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Three Applications of Structural Estimations in Oligopolistic and Auction Markets

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Publication Date
2012

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Three Applications of Structural Estimations in Oligopolistic and Auction Markets

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Economics

by

Hisayuki Yoshimoto

2012
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2012
ABSTRACT OF THE DISSERTATION

Three Applications of Structural Estimations in Oligopolistic and Auction Markets

by

Hisayuki Yoshimoto

Doctor of Philosophy in Economics

University of California, Los Angeles, 2012

Professor Ichiro Obara, Chair

This dissertation investigates empirical perspectives on strategic interactions in oligopolistic and auction markets. To support my claims, I structurally estimate, test, and simulate economic hypotheses regarding post-merger market prices (Chapter 1) and the effects of regret-averse attitudes in auction markets (Chapter 2). I also propose a structural estimation method for experimental auction data (Chapter 3).
The dissertation of Hisayuki Yoshimoto is approved.

Connan A. Snider

Jinyong Hahn

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Daniel A. Ackerberg

Ichiro Obara, Committee Chair

University of California, Los Angeles

2012
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CHAPTER 1


1.1 Introduction

Horizontal merger policy evaluations have been a central agenda in industrial organization. Not only have they served as an active field of research, but they also play a vital role in supporting antitrust policymaking. Because social welfare losses directly result from poor merger policy decisions, both academic researchers and antitrust agencies have paid significant attention to merger policy evaluations. In line with this social importance, economists have put an enormous amount of research effort into such various aspects as merger incentives, merger synergies, capacity expansions, and simulations for post-merger market consequences from both theoretical and empirical perspectives.

From an academic perspective, the horizontal merger analyses in homogeneous product industries have been a successful area wherein economic researchers have provided rich evaluation tools for both realized and potential mergers. Starting from a simple theoretical Cournot model (Salant, Switzer, and Reynolds, 1983) to a sophisticated dynamic model (Gowrisankaran, 1999), researchers are now well-equipped to investigate diversified aspects of horizontal mergers. In addition, a sizable body of literature represents retrospective studies on observed mergers in homogeneous product industries, including such industries as
the US steel industry (Stigler, 1950), the Italian banking industry (Focarelli and Panetta, 2003), the European bottled water industry (Compete, Jenny, and Rey, 2002), and the U.S. feminine hygiene goods industry (Weinberg, 2011)\(^1\).

In contrast, both the theoretical and the empirical literatures on horizontal mergers in differentiated-product industries are scant. In theoretical analysis, researchers inevitably characterize differentiated-product industries using Bertrand price competitions\(^2\). Since firms choose multiple prices, economic modeling analyses tend to be quite challenging\(^3\). In empirical analysis, differentiated-product firms tend to be either large-sized firms or firms that are locally concentrated, given their abilities to supply multi-differentiated products. As such, proposed mergers are likely to be challenged and blocked by local antitrust authorities\(^4\). Although researchers have proposed a small number of vital merger-evaluation tools, e.g. Nevo (2000, 2001), the dearth of empirical horizontal-merger observations in large differentiated-product industries inhibits investigation into these proposed tools’ performance. The left side of Figure 1.1 depicts the fundamental difficulty in the empirical horizontal-merger literature. Since researchers cannot observe post-merger market consequences when mergers are blocked, they are unable to investigate the performances of Nevo’s simulation method for these mergers\(^6\). Consequently, there are only a handful of realized-merger case studies relat-

---

\(^1\)See Werden and Froeb (2008) for more homogeneous industry merger examples.

\(^2\)Cournot quantity competition model cannot well-describe differentiated product industries, as it assumes centralized spot markets (or assumes the existence of market auctioneers) that provide prices for each differentiated product.

\(^3\)The exception is a static Bertrand model in which researchers can derive first-order necessary conditions. This research relies on such a static Bertrand framework. Dynamic extensions of differentiated-product industry mergers are also challenging due to the emergence of multiple equilibria which compromises the models’ policy implications.


\(^5\)Here exists another difficulty: Researchers usually obtain only price data in observed differentiated-product industry mergers. This presents a difficulty for empirical researchers who are unable to implement structural analyses that inevitably require sales quantity data. Empirical researchers try to use price-only data wisely to obtain merger-policy implications. See Ashenfelter, Hosken, and Weinberg (Working Paper) [3] for such use of price-only data.

\(^6\)More precisely, an investigation on the simulation performance inevitably requires following conditions: (1) a merger was realized; (2) both pre-merger and post-merger market data are available; (3) both price and
Figure 1.1: Left figure: Research with a blocked/retreated merger, Right figure: This research (outline)

Thus, in order to expand on the available literature regarding differentiated-product horizontal mergers, this paper investigates one specific merge that came from the Asian economic crisis\(^7\). Using a dataset that includes observations on post-merger market consequences, I evaluate the reliability of and potential improvements to Nevo’s (2000, 2001) post-merger price simulation method\(^8\). In particular, I examine vehicle pricing in the Korean automobile industry for the period 1991–2010. This period saw a large horizontal merger between two differentiated-product firms, Hyundai and Kia Motors (in November 1998), a merger that conglomerated 70 percent of the Korean automobile market. The right side of Figure 1.1 outlines the framework of this research. First, I estimate consumer preference and substitutes quantity data are available; (4) post-merger data are observed for a long period to evaluate long-run impacts of realized merger.

\(^7\)One can recognize the merger investigated in this research as a natural experiment caused by the Asian economic crisis in 1997.

\(^8\)The post-merger price simulation method proposed by Nevo (2000, 2001) has two computational challenges: First, the problem of non-linear minimization search with the nested fixed point algorithms proposed by with Berry, Levinsohn, and Pakes (1995) [5]. The details and severity of this problem are discussed thoroughly by Knittel and Metaxoglou (2011 and working paper) [24] [23]. Second, the large dimensional non-linear simultaneous equation problem associated with post-merger price simulations. I avoid the first challenge by using the instrumental variable nested-logit model estimation in this research.
tution patterns leading up to the merger. Second, I calculate marginal costs under a static Bertrand price competition framework. Third, I use these estimated preference and calculated marginal costs to simulate post-merger prices. I find that one can reasonably predict post-merger prices well in the short term; however, large discrepancies appear in the long run. Fourth, I use observed post-merger consumer incomes and preferences, marginal costs, and product lines to account for discrepancies between simulated and observed prices. It turns out that, by incorporating these observed post-merger information, I can account for 61 percent of long-run price discrepancies. By observing a large fraction of simulation discrepancies which one can account for in the observed post-merger information, this research suggests that when antitrust policy makers apply the results of simulations, they must take into account changes in factors which the simulation model takes as exogenous.

1.1.1 Literature

The recent literature on differentiated-product horizontal mergers evolves with the development of sophisticated differentiated-product demand estimation methods. Berry (1994) [4] and Berry, Levinsohn, and Pakes (1995, henceforth BLP) [5] propose differentiated product demand estimation methods that can be reliably used for horizontal-merger analysis. Nevo’s research (2000, 2001) [32] [33] forms the corner-stone, wherein he proposes a simulation method that emphasizes changes in firm ownership, using the demand-estimation method that BLP proposed a few years earlier. Nevo’s method provides the structural framework that enables us to derive post-merger prices using only pre-merger data and information on ownership transitions. Based on this seminal work, several analyses examining blocked mergers followed [10]. However, only two papers have applied Nevo’s simulation framework to a differentiated-product industry merger that actually occurred in the real world. Nevo

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9 In this research I avoid using the term “short run” since it generally assumes economic conditions remain unchanged. As explaining soon, the economic conditions (e.g. household income conditions) changed largely after the Hyudai–Kia merger.

(2000) [32] investigates two mergers in the U.S. cereal industry. His study, however, only uses short-term post-merger data and is unable to investigate the long-run consequences of observed mergers. Peters (2006) [35] investigates five airline mergers observed in the United States during the 1980s, and he faced significant modeling difficulties\textsuperscript{11}. By comparing simulated and observed short-term post-merger prices\textsuperscript{12}, Peters (2006) reports mixed results in simulation performance. In summary, the literature provides only two empirical case studies that investigate the short-term performance of the post-merger price simulation method, and leaving questions of its reliability\textsuperscript{13}. This paper contributes to the literature by evaluating simulation reliability both in the short term and in the long run after the merger\textsuperscript{14}.

\subsection{Settings and Organization of Paper}

I apply four important settings throughout this paper. First, all prices used in this research are adjusted for inflation using Korea’s consumer price index\textsuperscript{15}. Second, I uniformly applied a 1,000 won = 1 U.S. dollar exchange rate when representing prices\textsuperscript{16} for the sake of easily understandable prices. Third, since the announcement of the Hyundai–Kia merger in November 1998, I define January-1991 through November-1998 as the pre-merger regime and December-1998 through December-2010 as the post-merger regime\textsuperscript{17}. Lastly, I recognize the difficulty of applying demand estimation and supply-side modeling to the airline industry. Any consumer demand model has to include both hub and spoke airport demands. Any supply-side model must include complicated pricing systems such as mileage points, first versus economy class price differences, and early ticket purchase discounts.

