0342)	(0.0436)
$\Delta c_{t-1}^{+}\times$ Mainland	-0.2552***	-0.2554***	-0.2719***	-0.0938**	-0.2743***	-0.0937**
	(0.0220)	(0.0221)	(0.0289)	(0.0387)	(0.0290)	(0.0387)
$\left\|\Delta c_t^{-}\right\|\times$ Mainland	-0.2942***	-0.2934***	0.1327**	-0.2606***	0.1336**	-0.2586***
	(0.0217)	(0.0217)	(0.0614)	(0.0273)	(0.0615)	(0.0273)
$\left\|\Delta c_{t-1}^{-}\right\|\times$ Mainland	-0.1099***	-0.1081***	0.0686	-0.1873***	0.0655	-0.1858***
	(0.0226)	(0.0227)	(0.0421)	(0.0317)	(0.0421)	(0.0317)
$\Delta c_t^{+}\times$ Bridged	-0.3595***	-0.358***	-0.3899***	-0.1581***	-0.3890***	-0.1565***
	(0.0279)	(0.0280)	(0.0420)	(0.0518)	(0.0420)	(0.0519)
$\Delta c_{t-1}^{+}\times$ Bridged	-0.3095***	-0.309***	-0.3312***	-0.1467***	-0.3322***	-0.1459***
	(0.0268)	(0.0269)	(0.0367)	(0.0461)	(0.0368)	(0.0462)
$\left\|\Delta c_t^{-}\right\|\times$ Bridged	-0.3418***	-0.3405***	-0.1801**	-0.2583***	-0.1788**	-0.2567***
	(0.0255)	(0.0256)	(0.0812)	(0.0313)	(0.0814)	(0.0314)
$\left\|\Delta c_{t-1}^{-}\right\|\times$ Bridged	-0.0762***	-0.0766***	0.2464***	-0.1294***	0.2420***	-0.1302***
	(0.0271)	(0.0271)	(0.0619)	(0.0359)	(0.0619)	(0.0359)
$\Delta c_t^{+}\times$ Isolated	-0.0796	-0.0778	-0.1710	0.2566	-0.1684	0.2552
	(0.0828)	(0.0827)	(0.1135)	(0.1591)	(0.1135)	(0.1590)
$\Delta c_{t-1}^{+}\times$ Isolated	-0.0837	-0.0849	-0.0639	0.0709	-0.0605	0.0652
	(0.0829)	(0.0829)	(0.1165)	(0.1427)	(0.1164)	(0.1427)
$\left\|\Delta c_t^{-}\right\|\times$ Isolated	0.0161	0.0167	-0.2748	0.2808***	-0.2708	0.2820***
	(0.0815)	(0.0815)	(0.1637)	(0.1062)	(0.1637)	(0.1062)
$\left\|\Delta c_{t-1}^{-}\right\|\times$ Isolated	-0.1074	-0.1093	0.0514	-0.0946	0.0501	-0.0999
	(0.0799)	(0.0799)	(0.1614)	(0.1057)	(0.1612)	(0.1057)
Other covariates	No	Yes	No		Yes	
Station FE	Yes	Yes	Yes		Yes	
Quarter FE	Yes	Yes	Yes		Yes	
Observations	23,206	23,206	11,209	11,872	11,872	11,209
LRχ^2	3,168.02	3,190.55	1,810.01	3,441.75	3,475.43	1,834.15
Test for asymmetry						
Mainland	7.06***	7.63***	78.39***	33.22***	79.15***	32.84***
Bridged island	36.00***	35.59***	61.14	1.27	60.54***	1.31
Isolated island	0.37	0.35	0.00***	0.46	0.00	0.44

Note: All coefficients report marginal effects and the standard errors are in the parentheses. The variables of changes in wholesale prices are divided by 100. Other covariates include a constant, brands, self-service, convenience store, auto repair, population per station, the number of sedans per station, and the number of stations within a 2-km radius. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 2.5: Pricing dynamics of low-cost stations (focusing on stations on the mainland)

	Dependent Variable: $1(\Delta p_{i,t+1} = 0)$			
	Full vs. Self		Branded vs. Unbranded	
	(1)	(2)	(3)	(4)
Δc_t^+	-0.2427***	-0.2454***	-0.2500***	-0.2497***
	(0.0254)	(0.0254)	(0.0250)	(0.0250)
$\Delta c_t^+ \times$ Self-service	-0.2482***	-0.2299***		
	(0.0867)	(0.0886)		
$\Delta c_t^+ \times$ Unbranded			-0.2591**	-0.3011***
			(0.1036)	(0.1071)
Δc_{t-1}^+	-0.2776***	-0.2797***	-0.2630***	-0.2609***
	(0.0241)	(0.0242)	(0.0237)	(0.0238)
$\Delta c_{t-1}^+ \times$ Self-service	0.0585	0.0788		
	(0.0799)	(0.0834)		
$\Delta c_{t-1}^+ \times$ Unbranded			-0.2226**	-0.2725**
			(0.1029)	(0.1076)
$\lvert\Delta c_t^-\rvert$	-0.3074***	-0.3100***	-0.2950***	-0.2934
	(0.0237)	(0.0239)	(0.0231)	(0.0233)
$\lvert\Delta c_t^-\rvert \times$ Self-service	-0.0280	-0.0108		
	(0.0793)	(0.0816)		
$\lvert\Delta c_t^-\rvert \times$ Unbranded			-0.3583***	-0.4129***
			(0.1093)	(0.1138)
$\lvert\Delta c_{t-1}^-\rvert$	-0.1165***	-0.1178***	-0.1147***	-0.1121***
	(0.0251)	(0.0252)	(0.0245)	(0.0246)
$\lvert\Delta c_{t-1}^-\rvert \times$ Self-service	0.0512	0.0707		
	(0.0803)	(0.0822)		
$\lvert\Delta c_{t-1}^-\rvert \times$ Unbranded			0.0609	0.0144
			(0.1069)	(0.1105)
Other covariates	No	Yes	No	Yes
Station FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Observations	12,787	12,787	12,787	12,787
LR χ^2	1,576.82	1,593.58	1,585.73	1,606.09