\textsuperscript{11}I recognize the difficulty of applying demand estimation and supply-side modeling to the airline industry. Any consumer demand model has to include both hub and spoke airport demands. Any supply-side model must include complicated pricing systems such as mileage points, first versus economy class price differences, and early ticket purchase discounts.

\textsuperscript{12}Peters (2006) compares simulated prices and prices that were observed one year after airline mergers.

\textsuperscript{13}Specifically, the literature lacks investigations on this simulation’s long-run performance.

\textsuperscript{14}Potential weaknesses of this paper should be noted here. I do not have panel-market data, and I am unable to use the multi-marke-based instrument variables as suggested by Hausman, Leonard, and Zona (1994) [21]. In my post-merger price simulations, I solve 31 to 37 dimensional simultaneous non-linear system equations and computations tend to be unstable. I have plant-level production and input/output data. However, I do not have brand- (automobile model) level production data, and am unable to recover brand-level production marginal costs from the data available.

\textsuperscript{15}I use 2005 as my base year. The consumer price index data come from Statistics Korea (Korea’s national bureau of statistics). For U.S. car prices, I also used 2005 as my base year.

\textsuperscript{16}In general, there are many zeros in prices in Korean won, making it difficult to get a sense of numbers. Although the won-dollar exchange rate is volatile, the long-term average remains close to 1,000 won = 1 U.S. dollar. With this general exchange rate in mind, a Hyundai Sonata price of 20,829,000 won simply becomes U.S. $20,829.

\textsuperscript{17}I do not have data from prior to January 1991.
I concentrate my research on passenger cars, ignoring trucks\(^{18}\) and other commercial vehicles such as buses.

I organize the remainder of this paper as follows: Section 2 describes the automobile industry in Korea; Sections 3 and 4 explore the demand- and supply-side models and provide estimation results; Section 5 evaluates the benchmark simulation result and reports long-run simulation discrepancies; Section 6 lists potential causes in long-run simulation discrepancies; Section 7 accounts for long-run price discrepancies by using observed post-merger market data; and Section 8 concludes the study by suggesting future courses of research.

### 1.2 Description of the Automobile Market in Korea

Throughout this paper, I define the Korean automobile market as comprising the entirety of South Korea which remains geographically separated from other markets\(^{19,20}\). This market is distinct in the following four ways: (1) Korea experienced an economic crisis and sales shares of imported-cars have been extremely small ever since; (2) five Korean domestic

---

\(^{18}\)Unlike in the United States, pickup trucks are not popular in Korea.

\(^{19}\)South Korea (the Republic of Korea), located on the southern half of the Korean peninsula, is geographically separated from trade partners by North Korea and surrounding ocean.

\(^{20}\)The dataset used in this paper is a single-market dataset, similar to the dataset used in Berry, Levinsohn, and Pake (1995) [5]. I do not have smaller market data such as province-level sales data.
manufactures oligopolize the market; (3) the Hyundai–Kia merger occurred in November 1998 and conglomerated 70 percent of the market, before which there was only one entry, Samsung Motors (February 1998); and (4) vehicle prices in Korea have been increasing since the Hyundai–Kia merger. In this section, I describe the automobile market in Korea with emphasis on these four points, and make connections to estimations and simulations discussed in later sections.

1.2.1 The Asian Economic Crisis and Imported Car Sales

Figure 1.3 illustrates the monthly sales of domestically produced cars and imported cars (in number of automobiles sold) in South Korea for 1991–2010. There are two notable findings in Figure 1.3: First, the market experienced the Asian economic crisis in 1997–1999, during which time automobile sales slumped. This economic crisis led to mergers and acquisitions among Korean domestic automobile manufactures, which I will explain in the latter part of this section. Second, imported car sales shares have remained extremely low, typically less than 2 percent of total sales\(^{21}\), and the majority of Korean automobile buyers have

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\(^{21}\)Most of the imported cars sold in Korea are German luxury cars such as Audi, BMW, and Mercedes Benz. Note that the Korean Fair Trade Commission suspects collusive pricing among imported car dealers.

\(^{22}\)Of interest, it is important to determine which factors cause these low imported car sales. The tariff on imported cars decreased from 30 percent (in 1988) to 8 percent (in 1995), and since has remained constant at 8 percent. I interviewed several Korean native colleagues and asked the question: “Why do Korean people
Figure 1.4: Left figure: Monthly sales quantities by firm, Right figure: Percentage market shares by firm

Data source: Ward’s Automotive Yearbook and KAMA monthly Journal

purchased domestically-produced cars. Because of such small shares, I ignore imported car sales in the rest part of this paper.

1.2.2 Oligopoly with Five Domestic Automobile Manufactures

One can describe the Korean automobile market as highly concentrated in a five-firm oligopoly: Hyundai, Kia, (GM-)Daewoo, Ssangyong, and (Renault-)Sumsung Motors. The left side of Figure 3.1 reports monthly sales by firm. Although monthly sales by firm appear highly volatile\(^2\), Hyundai Motors’ sales numbers have been larger than those of any other firm. The right side of Figure 3.1 illustrates monthly market share. For the period 1991-2010, Hyundai Motor’s share has been around 40 to 50 percent; Kia Motors, the second largest automobile manufacture in Korea, holds 25 to 30. The remaining small firms, (GM-)Daewoo, Ssangyong, and (Renault-)Sumsung Motors, hold around 10 percent each. As a whole, Hyundai Motors occupies a larger part of Korea’s domestic market share, and this share

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not buy imported cars?” Their answers were: (1) Imported cars are expensive in Korea, (2) Korean culture does not allow workers to have cars more luxurious than those of their supervisors (Note: Imported cars in Korea are mostly luxury cars), (3) Auto insurance companies charge high premiums on imported cars, and (4) Compared to domestic cars, fewer maintenance dealers are available.

\(^2\)Part of the reason that supports this high volatility in sales quantities is labor strikes.
Table 1.1: Ownership transitions

<table>
<thead>
<tr>
<th>Firm Trade Name</th>
<th>(1) Hyundai Motors</th>
<th>(2) Kia Motors</th>
<th>(3) (GM-)Daewoo Motors</th>
<th>(4) Ssangyong Motors</th>
<th>(5) (Renault-)Samsung Motors</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1992</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1993</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1994</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>(Entry Announcement)</td>
</tr>
<tr>
<td>1995</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1996</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1997 (economic crisis)</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Ssangyong</td>
<td>—</td>
</tr>
<tr>
<td>1998 (economic crisis)</td>
<td>Hyundai</td>
<td>Kia</td>
<td>Daewoo</td>
<td>Daewoo</td>
<td>Samsung</td>
</tr>
<tr>
<td>1999</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>Daewoo</td>
<td>Daewoo</td>
<td>Samsung</td>
</tr>
<tr>
<td>2000</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>Daewoo</td>
<td>Daewoo</td>
<td>Samsung</td>
</tr>
<tr>
<td>2001</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>Daewoo</td>
<td>Daewoo</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2002</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>Daewoo</td>
<td>Daewoo</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2003</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2004</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2005</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2006</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2007</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2008</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
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<tr>
<td>2009</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
<tr>
<td>2010</td>
<td>Hyundai</td>
<td>Hyundai</td>
<td>GM-Daewoo</td>
<td>Ssangyong</td>
<td>Renault-Samsung</td>
</tr>
</tbody>
</table>

Note: Cells describe owner firms. For example, in year 2002, Kia Motors was owned by Hyundai Motors.

Data source: Official firm websites and various newspaper articles from The JoongAng Ilbo, The Dong-A Ilbo, and The Chosun Ilbo

Table 1.2: Korean economic crisis, merger, and acquisition timeline

<table>
<thead>
<tr>
<th>Date</th>
<th>Event</th>
</tr>
</thead>
<tbody>
<tr>
<td>Late 1996</td>
<td>&quot;∼ Jun. 1997&quot; Default problems gradually grew in the Korean economy</td>
</tr>
<tr>
<td>1997 Jul.</td>
<td>&quot; Asian economic crisis, triggered by the collapse of Thai baht</td>
</tr>
<tr>
<td>1997 Jul.</td>
<td>&quot; Kia Motors announced bankruptcy, triggered Korean economic crisis</td>
</tr>
<tr>
<td>1998 Nov.</td>
<td>&quot; Kia Motors came under creditor bank and court control</td>
</tr>
<tr>
<td>1998 Nov.</td>
<td>&quot; Creditor banks announced Hyundai Motors' acquisition of Kia Motors</td>
</tr>
<tr>
<td>1999 Jun.</td>
<td>&quot; (Ford Motors, 17% shareholder of Kia Motors before the bankruptcy, was also interested in acquisition)</td>
</tr>
<tr>
<td>2000 Apr.</td>
<td>&quot; Samsung Motors announced bankruptcy, and came under creditor bank and court control</td>
</tr>
<tr>
<td>2001 ∼ 2002</td>
<td>&quot; General Motors (GM) gradually proceeded with the acquisition of Daewoo Motors</td>
</tr>
</tbody>
</table>

Data source: Various newspaper articles from The JoongAng Ilbo, The Dong-A Ilbo, and The Chosun Ilbo

grew even larger after the Hyundai–Kia merger.
1.2.3 The Hyundai-Kia Merger (November 1998) and Samsung Motors Entry (February 1998)

The Korean automobile industry experienced substantial ownership changes between 1991 and 2010. Table 1.1 depicts firm ownership transition information. As would be expected, the Hyundai–Kia merger in November 1998 stands as the most important event during this period. Table 1.2 lists chronologically the timeline of this merger. One can consider the Hyundai–Kia merger exogenous, since Kia’s bankruptcy—a result of the Asian economic crisis—led to the merger24. Ford Motors, a 17 percent shareholder of Kia Motors before the bankruptcy, also expressed interest in this acquisition, but Ford retreated25. In the simulation section, I simulate a hypothetical scenario of Ford’s acquisition of Kia Motors.

Also, of particular note is that the merged Hyundai–Kia group has continued to use pre-merger merchandise marks (“Hyundai Motors” and “Kia Motors”), and two networks of retailers (Hyundai and Kia dealerships)26. Although the Korean automobile market is highly concentrated, there has been only one domestic automobile manufacturer entry. Samsung Motors entered the market in February 1998. One may consider Samsung’s entry political due to Korea’s presidential policy27 and I treat this entry as exogenous in this research. It is worth pointing out Daewoo Motor’s temporal acquisition of Ssangyong Motors. Ssangyong Motors is a firm that has been concentrating its production on SUV and Minivan size cars.

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24 The merger also had political aspects. In 2007, the president of Hyundai Motors, Chung Mong-Koo, was convicted of various bribery activities, potentially including Hyundai’s acquisition of Kia Motors. See: New York Times: http://www.nytimes.com/2007/02/06/business/06hyundai.html?ref=chungmongkoo

25 For details about how Ford Motors withdrew from the acquisition, see BBC News: http://news.bbc.co.uk/2/hi/business/196667.stm

26 Hyundai group initially owned 51 percent of Kia Motors’ share. Later, the percentage decreased to 35 percent.

27 I will sum up the anecdotal political stories related to Samsung Motors’ entry. They include the following: (1) It was Kun-Hee Lee’s, the president of Samsung group, long-term desire to own an automobile company; (2) Samsung group and Hyundai group are long time rivals; (3) Kim Young-Sam (the seventh president of Korea) competed with Jeong Juyeong (the founder of Hyundai group and the owner of Hyundai Motors) in the 1992 Korean presidential election. Kim Young-Sam won the race; (4) After the 1992 presidential election, Kim Young-Sam’s administration prosecuted Jeong Juyeong for violations of election law, and Kim Young-Sam’s administration and the Hyundai group continued to experience political tensions; (5) Kim Young-Sam had been elected from the Busan area, the second-largest metropolitan area in Korea; (6) Samsung announced its entry into the automobile market in 1994 along with a plan to build an automobile plant in Busan, one and a half years after Kim Young-Sam had been elected president. (7) Samsung Motors began to produce passenger vehicles in the newly constructed Busan plant in February 1998. In the same month, Kim Young-Sam completed his presidential term.
In 1998, right after Asian Economic Crisis, Daewoo Motors acquired financially troubled Ssangyong Motors. As Daewoo Motors did not produce any SUV and Minivan car brands at the point of 1998, the primary purpose was building up Daewoo’s SUV and Minivan section through the acquisition\textsuperscript{28}. In 2002, Daewoo Motors financially troubled and was acquired by General Motors (GM). At that time, The Daewoo’s SUV and Minivan section was spun off and Ssangyong Brand (and Ssangyong Motors) was revived as an independent firm.

1.2.4 Post-Merger Vehicle Price Increases

After the Hyundai–Kia merger in November 1998, the market saw significant hikes in vehicle prices. The left side of Figure 1.9 indicates aggregated (market level) sales-weighted vehicle transaction prices in Korea\textsuperscript{29}. The aggregate prices increased after the Hyundai-Kia merger. During the pre-merger regime (1991–1998) the average price was only $13,998; in the post-merger regime (1999–2010) the average price was $19,035, an increase of 35.98 percent (=\textsuperscript{28})

\textsuperscript{28} This Daewoo’s acquisition of Ssangyong has only negligible effect on my merger simulation. In 1998, Daewoo concentrated its production on sedan car brands while Ssangyong concentrated on SUV and Minivans. I computed cross-price elasticities between Daewoo’s sendan cars and Ssangyong’s SUV/Minivan cars, and they are close to zero, meaning negligible effect on merger simulation.

\textsuperscript{29} Appendix explains the construction of these aggregate prices. I also calculated the index-weighted aggregate prices.
Figure 1.6: Left figure: Compact car prices, Right figure: Mid-size car prices

Data source: Motor Magazine and Carlife Magazine

The right side of Figure 1.9 illustrates sales-weighted vehicle transaction prices by firm. These prices show that consumers saw more expensive Hyundai–Kia group cars after the merger. Figure 1.6 depicts vehicle pricing among compact (left side of Figure 1.6) and mid-size (right side of Figure 1.6) class cars. This offers three notable findings. First, vehicle prices had been decreasing before the 1998 Hyundai–Kia merger. Second, although the merger was announced in November 1998, the post-merger price increases did not occur until 2003. During 1999–2003, the merged Hyundai-Kia group refrained from making unilateral price increases. Third, after year 2003, the merged Hyundai-Kia group seems to have adopted unilateral pricing strategies. As a whole, one can clearly observe long-run price increases in Figure 1.6.

Some may question whether vehicle price increases in Korea were caused by product quality improvements. To investigate this possibility, I compare Hyundai-Sonata and Hyundai-Sonata...

See Appendix for pricing history of other classes of vehicles.

Several reasons explain these non-immediate post-merger price increases: (1) Hyundai–Kia group improved its plant-level productivities, and marginal costs decreased. Appendix contains results from plant-level production function estimations, and I find statistically significant post-merger productivity increases among Hyundai–Kia group plants. (2) The merged firm most likely was concerned about public backlash (mass media and consumer reactions) against any immediate post-merger price increases; (3) The newly merged firm needed time to make management-level integrations.
Figure 1.7: Left figure: Hyundai Sonata prices in the United States versus in Korea, Right figure: Hyundai Avante/Elantra prices in the United States versus in Korea

Data source: *Ward’s Automotive Yearbook* (annual U.S. prices), *Motor Magazine* and *Carlife Magazine* (Korean prices)

Basement prices and ratios are:

Hyundai Sonata price in the United States in 1992 = 1, Hyundai Sonata price in Korea in December 1992 = 1

Hyundai Elantra price in the United States in 1992 = 1, Hyundai Avante/Elantra price in Korea in December 1992 = 1

Note: (1) The Korean won was relatively strong (appreciated) in 1992 (due to the post-Seoul-Olympics boom); (2) I choose 1992 as the base year of comparison as the U.S. prices before 1992 are not available; (3) In Korea, the Hyundai Elantra has been sold under the name Avante since February 1995.

Avante\(^{32}\) pricing histories in the United States and in Korea. Figure 1.7 indicates that prices in Korea largely increased after the merger, while prices in the United States increased only moderately. Assuming that market competition conditions in the United States remained unchanged, a quality increase alone could not explain the drastic price increases observed in Korea\(^{33}\).

\(^{32}\)Hyundai Avante is sold under the name of Elantra in the United States.