Note: All coefficients report marginal effects and the standard errors are in the parentheses. The variables of changes in wholesale prices are divided by 100. Other covariates include a constant, brands, self-service, convenience store, auto repair, population per station, the number of sedans per station, and the number of stations within a 2-km radius. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 2.6: Station price dispersion regressions

Dependent Variable (won/liter)	Standard Deviation by Dong	Standard Deviation of stations within 2 km	Standard Deviation of stations within 5 km for rural and 2km for urban	Max-Min Spreads of stations within 2 km	Max-Min Spreads of stations within 5 km for rural and 2km for urban
	(1)	(2)	(3)	(4)	(5)
$\text{Margin}_{t-1}\times$ Mainland	5.0175***	3.8611***	3.5696***	6.2815***	6.9203***
	(0.6079)	(0.2698)	(0.2369)	(0.4968)	(0.5721)
$\text{Margin}_{t-1}\times$ Bridged	2.9638***	3.2891***	2.6809***	3.8126***	4.2178***
	(0.6160)	(0.2941)	(0.2482)	(0.5165)	(0.5943)
$\text{Margin}_{t-1}\times$ Isolated	1.7593*	-0.1941	0.3087	-0.4853	-0.4521
	(0.9654)	(0.6365)	(0.5115)	(0.8833)	(0.9840)
Δp_t^+	0.0981***	0.0395***	0.0429***	-0.0049	0.0029
	(0.0217)	(0.0087)	(0.0077)	(0.0147)	(0.0178)
$\lvert\Delta p_t^-\rvert$	0.0518**	0.0248**	0.0572***	0.0475***	0.1455***
	(0.0254)	(0.0100)	(0.0091)	(0.0165)	(0.0208)
Constant	18.0114***	20.8242***	21.9853***	45.5644***	62.1712***
	(0.6304)	(0.2831)	(0.2464)	(0.5034)	(0.5833)
Dong FE	Yes	Yes	Yes	Yes	Yes
Station FE	No	Yes	Yes	Yes	Yes
Observations	5,907	19,832	23,165	24,419	24,419
R^2	0.7899	0.7571	0.7622	0.8505	0.8119

Note: The standard errors are in the parentheses. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 2.7: Regression on duration of sticky pricing

	Dependent Variable: Duration (Weeks) of Sticky Pricing			
	Full Sample		Isolated Island Only	
	within 2 km	within 5 km	within 2 km	within 5 km
	(1)	(2)	(3)	(4)
$\text{Margin}_{t-1} \times$ Mainland	-0.2664***	-0.3877***		
	(0.0522)	(0.0555)		
$\text{Margin}_{t-1} \times$ Bridged	-0.0645	-0.1427**		
	(0.0552)	(0.0577)		
$\text{Margin}_{t-1} \times$ Isolated	0.2274**	0.2176**	0.3756*	0.4047*
	(0.0975)	(0.0988)	(0.2195)	(0.2213)
Δp_t^+	-0.0674***	-0.0718***	-0.0466***	-0.0465***
	(0.0015)	(0.0016)	(0.0115)	(0.0120)
$\Delta p_t^+ \times$ Rainy			-0.0059	-0.0097
			(0.0172)	(0.0179)
$\lvert \Delta p_t^- \rvert$	-0.0752***	-0.0776***	-0.0803***	-0.0845***
	(0.0016)	(0.0018)	(0.0098)	(0.0102)
$\lvert \Delta p_t^- \rvert \times$ Rainy			0.0101	0.0044
			(0.0215)	(0.0231)
Constant	3.9423***	4.071***	5.8689***	5.8371***
	(0.0534)	(0.0563)	(0.4246)	(0.4277)
Station FE	Yes	Yes	Yes	Yes
Observations	24,419	24,419	1,498	1,498
R^2	0.4561	0.4458	0.5654	0.5657

Note: The standard errors are in the parentheses. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Table 2.8: Asymmetric price adjustment of low- vs. high-cost stations