\(^{33}\)Automobile buyers generally perceive that Korean automakers have increased their product quality in recent years. In the United States, Hyundai-Sonata and Hyundai-Elantra prices have increased about 10 percent, and I attribute these price increases to the quality improvement. Note that the prices of Hyundai-Sonata and Hyundai-Elantra have increased 26 percent and 38 percent in Korea.
1.2.5 Data Source

I collected data from various sources. First, I compiled monthly passenger vehicle price data from two monthly automobile magazines widely circulated in South Korea, *Carlife Magazine* and *Motor Magazine*. These two monthly magazines maintain lists of new car prices from the late 1980s\(^{34}\). Second, *Ward’s Automotive Yearbook 1992–2011*\(^{35}\) sources the monthly brand-level sales quantities. Since Ward’s Automotive Yearbook does not contain brand-level sales quantity data before 1994, I collected the 1991–1994 brand-level monthly sales data from the *Monthly Korean Automotive Industry Journal* published by the Korean Automobile Manufacturers Association (KAMA). Third, I use the two car magazines described above along with the annual report, *Korean Automobile Industry: Annual Version*, released by KAMA, to gather the car specification data. Fourth, I obtained plant-level\(^{36}\) production output and input data from the *Annual Mining and Manufacturing Survey* conducted by the Statistics Korea\(^{37}\). Fifth, I compiled ownership (merger) transition processes and timing information from three Korean newspapers; *The JoongAng Ilbo*\(^{38}\), *The Dong-A Ilbo*\(^{39}\), *The Chosun Ilbo*\(^{40}\), and official company websites. Sixth, price index, demographic (such as numbers of households used as market sizes), worker wage, and bank loan rate data come from the Bank of Korea (BOK) and the Statistics Korea.

\(^{34}\)To collect vehicle prices, the editors of these two magazines call local dealers and gather dealership-level prices. Prices of a specific automobile brand in a specific month listed in these magazines prove close but not identical. Typically, price differences come within $500 of each other. I believe such non-identical prices are a good signal of accuracy, since they seem to reflect dealership-level price heterogeneities.

\(^{35}\)Berry, Levinsohn, and Pake (1995) [5] also extracted price and sales quantity data for the U.S. automobile industry from these yearbooks.

\(^{36}\)I could not obtain vehicle brand-level production data. Since a single automobile plant produces multiple vehicle brands, this dataset does not allow me to recover the brand-level production marginal costs. However, I was able to evaluate productivity improvement (merger synergy) after the Hyundai-Kia merger through the production function estimation analysis. See Appendix for details.

\(^{37}\)http://kostat.go.kr/portal/english/surveyOutlines/6/2/index.static

\(^{38}\)http://joongangdaily.joins.com/

\(^{39}\)http://english.donga.com/

\(^{40}\)http://english.chosun.com/
1.3 Demand Side Model and Estimations

This section describes the demand side model and estimation results. I use these estimates to compute substitution patterns in post-merger price simulations in later sections of this paper.

1.3.1 Demand Model

The demand model builds upon Berry’s (1994) instrumental variable (henceforth IV) nested-logit model. For notational simplicity, I denote \( t \in \{1, \ldots, T\} \) to index months, \( i \in \{1, \ldots, I_t\} \) to index households at time \( t \), \( j \in \{1, \ldots, J_t\} \) to represent supplied automobile brand index at time \( t \), \( q \in \{1, \ldots, Q\} \) to be quarter dummy, and \( g \in \{1, \ldots, G\} \) to be automobile type group index\(^{41}\). In particular, \( g_j \) indicates the automobile type group to which brand \( j \) belongs. The (after taking log) Cobb-Douglas utility function is expressed as

\[
u_{ijt} = \sum_{q=2}^{Q} \theta_q d_q + \alpha p_{jt} + x_{jt} \beta + \xi_{jt} + \zeta_{igj} + (1 - \sigma) \varepsilon_{ijt}
\]  

(1.1)

where \( d_q \) is quarter dummy, \( p_{jt} \) is brand \( j \)’s price at time \( t \), \( x_{jt} \) is brand \( j \)’s observable characteristics vector, \( \xi_{jt} \) is an unobserved (by researchers) product characteristic. Quarter dummies are included to proxy incomes. Consumer taste parameters \( \{ (\theta_2, \ldots, \theta_Q), \alpha, \beta, \sigma \} \) are to be estimated. Note that \( \zeta_{igj} \) captures individual \( i \)’s taste over group \( g_j \), and \( (1 - \sigma) \varepsilon_{ijt} \) captures individual \( i \)’s idiosyncratic taste for product \( j \). Specifically, the parameter \( \sigma \in [0, 1] \) captures the degree of inside group substitutions. If \( \sigma \) is close to one, consumer \( i \) becomes more likely to substitute to products within the same automobile type group. On the other hand, if \( \sigma \) is close to zero, consumer \( i \) substitutes across all type groups. Following Berry (1994) [4], I make distributional assumptions. Both \( \varepsilon_{ijt} \) and \( \zeta_{igj} + (1 - \sigma) \varepsilon_{ijt} \) follow an i.i.d. type I extreme value distribution. By integrating, I obtain the analytic market shares as

\(^{41}\)In the estimation, I categorize automobile brands in to four groups (1) the Small- and Compact-size group, (2) the Mid-size group, (3) the Mid- and Full-size luxury group, and (4) the Jeep, SUV, and Minivan group, according to their price differences and functionalities.
Table 1.3: Automobile nesting groups for instrumental variable nested-logit estimation

<table>
<thead>
<tr>
<th>Nesting group</th>
<th>Price range</th>
<th>Size/Functionalities</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>(i) Small- &amp; Compact-size group</td>
<td>$4,000–$15,000</td>
<td>Small interior, Fuel-efficient,</td>
<td>Daewoo-Matiz, Hyundai-Accent</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Commuter vehicle</td>
<td>Hyundai-Avante, Samsung-SM5</td>
</tr>
<tr>
<td>(ii) Mid-size group</td>
<td>$16,000–$29,000</td>
<td>Medium interior</td>
<td>Hyundai-Sonata, Kia-Optima</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Commuter vehicle</td>
<td>Kia-Credos, Samsung-SM5</td>
</tr>
<tr>
<td>(iii) Mid- &amp; Full-size luxury group</td>
<td>$30,000–$76,000</td>
<td>Luxury-oriented</td>
<td>Hyundai-Grandeur, Hyundai-Equus</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Commuter vehicle</td>
<td>Kia-Enterprise, Ssangyong-Chairman</td>
</tr>
<tr>
<td>(iv) Jeep, SUV &amp; Minivan group</td>
<td>$18,000–$36,000</td>
<td>Large interior, Sports-oriented</td>
<td>Hyundai-SantaFe, Kia-Carnival</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Family, Commercial use</td>
<td>Hyundai-Tucson, Daewoo-Rezzo</td>
</tr>
</tbody>
</table>

See Table 1.11 in Appendix for details of these group categorizations.

follows

\[ s_{jt} = \frac{\exp\left(\frac{\delta_{jt}}{1-\sigma}\right)}{\sum_{k \in g_j} \exp\left(\frac{\delta_{kt}}{1-\sigma}\right)} \cdot \left[ \sum_{g=1,\cdots,G} \sum_{t \in g} \exp\left(\frac{\delta_{lt}}{1-\sigma}\right) \right]^{1-\sigma}, \]  

(1.2)

where \( I \) denote a mean utility\(^{42}\)

\[ \delta_{jt} = \sum_{q=2}^{Q} \theta_i d_{qt} + \alpha p_{jt} + x_{jt} \beta + \xi_{jt}. \]

Berry (1994) \(^{4}4\) inverted the above market share and obtained

\[ \ln\left(\frac{s_{jt}}{s_{0t}}\right) = \sum_{q=2}^{Q} \theta_i d_{qt} + \alpha p_{jt} + x_{jt} \beta + \sigma \ln\left(\frac{s_{jt}}{s_{gjt}}\right) + \xi_{jt} \]  

(1.3)

where \( s_{0t} \) is an outside goods (not purchasing cars) share\(^{43}\) and \( s_{gjt} \) is the market share of group \( g_j \) at time \( t \).

1.3.2 Automobile Brand Nesting Group Categorizations

Table 1.3 describes the automobile brand group categorization used in this research: (i) Small- and Compact-size, (ii) Mid-size, (iii) Mid- and Full-size luxury, and (iv) Jeep, Sports Utility Vehicle (SUV), and Minivan. I categorize these four groups based on price differences and functionalities. The Small- and Compact-size group cars are priced substantially lower than cars in other groups, and the restrictions on consumer budgets keep substitutions to

\(^{42}\)The outside option (not purchasing a car) at time \( t \) is \( \delta_{0t} = \sum_{q=2}^{Q} \theta_i d_{qt} \) in this model. I normalize quarter 0 outside option mean utility to be \( \delta_{00} = 0 \).

\(^{43}\)I define the market size as the number of households in Korea, extracted from the Korean National Census in 1990, 1995, 2000, 2005, and 2010.
other groups implausible. The cars in the Mid- and Full-size luxury group are priced higher than cars in the other groups. The Mid-size group and the Jeep, SUV, and Minivan group are divided based on their functionalities. Buyers of the Jeep, SUV, and Minivan group’s cars are expected to evaluate large spaces or sports-oriented functionalities, while Mid-size group car buyers do not. Based on these four groups, inside group shares are calculated and used in demand estimations.