	(1) Full vs. Self		(2) Branded vs. Unbranded	
	Full-service	Interaction Self-service	Branded	Interaction Unbranded
Δc_t^+	0.1249***	0.0443	0.1307***	-0.0095
	(0.0082)	(0.0274)	(0.0081)	(0.0330)
Δc_{t-1}^+	0.1103***	0.0610**	0.1186***	-0.0242
	(0.0088)	(0.0272)	(0.0087)	(0.0315)
Δc_{t-2}^+	0.1470***	-0.0144	0.1499***	-0.0676**
	(0.0087)	(0.0283)	(0.0086)	(0.0317)
Δc_{t-3}^+	0.1106***	-0.0023	0.1126***	-0.0392
	(0.0093)	(0.0298)	(0.0093)	(0.0348)
Δc_{t-4}^+	0.0328***	0.0176	0.0355***	-0.0062
	(0.0089)	(0.0314)	(0.0087)	(0.0392)
Δc_t^-	0.0367***	0.0153	0.0395***	-0.0289
	(0.0077)	(0.0258)	(0.0075)	(0.0342)
Δc_{t-1}^-	0.0860***	0.0568**	0.0938***	-0.0191
	(0.0090)	(0.0262)	(0.0089)	(0.0316)
Δc_{t-2}^-	0.0934***	0.0201	0.0979***	-0.0121
	(0.0086)	(0.0268)	(0.0085)	(0.0313)
Δc_{t-3}^-	0.0668***	0.0199	0.0690***	0.0034
	(0.0086)	(0.0266)	(0.0084)	(0.0324)
Δc_{t-4}^-	0.0576***	-0.0080	0.0572***	-0.0141
	(0.0084)	(0.0264)	(0.0083)	(0.0321)
Δp_{t-1}^+	-0.0085	0.0001	-0.0127	0.0744
	(0.0135)	(0.0481)	(0.0134)	(0.0549)
Δp_{t-2}^+	0.0936***	-0.0187	0.0872***	0.0830
	(0.0125)	(0.0465)	(0.0125)	(0.0531)
Δp_{t-3}^+	0.1291***	-0.0499	0.1242***	0.0054
	(0.0118)	(0.0452)	(0.0117)	(0.0519)
Δp_{t-4}^+	0.1147***	-0.0127	0.1117***	0.0268
	(0.0115)	(0.0411)	(0.0114)	(0.0491)
Δp_{t-1}^-	-0.0842***	-0.0110	-0.0816***	-0.0568
	(0.0135)	(0.0472)	(0.0134)	(0.0512)
Δp_{t-2}^-	-0.0061	0.0251	-0.0085	0.0722
	(0.0132)	(0.0465)	(0.0131)	(0.0516)
Δp_{t-3}^-	0.0455***	0.0921**	0.0494***	0.0498
	(0.0127)	(0.0440)	(0.0126)	(0.0479)
Δp_{t-4}^-	0.0890***	0.0662	0.0928***	0.0159
	(0.0121)	(0.0427)	(0.0120)	(0.0454)
$\hat{\eta}_{i,t-1}$	-0.1597***		-0.1589***	
	(0.0061)		(0.0061)	
Other covariates	Yes		Yes	
Station FE	Yes		Yes	
Observations	12,158		12,158	
R^2	0.3763		0.3756	

Note: Other covariates include a constant, brands, self-service, convenience store, auto repair, population per station, the number of sedans per station, and the number of stations within a 2-km radius. The standard errors are in the parentheses. *, **, and ***refer to the 10%, 5%, and 1% significance levels, respectively.

Figure 2.1: Examples of pricing strategies

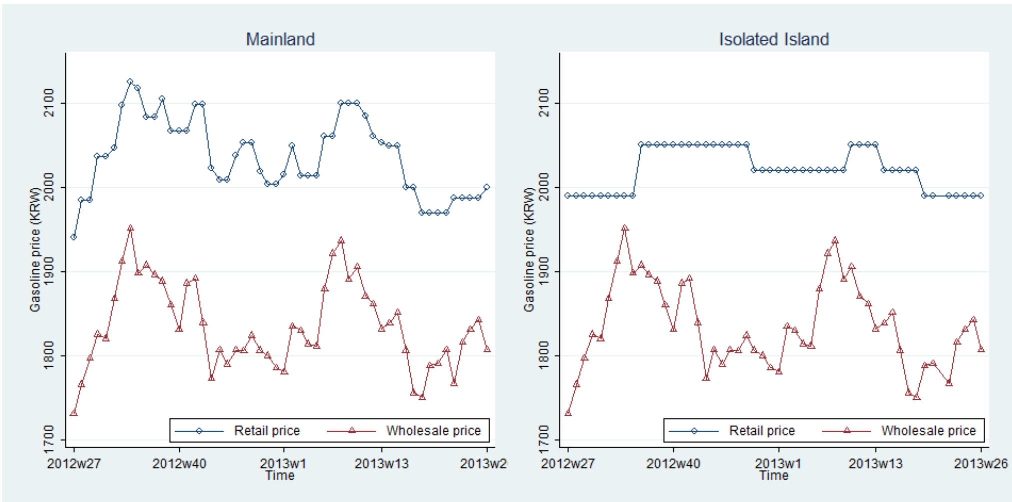


Figure 2.2: Part of the map with the location of stations

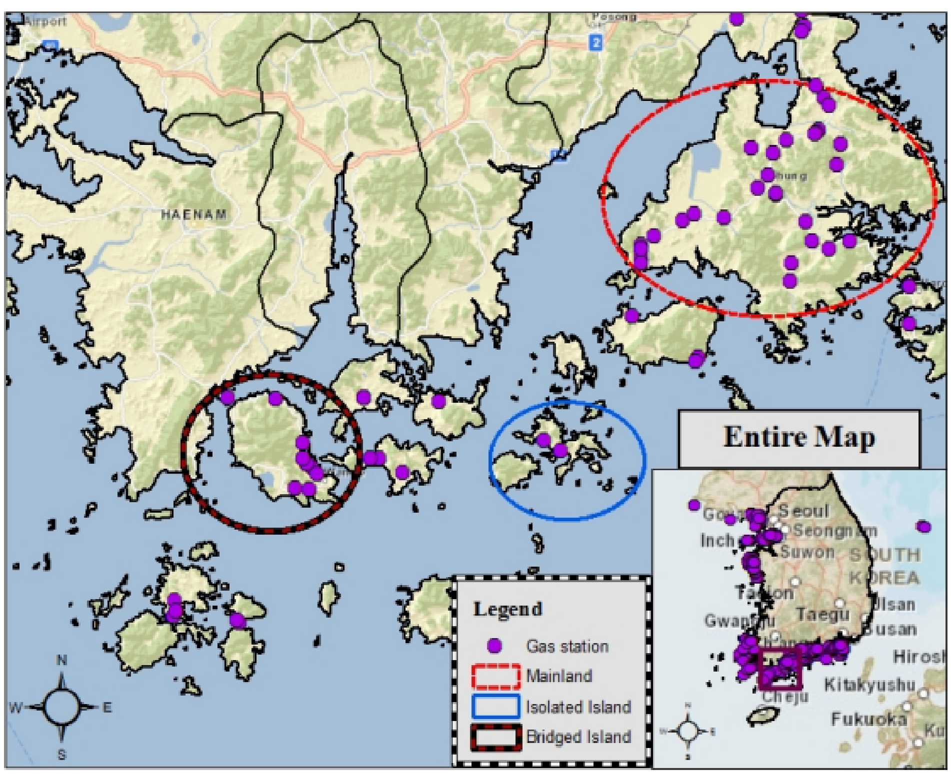


Figure 2.3: Asymmetric price adjustment by island types

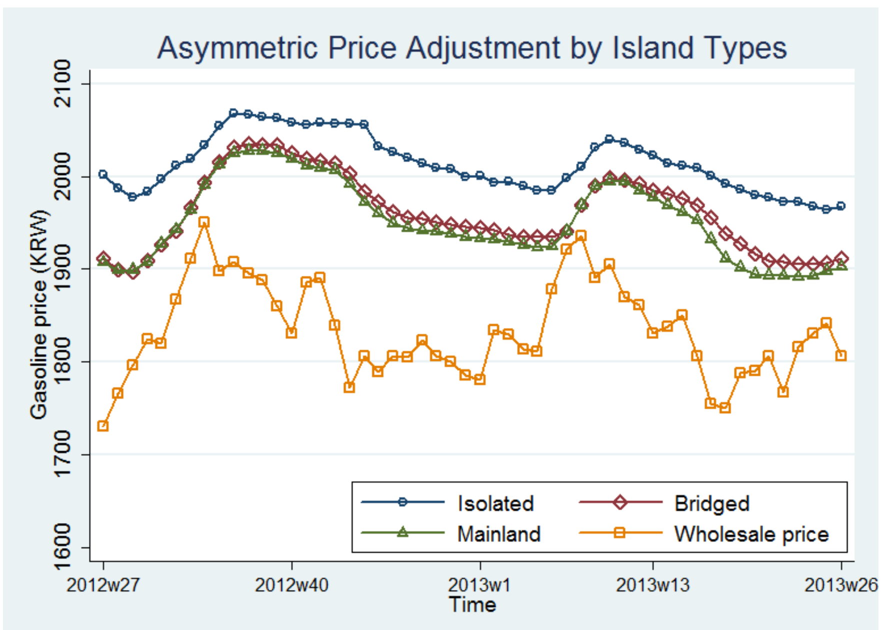
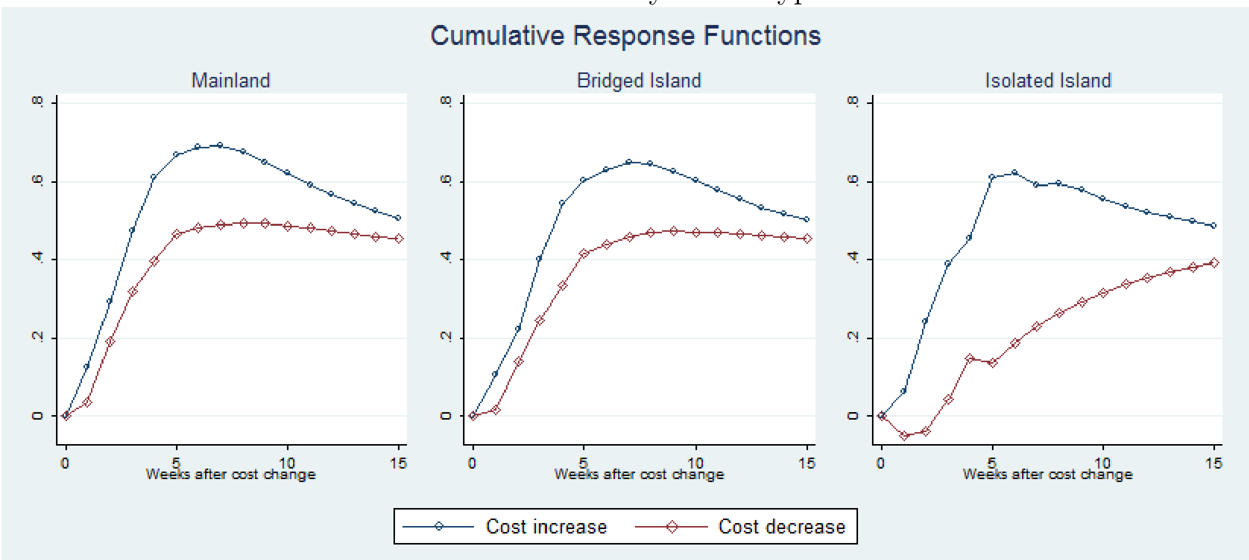