1.3.3 Price Elasticities

The advantage of the instrumental variable nested-logit is its simplicity in computing price elasticities. From equation (1.2), one can derive own and cross price elasticities,

\[
\begin{aligned}
\frac{\partial s_{jt}}{\partial p_{jt}} &= \alpha \left( 1 - \sigma \left( \frac{s_{jt}}{s_{gt}} \right) - (1 - \sigma) s_{jt} \right) p_{jt} \quad \text{(Own price elasticity)} \\
\frac{\partial s_{jt}}{\partial p_{jt}} &= \frac{\alpha}{1 - \sigma} \left( -\sigma \left( \frac{s_{jt}}{s_{gt}} \right) - (1 - \sigma) s_{jt} \right) p_{jt} \quad \text{if } k \in g_j \quad \text{(Within group cross price elasticity)} \\
\frac{\partial s_{jt}}{\partial p_{jt}} &= -\alpha s_{jt} p_{jt} \quad \text{if } l \notin g_j \quad \text{(Outside group cross price elasticity)}. \tag{1.4}
\end{aligned}
\]

and one can calculate these elasticities based on estimated \((\alpha, \sigma)\) and observed market shares\(^{44}\).

1.3.4 Descriptive Statistics

Table 3.1 lists descriptive statistics. By comparing pre- and post-merger variables, several notable differences appear. First, the mean of the inflation adjusted vehicle price is higher in the post-merger regime, as a natural consequence of market conglomeration after the Hyundai–Kia merger. Second, the mean size had increased (and mean of Km/l has decreased), since a greater variety of large size cars, SUVs, and minivans became available in 2000s. Third, as numbers of supplied vehicle brands had increases after the Hyundai–Kia merger, the mean of shares (and the mean of in-group share) decreased.

\(^{44}\)Price derivatives are

\[
\begin{aligned}
\frac{\partial s_{jt}}{\partial p_{jt}} &= \frac{\alpha}{1 - \sigma} \left( 1 - \sigma \left( \frac{s_{jt}}{s_{jt}} \right) - (1 - \sigma) s_{jt} \right) s_{jt} \quad \text{(Own price derivative)} \\
\frac{\partial s_{kt}}{\partial p_{jt}} &= \frac{\alpha}{1 - \sigma} \left( -\sigma \left( \frac{s_{jt}}{s_{jt}} \right) - (1 - \sigma) s_{jt} \right) s_{kt} \quad \text{if } k \in g_j \quad \text{(Within group cross price derivative)} \\
\frac{\partial s_{lt}}{\partial p_{jt}} &= -\alpha s_{jt} s_{lt} \quad \text{if } l \notin g_j \quad \text{(Outside group cross price derivative)}. \tag{1.5}
\end{aligned}
\]

These derivatives are used for simulations.
Table 1.4: Descriptive statistics: Variables in the pre-merger regime (left table), Variables in the post-merger regime (right table)

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
</tr>
<tr>
<td>s&lt;sub&gt;j,t&lt;/sub&gt;</td>
<td>0.0002657</td>
<td>0.0003224</td>
</tr>
<tr>
<td>s&lt;sub&gt;jt&lt;/sub&gt;</td>
<td>0.9934809</td>
<td>0.0018015</td>
</tr>
<tr>
<td>s&lt;sub&gt;j&lt;/sub&gt;&lt;sup&gt;2&lt;/sup&gt;/ s&lt;sub&gt;jt&lt;/sub&gt;&lt;sup&gt;2&lt;/sup&gt;</td>
<td>0.1634075</td>
<td>0.1665415</td>
</tr>
<tr>
<td>Price</td>
<td>18804.89</td>
<td>12458.19</td>
</tr>
<tr>
<td>HP/kg</td>
<td>0.0996633</td>
<td>0.0255246</td>
</tr>
<tr>
<td>Km/l</td>
<td>14.07257</td>
<td>3.71396</td>
</tr>
</tbody>
</table>

1.3.5 Choice of Instrumental Variables

The major difficulty in estimating equation (1.3) is the endogeneity in ξ<sub>j,t</sub>. An individual <i>i</i> prefers automobile brands that have large observed characteristics, and firms optimally respond by pricing such brands higher. Therefore, an observed price <i>p</i><sub>j,t</sub> is positively correlated with an unobserved product characteristic ξ<sub>j,t</sub>, creating positive bias in price coefficient estimations. To solve this endogeneity problem, the literature suggests several specific types of instrumental variables; herein follows the conventional usages of instruments. From, Levinsohn, and Pakes (1995) [5], I use

**Instrument Variables:**

1. Cost shifter = (Kilogram of vehicle) × (Importer Price Index)
2. Within the same class sum of competing firm product size
3. Within the same class sum of competing firm product horsepower per kilogram
4. Within the same class sum of competing firm product kilometer per liter

in this research. Since Korea is a natural-resource importing county, and since material costs in the production of one vehicle remain roughly proportional to that vehicle’s weight, (1) measures variable material costs in productions<sup>45</sup>. As material costs are positively correlated with price, but unlikely to be correlated with unobserved product characteristics, the

<sup>45</sup>Because the Korean won historically has highly volatile exchange rates, Korea’s Importer Price Index is also volatile. See Figure 1.10.
above cost shifter becomes a valid instrument. Furthermore, (2)-(4) measure the degree of market competition. The more products other firms offer, the more severe the competition. To measure precisely the degree of competition, I classified the vehicles into nine classes (automobile types), and take summations of each observed product characteristic within each class (see Table 1.11 in Appendix for details of classifications). Since competition becomes more severe with a larger number of competing products, instruments (2)-(4) are negatively correlated with observed prices. However, instruments (2)-(4) are unlikely to be correlated with unobserved product characteristics $\xi_{jt}$.\(^{46}\)

1.3.6 Demand Estimation Results and Estimated Elasticities

Table 1.5 reports estimation results and calculated own elasticities based on equation (1.4). In addition to the instrumental variable nested-logit demand model, I also estimate OLS logit and instrumental variable logit demand models for comparisons. I separate the dataset into pre-merger regime data (years 1991–1998) and post-merger regime data (years 1999–2007), since I use only pre-merger regime data for the benchmark simulation. Price coefficients derived from each estimation method agree with general findings reported in the automobile literature\(^{47}\). Price coefficients from OLS logit estimation suffer from the endogeneity problems, and are positively biased. Instrumental variable logit estimations alleviate endogeneity.

\(^{46}\)I recognize there is a subtle endogenous product line choice concern in this statement. There are at least four possible scenarios of endogeneity:

(A) If $\xi_{jt}$ is large, i.e., product $j$ is attractive

⇒ (A-1) competing firms introduce copy-cat products into a market

⇒ (A-2) competing firms consider competition with product $j$ difficult, and do not introduce rivaling products

(B) If $\xi_{jt}$ is small (or very negative), i.e. product $j$ is unattractive

⇒ (B-1) competing firms consider a profit opportunity, and introduce rivaling products that beat out product $j$

⇒ (B-2) competing firms do not consider producing similar cars profitable, and do not introduce rival products

These four scenarios provide opposite consequences in terms of endogenous product line choices. I believe all of these scenarios are possible and, in general, $\xi_{jt}$ does not correlate to (2)-(4). Berry, Levinsohn, and Pakes (1995) \(^5\) use similar instruments.