Figure 2.4: Cumulative response functions

Panel A. CRFs by island types



Panel B. CRFs by island types and margins

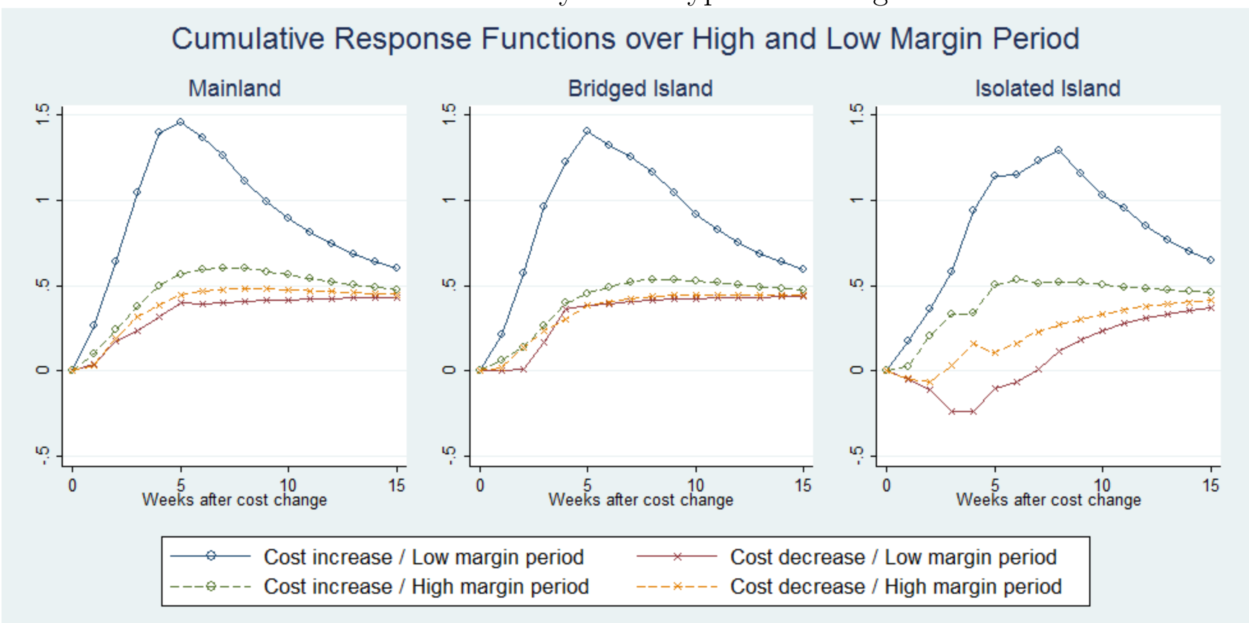
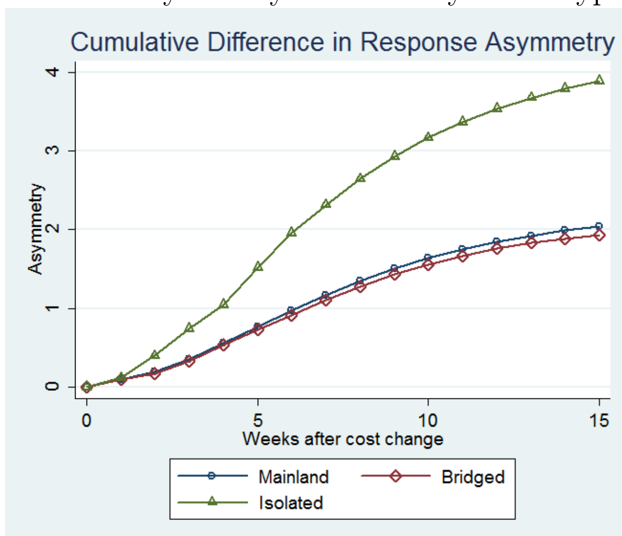


Figure 2.5: Response asymmetry functions

Panel A. Asymmetry functions by island types



Panel B. Asymmetry functions by island types and margins

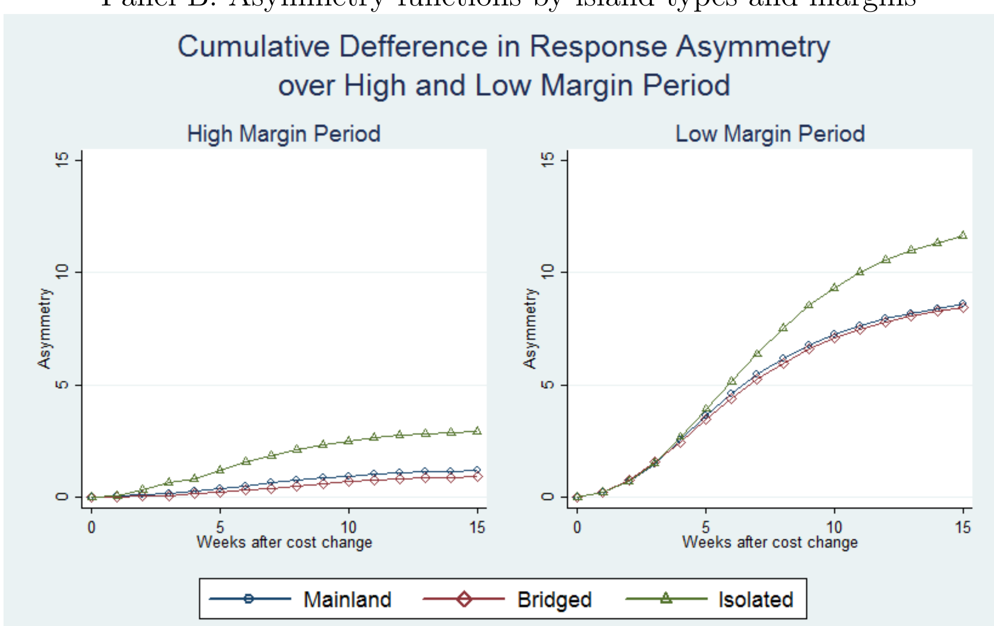
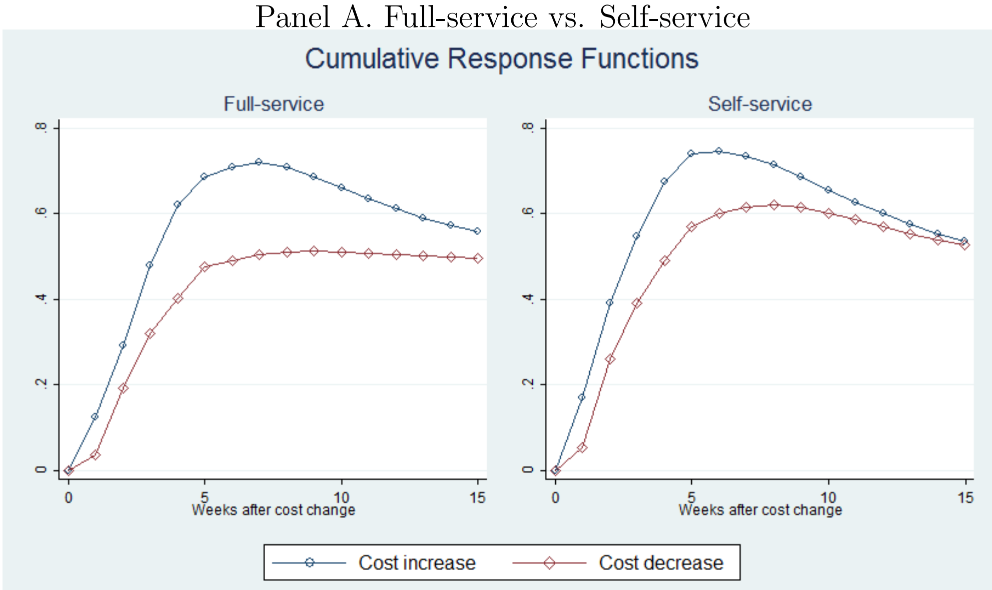
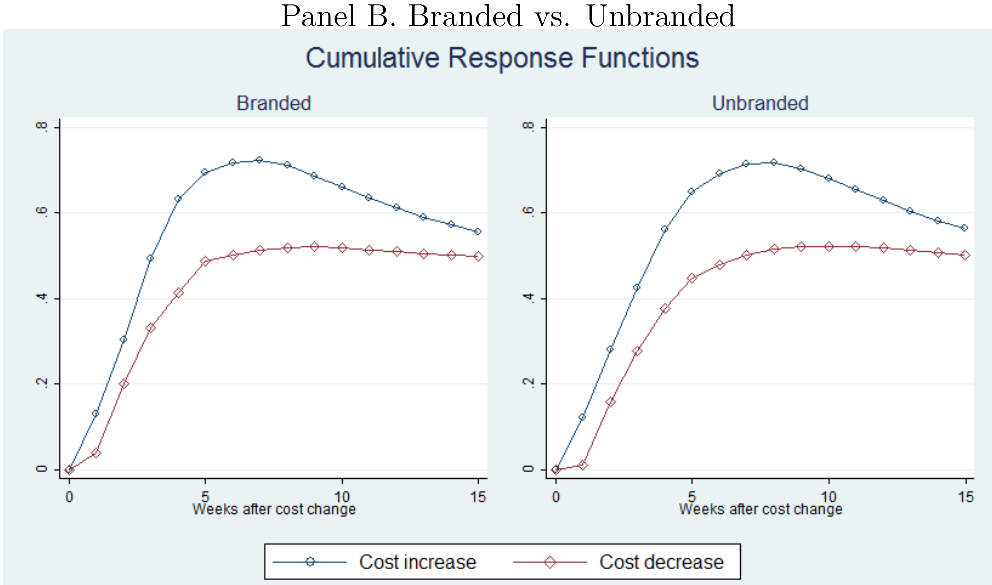


Figure 2.6: CRFs of low- and high-cost stations

Panel A. Full-service vs. Self-service



Panel B. Branded vs. Unbranded



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Appendix A

APPENDIX TO CHAPTER 1

A.1 Co-movements of price dispersion within and between markets

According to the theory presented in Section 1.3, the dynamics of price variations across markets resembles those among stations, from which we derive a possible justification for using daily average prices at the city level to infer the behaviors of individual stations. To provide further evidence supporting the discussion, we collect *ex-post* supplementary data from OPINET, which contain daily price information on all operating stations in Seoul for a 30-day period, April 10 to May 9, 2013.[1] Using the data, we create two dispersion measures to represent price variations between and within markets: district-level and station-level price dispersion. The district-level dispersion measure is calculated using the squared residuals obtained from equation (1.3), as if we were only to observe average gasoline prices at the district level (as in this paper) instead of at the station level.[2] The station-level dispersion measure that we would have employed if price data had been available for individual stations is computed in the same manner but replacing city fixed effects with station fixed effects.