\(^{47}\)See Table III in Berry, Levinsohn, and Pakes (1995) \(^5\), and Table 4 in Petrin (2002) \(^{36}\).
<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-merger OLS logit</th>
<th>Pre-merger IV logit</th>
<th>Pre-merger IV nested-logit</th>
<th>Post-merger OLS logit</th>
<th>Post-merger IV logit</th>
<th>Post-merger IV nested-logit</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\alpha)</td>
<td>-0.000068**</td>
<td>-0.000117**</td>
<td>-0.000082**</td>
<td>-0.0000642**</td>
<td>-0.0001094**</td>
<td>-0.0000582**</td>
</tr>
<tr>
<td>Price in thousand won</td>
<td>(0.000004)</td>
<td>(0.0000116)</td>
<td>(0.0000040)</td>
<td>(0.0000257)</td>
<td>(0.0000188)</td>
<td>(0.0000056)</td>
</tr>
<tr>
<td>(\sigma)</td>
<td></td>
<td></td>
<td></td>
<td>0.6677716**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>In-group substitution</td>
<td>(0.0793395)</td>
<td></td>
<td></td>
<td>(0.0733306)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\beta_1)</td>
<td>0.0321820</td>
<td>0.2328088**</td>
<td>0.0254591</td>
<td>0.2352142**</td>
<td>0.4481224**</td>
<td>0.2457095**</td>
</tr>
<tr>
<td>Size in meter(^2)</td>
<td>(0.0347774)</td>
<td>(0.053974)</td>
<td>(0.0193732)</td>
<td>(0.0148575)</td>
<td>(0.0417942)</td>
<td>(0.0206055)</td>
</tr>
<tr>
<td>(\beta_2)</td>
<td>2.24454</td>
<td>14.26855**</td>
<td>14.92290**</td>
<td>8.752657**</td>
<td>31.59749**</td>
<td>10.07068**</td>
</tr>
<tr>
<td>Horsepower per kilogram</td>
<td>(2.662645)</td>
<td>(3.537377)</td>
<td>(1.967729)</td>
<td>(1.653547)</td>
<td>(4.449519)</td>
<td>(2.169522)</td>
</tr>
<tr>
<td>(\beta_3)</td>
<td>-0.0386531**</td>
<td>-0.0501671**</td>
<td>-0.0366461**</td>
<td>0.1540414**</td>
<td>0.0420579*</td>
<td>0.0433083</td>
</tr>
<tr>
<td>Kilometer per liter</td>
<td>(0.0152014)</td>
<td>(0.0149092)</td>
<td>(0.0098004)</td>
<td>(0.0098804)</td>
<td>(0.0235171)</td>
<td>(0.010823)</td>
</tr>
<tr>
<td>Constant</td>
<td>(7.728814)</td>
<td>(8.051303)</td>
<td>(3.327289)</td>
<td>(3.871796)</td>
<td>(4.878732)</td>
<td>(0.66416)</td>
</tr>
<tr>
<td>Measure of fit: R-square</td>
<td>0.22971</td>
<td>0.222</td>
<td>0.1016</td>
<td>-</td>
<td>0.629</td>
<td></td>
</tr>
<tr>
<td>or Sargan Test (5% value)</td>
<td>-</td>
<td>(3.84)</td>
<td>-</td>
<td>(3.84)</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>First-stage R-square</td>
<td>-</td>
<td>0.8190</td>
<td>-</td>
<td>-</td>
<td>0.7379</td>
<td></td>
</tr>
<tr>
<td>Sample size</td>
<td>2330</td>
<td>2330</td>
<td>2340</td>
<td>3978</td>
<td>3978</td>
<td>3975</td>
</tr>
<tr>
<td># of inelastic demand (%)</td>
<td>1072 (46.6%)</td>
<td>992 (44.8%)</td>
<td>12 (0.5%)</td>
<td>1576 (49.6%)</td>
<td>695 (17.5%)</td>
<td>478 (12.6%)</td>
</tr>
<tr>
<td>Mean own elasticity</td>
<td>-1.291635</td>
<td>-2.199729</td>
<td>-4.127113</td>
<td>-1.256478</td>
<td>-2.070645</td>
<td>-2.322169</td>
</tr>
<tr>
<td>Median own elasticity</td>
<td>-1.074259</td>
<td>-1.829523</td>
<td>-1.136359</td>
<td>-1.162262</td>
<td>-1.915378</td>
<td>-2.118278</td>
</tr>
<tr>
<td>Max own elasticity</td>
<td>-0.2778367</td>
<td>-0.4731717</td>
<td>-0.853698</td>
<td>-0.2489306</td>
<td>-0.4102315</td>
<td>-0.488998</td>
</tr>
</tbody>
</table>

Numbers in parentheses represent standard errors.

** indicates t-statistics are significant within 5 percent.

IV used: IV logit model - Cost-shifter for both pre- and post-merger data (thus, just-identified model).

IV used: IV Nested logit model - (1), (2), and (4) for pre-merger data; (1), (2), and (3) for post-merger data.

Note that in the instrumental variable nested-logit estimations, I removed IV (3) for pre-merger data and IV (4) for post-merger data to avoid over-identifications detected by Sargan statistics.

bias, although estimated elasticities tend to be inelastic\(^{48}\). Pre-merger instrumental variable nested-logit estimation provides reasonable elasticities, and I observe that only 0.5 percent

\(^{48}\)Such inelasticities come from own price elasticity equation in the logit demand model. The logit demand model provides elasticity equations

\[
\begin{align*}
\frac{\partial s_{jt}}{\partial p_{jt}} &= \alpha (1 - s_{jt}) p_{jt} \quad \text{(Own price elasticity)} \\
\frac{\partial s_{kt}}{\partial p_{jt}} s_{kt} &= -\alpha s_{jt} p_{jt} \quad \text{(Cross price elasticity)}
\end{align*}
\]

In this research, I define market size as all households in Korea, and only tiny portions of the households buy automobiles in any given month. Thus, \(s_{jt}\) is close to zero. Then, own price elasticities are almost perfectly proportional to prices. As a result, low-price cars tend to have inelastic demands. This result contradicts our empirical observation that buyers of low price cars are elastic and price sensitive. Thus, the logit-demand model remains inappropriate in this research. Note that the nested logit demand model improves this defect by accounting for in-group shares in elasticity calculations.
of demands are inelastic. I use these pre-merger IV nested-logit estimates in simulations.

This analysis reveals drastic differences between the estimated pre-merger and post-merger regimes’ preferences. To understand such drastic preference changes, I briefly note the history of the Korean economy and its motorization. After the 1988 Seoul Olympics, Korea’s economy entered a high growth period, and many households obtained their initial opportunity to purchase a vehicle. For their initial car choices, Korean households were mainly concerned about prices and, therefore, this concern compromised other vehicle characteristics. Under such economic circumstances, Korean households mainly bought small and fuel-inefficient but cheap cars in the pre-merger regime (1991–1998). Note that the Organization for Economic Co-operation and Development (OECD) officially endorsed South Korea as a developed country in 1996, although the recession of 1997–1998 set back economic growth. My pre-merger regime estimation results agree closely with this historical observation.

\[ \text{In Table V of Berry, Levinsohn, and Pakes (1995) [5], they report year 1990 US automobile buyers’ elasticities; these are close to my pre-merger elasticities derived from the instrumental variable nested-logit estimation.} \]

\[ \text{Moreover, in Copeland, Dunn, and Hall (2011) [11] Table 5, they report own price elasticities among US automobile buyers during 1999–2004. The their elasticities are [-3.6, -1.5], which is less elastic than the mean elasticity of my pre-merger IV nested-logit model. I recognize that income level difference between United States and Korea causes this discrepancy in elasticities. Income in Korea (during 1991–1998) was expected to be lower than that of the United States (during 1999–2004). Note that my post-merger IV nested-logit estimates provide elasticities closer to Copeland, Dunn, and Hall’s results.} \]

\[ \text{Note that the coefficient of size is not statistically significant in the instrumental variable nested-logit estimation with pre-merger data.} \]

\[ \text{During the Korean recession (1997–1998), the majority of vehicles bought in Korea were small- and} \]
vation. Consumers were relatively elastic and preferred non-large-size and fuel-inefficient (but cheap) vehicles in the pre-merger regime (1991–1998). The household environment dramatically changed after the recession. As the economy escaped from the recession and the recovery boom arrived in 2000–2002. Rebounding from recession, banks largely relaxed their credit-inquiry requirements, and households obtained generous loan opportunities, including auto loans. They also began to replace their initial cars, and households typically chose more expensive cars than the cars they had initially purchased. After 2002, the Korean economy has continued to grow without serious economic stagnation (the average worker wage increased 30 percent compared to that of pre-merger regime, see Table 1.7), and more and more expensive cars became affordable to Korean households. Post-merger regime estimation results agree with these observations. Korean automobile buyers became relatively inelastic with higher wages and more access to auto loans. In addition, they preferred larger size cars, and they also evaluated fuel-efficiency in the post-merger regime. These estimated preferences reflect the introduction of a number of SUVs into the Korean domestic market and the continued rise of gasoline prices during the 2000s.

Figure 1.8 plots the relations between calculated elasticities and vehicle sizes (in square meter) in both pre- and post-merger regimes. I observe that luxury and sports cars have large (in absolute value) elasticities. This occurs because elasticities in nested-logit demand are roughly linear in price, and luxury and sports cars have higher prices. I recognize elasticities among those cars are likely to be inflated, although these cars have relatively tiny market shares, and inflated elasticities have limited effects in this research.

1.4 Supply Side Model

In this section, I describe the supply side model used to recover marginal costs and post-merger price simulations. Here, I strictly follow the simulation framework proposed by Nevo compact-size cars.

\[ A \text{credit-card boom was observed during 2000–2003 in Korea.} \]

\[ ^{54} \text{Note that Berry, Levinsohn, and Pakes (1995) [5], who use the logit demand model as their basis, also have this linear-in-price problem.} \]

\[ ^{55} \text{In simulations, I fixed full-size luxury and sports car shares to alleviate computational difficulties.} \]
1.4.1 Firms’ Optimization Problem

I assume firms engage in static Bertrand competitions. The Bertrand price competition model is especially suitable for describing the Korean automobile market for the following three reasons. First, Korean automobile dealers explicitly post price tags on cars in their dealerships. Second, brochures available in dealerships explicitly list prices. Third, widely circulated automobile magazines, containing lists of automobile prices, have been available since the late 1980s, and automobile buyers have been well-informed about automobile prices. Other forms of competition, such as competition through choosing sales quantities, are highly unlikely to reflect these three observed facts. As some may argue over my choice of the static competition model, I will return to this point in a later portion of this paper. Firms that choose automobile band prices maximize profits as follows:

$$\Pi_{ft} = \sum_{j \in F_{ft}} (p_{jt} - m_{cj}) \cdot s_{jt}(p_t) \cdot M_t - C_{ft}$$

where $f \in [1, \cdots, F]$ represents a firm, $F_{ft}$ is a set of products which firm $f$ supplies to the market at time $t$, $m_{cj}$ is the marginal cost of product $j$, $p_t$ is a price vector and its dimension is equal to the number of total products available at time $t$, $M_t$ is the number of households in Korea, and $C_{ft}$ is fixed cost. The first-order necessary condition can be derived as

$$p_t - m_{ct} = \{\Omega_t \times S_t(p_t)\}^{-1} s_t(p_t)$$  (1.6)

where $\Omega_t$ and $S_t(p_t)$ are a square product ownership and substitution matrices with $(m, n)$ entries are ($m$: row index and $n$: column index)

$$\Omega_{t,mn} = \begin{cases} 1 & \text{if product } m \text{ and } n \text{ are supplied by the same firm} \\ 0 & \text{otherwise} \end{cases}$$

$$S_{t,mn} = \frac{\partial s_{nt}}{\partial p_{mt}}$$

and $\times$ is the entry-by-entry multiplication. All of the right-hand side variables in equation (1.6) are observed or estimated; $\Omega_t$ is observed in data, $S_t$ can be calculated from equation
Table 1.6: Recovered markups and marginal costs in pre-merger regime (January 1991–November 1998)

<table>
<thead>
<tr>
<th>Manufacturer</th>
<th>Band</th>
<th>Class Category</th>
<th>Average of pre-merger observed prices: $p_{jt}$</th>
<th>Average of pre-merger markups: $p_{jt} - mc_{jt}$</th>
<th>Average of pre-merger marginal costs: $mc_{jt}$</th>
<th>Markup Percentage</th>
<th>Post-merger brand termination status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyundai</td>
<td>Atoz</td>
<td>City/Small</td>
<td>$6,316$</td>
<td>$523$</td>
<td>$5,796$</td>
<td>8.28%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Pride</td>
<td>City/Small</td>
<td>$6,965$</td>
<td>$782$</td>
<td>$6,182$</td>
<td>11.22%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Hyundai</td>
<td>Accent</td>
<td>Sub-compact</td>
<td>$8,194$</td>
<td>$991$</td>
<td>$7,203$</td>
<td>12.09%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Avella</td>
<td>Sub-compact</td>
<td>$7,929$</td>
<td>$667$</td>
<td>$7,262$</td>
<td>8.41%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Hyundai</td>
<td>Avente</td>
<td>Compact</td>
<td>$11,517$</td>
<td>$2,037$</td>
<td>$9,480$</td>
<td>17.69%</td>
<td>Not terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Sephia</td>
<td>Compact</td>
<td>$10,709$</td>
<td>$903$</td>
<td>$9,806$</td>
<td>9.55%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Shuma</td>
<td>Compact</td>
<td>$9,821$</td>
<td>$853$</td>
<td>$8,967$</td>
<td>8.40%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Hyundai</td>
<td>Sonata</td>
<td>Mid-size</td>
<td>$17,593$</td>
<td>$83,311$</td>
<td>$14,282$</td>
<td>18.82%</td>
<td>Not terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Credos</td>
<td>Mid-size</td>
<td>$16,471$</td>
<td>$529$</td>
<td>$14,941$</td>
<td>8.40%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Retona</td>
<td>Compact Jeep</td>
<td>$12,041$</td>
<td>$874$</td>
<td>$11,167$</td>
<td>7.26%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Hyundai</td>
<td>Gallopper</td>
<td>Jeep</td>
<td>$21,721$</td>
<td>$2,037$</td>
<td>$19,480$</td>
<td>10.60%</td>
<td>Not terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Sportage</td>
<td>Compact crossover SUV</td>
<td>$17,746$</td>
<td>$1,903$</td>
<td>$15,843$</td>
<td>10.60%</td>
<td>Terminated</td>
</tr>
<tr>
<td>Hyundai</td>
<td>Santamo</td>
<td>Minivan</td>
<td>$19,395$</td>
<td>$2,037$</td>
<td>$17,358$</td>
<td>11.75%</td>
<td>Not terminated</td>
</tr>
<tr>
<td>Kia</td>
<td>Carnival</td>
<td>Minivan</td>
<td>$19,884$</td>
<td>$2,356$</td>
<td>$17,528$</td>
<td>11.75%</td>
<td>Not terminated</td>
</tr>
</tbody>
</table>

Hyundai and Kia Motors brands supplied in Nov 1998 (merger announcement month).

1000 won = 1 United States dollar exchange rate applied for prices listed on this table.

Note: Kia Sportage was brought back in Aug. 2004

(1.5) with estimated parameters, and $s_t$ is observed market share. Therefore, one can calculate markups from observed data and estimated parameters. Furthermore, by subtracting markups from observed prices, we can also calculate marginal costs. Table 1.6 contains calculated markups and marginal costs for brands that were supplied in November 1998 (merger announcement month). Since the calculated markups and marginal costs fluctuate month to month, I take the averages over months in the pre-merger regime. Recovered markups roughly agree with those reported in BLP (1995) and calculated marginal costs are used for post-merger price simulations.

1.5 Post-Merger Price Benchmark Simulation

In this section, I describe the post-merger price simulation framework, benchmark simulation assumptions, and benchmark simulation results. I use the simulation framework explained in
this section throughout the rest of this paper, although I will change simulation assumptions.

1.5.1 Simulation Framework

The post-merger price simulation follows the framework suggested by Nevo (2000, 2001) [32] [33]. The simulation process comprises the inverse operation of calculating markups and marginal costs. Rewriting the firms’ profit maximizing first-order condition equation (1.6) with slight notational modifications,

\[
\Omega_{\text{post-merger}} \times S(p) \cdot (p - \overline{mc}) - s(p) = 0
\]  

(1.7)

where \( \overline{mc} \) is the vector of estimated pre-merger marginal cost (averaged out over the pre-merger period) and \( \Omega_{\text{post-merger}} \) is the post-merger ownership matrix. A vector of prices \( p = [p_1, p_2, \ldots, p_J] \) solves this system of non-linear equations.

1.5.2 Benchmark (Conventional) Simulation Assumptions

Here, I list the assumptions for a post-merger price simulation, which are conventionally assumed in the differentiated-product industry horizontal-merge literature. These assumptions are de-facto standard assumptions in such post-merger price simulation analyses as Nevo (2000) 56, Dube (2005) [13], and Peters (2006) [35].

Benchmark (Conventional) Assumptions:

(I-1) Consumer income conditions will remain the same after a merger

(II-1) Consumer preferences (including unobserved product characteristics) will remain the same after a merger

(III-1) Marginal costs will remain the same after a merger

56Note that Nevo (2000) [32], the inventor of this simulation method, clearly expressed his concerns about these simulation assumptions, “However, this approach is not consistent with firms changing their strategies in other dimensions [than price dimension] that may influence demand. For example, if as a result of the merger the level of advertising changes, and advertising influences price sensitivity, then the estimate of the post-merger equilibrium price based on [simulation equation] will be wrong. In addition, this implies that characteristics, observed and unobserved, and the value of the outside good are assumed to stay the same pre- and post-merger. Therefore, I am implicitly assuming that the price of the outside good is exogenous and does not change in response to the merger.” See (p.403) of his paper.
(IV-1) Product line will remain the same after a merger

In the benchmark simulation computation, I materialize the above (I-1)-(IV-4) by using,

**Benchmark (Conventional) Assumptions: Implementations**

(I-2) Applying the average of pre-merger quarter dummies (which are income proxies), \( \bar{\theta}_{qt} \)

(II-2) Applying pre-merger consumer preference \((\hat{\alpha}, \hat{\beta}, \hat{\sigma})\) and average of pre-merger unobserved characteristics \( \bar{\xi}_{jt} \)

(III-2) Applying the average of pre-merger marginal costs \( \bar{mc}_{jt} \)

(IV-2) Using the pre-merger product line (product line supplied in Nov. 1998, the merger announcement month)

One should recognize these assumptions as averaged pre-merger information. By using them, I am explicitly assuming that market conditions of (I-2)-(IV-2) will not change after the merger. In the next section, I re-compute observed changes in each of (I-2)-(IV-2) with other factors fixed (Ceteris Paribus approach).