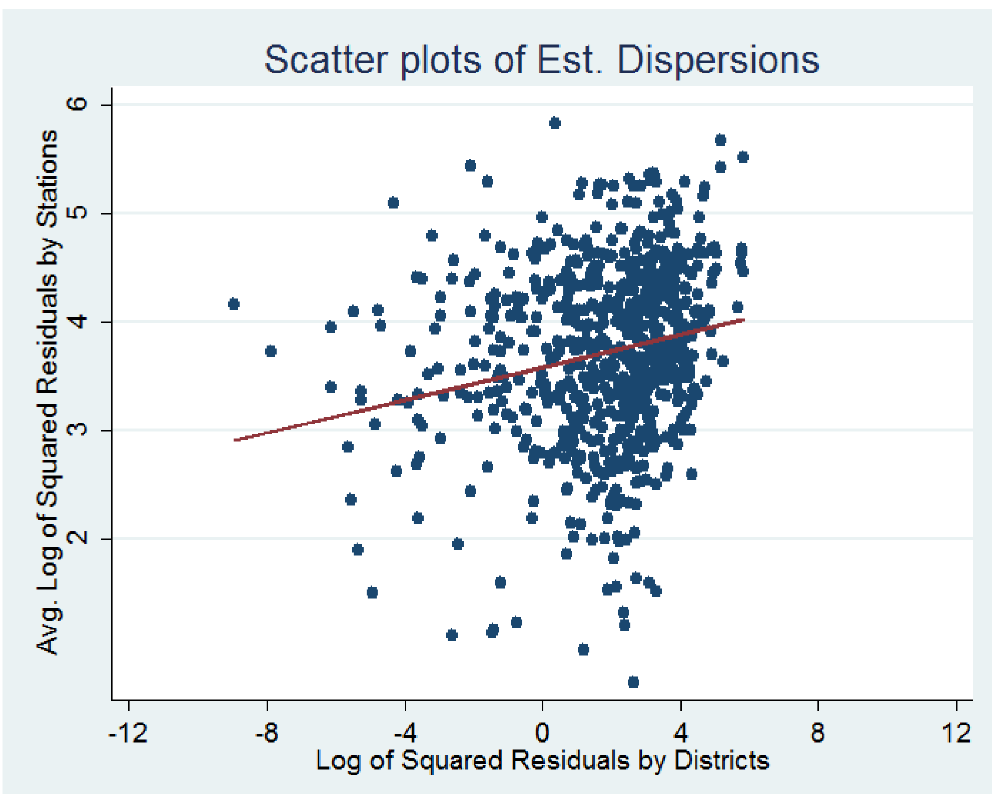
Figure A.1 depicts the scatter plot of the average of the logarithms of station-level dispersion (y-axis) and the logarithm of district-level dispersion (x-axis) under a linear fit. This figure clearly demonstrates that the two measures are positively correlated. The simple correlation coefficient of the two measures in levels is 0.5808. Additionally, we estimate an ancillary regression of the district-level dispersion on the station-level dispersions of each

[1]We collected the real-time price data between 10 A.M. and 1 P.M. from OPINET for 30 days. The maximum number of operating stations on a given day is 614, and the minimum is 604. The total number of observations is 18,339.

[2]Recall that a district in metropolitan city such as Seoul is comparable to a city in a province. See footnote 17.

station within the district.[3] Then, the goodness-of-fit measures from the regressions will represent how well the district-level measure conveys the information of price variations of each station within the district. Table A.1 presents the R^2 and adjusted R^2 of the ancillary regressions, indicating that the average of the goodness-of-fit measures are large and are clustered around the median. All of the results indicate that price dispersion within and between cities are highly correlated, as theory indicates, and thus suggest that district-level dispersion is an appropriate proxy for station-level dispersion to infer stations' behaviors in this paper.

Figure A.1: Scatter plot of estimated dispersions



[3]Denote $\hat{e}^2_{ct}$ as the district-level dispersion measure of district c at time t and $\hat{e}^2_{st}$ as the station-level dispersion of a station $s = 1, ..., S$ at time t. Then the estimation model becomes: $\hat{e}^2_{ct} = \alpha + \sum_{s=1}^{S} \beta_s \hat{e}^2_{st} + \varepsilon_t$ for each district c. For the estimation, we only focus on 19 districts of a total of 25, where the number of operating stations is below 28.

Table A.1: Goodness-of-fit measures of ancillary regression

Variable	Obs.	Mean	Std. Dev.	p25	Median (p50)	p75
R^2	19	0.9037	0.1330	0.9080	0.9564	0.9705
Adjusted R^2	19	0.7615	0.2836	0.7880	0.8443	0.9216

A.2 Identifying structural breaks

The underlying estimation model of Bai and Perron (1998, 2003) is a multiple linear regression with m breaks ($m+1$ regimes):

$$y_t = {x'}_t\beta + {z'}_t\delta_j + u_t, \qquad t = T_{j-1}+1, ..., T_j \tag{A.1}$$

for $j = 1, ..., m+1$. y_t is the observed dependent variable, $x_t(p \times 1)$ and $z_t(q \times 1)$ are vectors of covariates, and β and δ_j ($j = 1, ..., m+1$.) are corresponding vectors. u_t is the disturbance at time t. The purpose of the BP method is to statistically detect possible structural breaks that minimize the sum of squared residuals of the model. To apply the BP method to identify the macroeconomic cost shocks, we consider a simple pure structural change model ($p = 0$): y_t is the weekly average wholesale price of gasoline from 2008:05/w1 to 2011:12/w5, z_t is a constant, and u_t is allowed to be serially correlated and heteroskedastic across regimes. This simple model relies on there being no average wholesale price trend if we hypothetically assume that no relevant shock occurs.[4]

Table A.2 replicates Table 1 of BP (2003) using our data. Panel A presents the results of tests for the presence of at least one break, where the null hypothesis is no break: i) $SupF_T(m)$ tests for the presence of m breaks and ii) UDmax and WDmax test for the presence of an unknown number of breaks given some upper bound. All tests reject the null hypothesis that there is no structural break at the 5 percent significance level. In

[4]In this hypothetical situation, it is also possible to have a moderately increasing linear trend due to inflation. If we include a linear trend in the model, it is difficult to distinguish between an increasing linear trend due to inflation and an increasing or decreasing linear trend due to economic shocks. Therefore, only including a constant in the model is a conservative approach to avoid this identification problem.

panel B, several estimations of the number of structural breaks are provided. Yao (1998) suggests the use of the Bayesian Information Criterion (BIC), while Liu, Wu, and Zideck (1997) propose the modified Schwarz criterion (LWZ). BP argue that their sequential method performs better in more general environments.[5] In essence, the sequential method tests the null of $l + 1$ breaks given that l breaks are present sequentially, using the $SupF_T\,(l{+}|\,l)$ test. Two criteria suggest 4 breaks, while only the BIC indicates 5 breaks. BP (2003) also note that when selecting the number of structural breaks, the BIC performs poorly when serial correlation is present, while the LWZ and the sequential procedure are robust to serial correlation. Therefore, when allowing for serial correlation in the wholesale gasoline price, we selected 4 breaks. Panel C tabulates break points detected by the sequential procedure.[6]

Table A.2: Structural break tests on gasoline wholesale prices

A. Structural break test: no break vs. presence of at least one break ^{a}						
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$	$UDmax$	$WDmax$
88.3740**	19.7151**	66.4193**	81.9209**	89.5473**	89.5473**	151.7469**
B. Number of breaks selected^b						
Sequential	4					
LWZ	4					
BIC	5					

C. Estimated four breaks with 95% confidence intervals^c			
$\hat{T}_1$	$\hat{T}_2$	$\hat{T}_3$	$\hat{T}_4$
08: 10/w2	09: 5/w4	09: 12/w5	10: 12/w2
(08: 9/w1 - 10/w3)	(09: 4/w4 - 9/w4)	(09: 11/w1 - 1/w3)	(10: 11/w1 - 12:w3)

Notes:

a. The $SupF_T(m)$ tests and the reported standard errors and confidence intervals allow for the possibility of serial correlation in the disturbances. The heteroscedasticity and autocorrelation consistent (HAC) covariance matrix is constructed following Andrew (1991) and Andrew and Monahan (1992) using a quadratic kernel with automatic bandwidth selection based on an AR(1) approximation.

b. 5% size is used for the sequential test $SupF_T(l+1|l)$.

c. 95% confidence intervals are presented in the parentheses.

[5] BP (2003) present practical recommendations regarding which test to employ to determine the number of breaks. See 5.5 of BP (2003) for more details.

[6] In applying the sequential procedure, we allow up to 5 breaks and use a trimming of $\varepsilon = 0.15$. Thus, each segment has at least 29 observations.

Appendix B
APPENDIX TO CHAPTER 2

B.1 Calculating the CRFs

To formulate the cumulative price response to cost changes, consider a simplified version of the regression equation, as follows:

$$\Delta p_{it} = \sum_{j=1}^{J} \left(\alpha_j^+ \Delta p_{i,t-j}^+ + \alpha_j^- \Delta p_{i,t-j}^-\right) + \sum_{j=0}^{J} \left(\beta_j^+ \Delta c_{i,t-j}^+ + \beta_j^- \Delta c_{i,t-j}^-\right) + \theta\eta_{i,t-1} + X_{it}\gamma + \xi_i + \varepsilon_{it} \quad \text{(B.1)}$$

where $\eta_{i,t-1} = p_{i,t-1} - \delta_i - \phi c_{i,t-1}$.

For a unit increase in wholesale price at time t ($\Delta c_{it} = 1$), the cumulative adjustment of prices after k period is now given by

$$\begin{aligned}
CRF_0^+ &= \beta_0^+ \\
CRF_1^+ &= CRF_0^+ + \beta_1^+ + \theta\left(CRF_0^+ - \phi\right) + \alpha_1^+ \max\left(0, CRF_0^+\right) + \alpha_1^- \min\left(0, CRF_0^+\right) \\
&\vdots \\
CRF_k^+ &= CRF_{k-1}^+ + \beta_k^+ + \theta\left(CRF_{k-1}^+ - \phi\right) \\
&\quad + \sum_{i=1}^{\max(J,k)} \left[\alpha_i^+ \max\left(0, CRF_{k-i}^+ - CRF_{k-i-1}^+\right) + \alpha_i^- \min\left(0, CRF_{k-i}^+ - CRF_{k-i-1}^+\right)\right]
\end{aligned}$$

The CRFs comprise four parts: (1) the cumulative changes in prices until previous period, (2) the current price changes directly affected by the past cost changes, (3) the reversion effects by the error correction term, and (4) the effects by the lagged price changes. Similarly, we can derive the CRFs from a negative cost shock.

To apply this formula to our regression model, we only need to modify the coefficients of α's and β's. For example, we replace α_k^+ with $\alpha_k^{+,m} + \alpha_k^{+,is}$ and β_k^+ with $\beta_k^{+,m} + \beta_k^{+,is}$ to calculate the CRFs for stations on isolated islands.