### 1.5.3 Benchmark Simulation Results

The simulated post-merger aggregate price is obtained as follows. I first obtain simulated prices for all vehicle brands by solving the non-linear simultaneous equation (1.7). Then, using the equation (1.2), I calculate market shares for each vehicle brand, and sales weighted aggregate market prices are calculated. Figure 1.9 reports the simulation results with benchmark assumptions. I find that the simulation with conventional assumptions can well-predict post-merger short-term (1999–2003) prices\(^{57}\). The averaged observed short-term (1999–2003) sales weighted price is $17,109, and the simulation predicts $16,741. The short-term price

\(^{57}\)This result should be interpreted with the following strong cautions. First, even in the short-term, market conditions changed significantly. Consumer incomes conditions (including automobile loan opportunities), supply side marginal costs, and product lines changed greatly as I will explain in the next section. Second, the merged Hyundai–Kia group seemed to refrain from making unilateral price increases until the end of 2002. Thus, the benchmark simulation assumptions (I-2)-(IV-2) did not hold even in the short term, and the simulated price is close to the observed price almost by coincidence.
Note: All prices in these figures are sales weighted aggregate (market level) prices. The difference gap is $368 (=$17,109 - $16,741), and the simulation only under-predicts by 2.15 percent ($17,109 - $16,741 / $17,109 * 100). However, the simulation, in large part, under-predicts long-run prices. The averaged observed long-run (2004–2010) sales weighted price is $20,433, while the simulation predicts only $16,741. The long-run price difference gap is $3,692 ($20,433 - $16,741), and the simulation under-predicts by 18.07 percent ($20,433 - $16,741 / $20,433 * 100). There are several potential reasons for this long-run price discrepancy, and I will investigate them in the next section\(^{58}\).

### 1.6 Potential Causes in Long-Run Simulation Discrepancies

There are several possible reasons for long-run price discrepancies. In this section, I list potential causes using observed post-merger data. These causes become the basis for the simulated price discrepancy analysis discussed in the next section.

---

\(^{58}\)Another notable finding is that it took two and-a-half years from the time the merger was announced for market participants to reach predicted post-merger prices. In theoretical merger models, if a merger happened yesterday, a merged firm increases its product prices today (and rival firms also increase prices today). In reality, the effect of a merger does not appear immediately because of many real-world conditions such as (1) a merged firm needs time to be organizationally reconciled, (2) menu costs, or (3) fear of consumers and media backlash in the wake of price increases.
Table 1.7: Average monthly wage Korea (1991-2010)

<table>
<thead>
<tr>
<th>Period</th>
<th>Average monthly wage</th>
<th>Change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pre-merger (1991-1998)</td>
<td>$1,891</td>
<td>—</td>
</tr>
<tr>
<td>Post-merger short term</td>
<td>$2,024</td>
<td>+7.1%</td>
</tr>
<tr>
<td>Post-merger long run</td>
<td>$2,475</td>
<td>+30.9%</td>
</tr>
<tr>
<td>(2004-2010)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

I: Post-Merger Changes in Consumer Income

The first factor to review is the change in consumer (household) income. Table 1.7 lists the average monthly wage in Korea for 1991–2010. I observe that wages steadily increased in the post-merger regime (1999–2010). Compared to the pre-merger regime average wage, workers in Korea are 7.1 percent wealthier in the short term (1999–2003), and 30.9 percent wealthier in the long–run (2004–2010). In the demand side of the model, one can expect that the quarter dummies (income proxies) of consumers’ utility function in equation (1.1) increase with these increases in wages. Given this increase in wages, and given other factors remain unchanged, it is optimal for firms to charge prices higher than pre-merger regime prices. Therefore, changes in wages (incomes) are part of the explanation for price increases.

II: Post-Merger Changes in Consumer Preferences

Changes in consumer preferences constitute the second and largest factor. Table 1.5 indicates that automobile buyers in Korea had become price inelastic in the post-merger regime. The mean elasticity with instrumental variable nested-logit model in pre-merger regime is $-4.13$, while it is $-2.32$ in the post-merger regime. Given that other factors remain unchanged, firms can charge higher vehicle prices without losing much demand with this estimated post-merger preference. Thus, one can expect that the non-trivial portions of price increases can be explained by preference changes.
Table 1.8: Pre- and Post-merger marginal cost comparison

<table>
<thead>
<tr>
<th>Manufacturer-Brand</th>
<th>Class</th>
<th>Pre-merger average price</th>
<th>Pre-merger average markup</th>
<th>Pre-merger average mc</th>
<th>Pre-merger mc/price ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyundai-Avante</td>
<td>Sub-compact</td>
<td>$11,517</td>
<td>$2,037</td>
<td>$9,489</td>
<td>0.82</td>
</tr>
<tr>
<td>Hyundai-Sonata</td>
<td>Mid-size</td>
<td>$17,593</td>
<td>$3,311</td>
<td>$14,282</td>
<td>0.81</td>
</tr>
<tr>
<td>Hyundai-Grandeur</td>
<td>Mid-size luxury</td>
<td>$37,205</td>
<td>$4,898</td>
<td>$32,325</td>
<td>0.86</td>
</tr>
<tr>
<td>Kia-Carnival</td>
<td>Minivan</td>
<td>$19,884</td>
<td>$2,336</td>
<td>$17,547</td>
<td>0.88</td>
</tr>
<tr>
<td>Ssangyong-Chairman</td>
<td>Large-size Luxury</td>
<td>$60,863</td>
<td>$6,064</td>
<td>$54,799</td>
<td>0.90</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Manufacturer-Brand</th>
<th>Class</th>
<th>Post-merger average price</th>
<th>Post-merger average markup</th>
<th>Post-merger average mc</th>
<th>Post-merger mc/price ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyundai-Avante</td>
<td>Sub-compact</td>
<td>$12,806</td>
<td>$2,614</td>
<td>$10,192</td>
<td>0.80</td>
</tr>
<tr>
<td>Hyundai-Sonata</td>
<td>Mid-size</td>
<td>$19,746</td>
<td>$4,453</td>
<td>$15,293</td>
<td>0.77</td>
</tr>
<tr>
<td>Hyundai-Grandeur</td>
<td>Mid-size luxury</td>
<td>$28,593</td>
<td>$5,114</td>
<td>$23,479</td>
<td>0.84</td>
</tr>
<tr>
<td>Kia-Carnival</td>
<td>Minivan</td>
<td>$21,850</td>
<td>$2,954</td>
<td>$18,896</td>
<td>0.91</td>
</tr>
<tr>
<td>Ssangyong-Chairman</td>
<td>Large-size Luxury</td>
<td>$48,050</td>
<td>$4,368</td>
<td>$43,682</td>
<td>0.91</td>
</tr>
</tbody>
</table>

Note: Post-merger marginal costs are derived with IV nested-logit post-merger demand estimation results that use post-merger data. Only five brands listed above were consistently sold from December 1999 through December 2010 without brand terminations.

III: Post-Merger Changes in Marginal Costs

Reductions in marginal costs forms the third dimension of post-merger change. One can expect that, once merged, the new Hyundai–Kia would improve productivity due to merger synergy. Unfortunately, since Korean automobile manufactures frequently changed their product lines both before and after the merger, direct marginal cost comparisons are difficult. Table 1.8 compares the marginal costs in both pre- and post-merger regimes among brands that had been continuously sold without brand terminations. Note that I recover these marginal costs from estimated demand elasticities, observed shares, and observed prices by using equation (1.6). I observe that both prices and marginal costs increased in the post-merger regime, while the \((\frac{mc}{price})\) ratio decreased.

Since direct comparisons of vehicles’ pre- and post-merger marginal costs are difficult due to frequent brand terminations, I use the plant-level input/output data to measure

---

59 Post-merger marginal cost reductions, called merger synergy, are heavily debated in the homogeneous product industry merger literature. See Gowrisankaran (1999) [18] for the literature review.

60 I had a chance to interview a former Kia Motors worker. He mentioned that Kia Motors had better large-size engine production technologies (for SUVs and Minivans) than Hyundai did before the merger, whereas Hyundai held advantages in sedan production.
marginal cost improvement. In Appendix, I implement value-added-base production function estimations, and observe the statistically significant merger synergy effects among Hyundai–Kia group plants. Thus, the (value-added basis) marginal production costs of Hyundai–Kia group cars decreased after the merger, and affected post-merger vehicle prices.

IV: Post-Merger Changes in Product Lines

Product lines make up the fourth factor of post-merger change. For a merged firm, terminating intra-firm competing products would seem to be one of the optimal strategies for increasing profits. Table 1.9 demonstrates that a significant number of Hyundai–Kia groups’ vehicle bands were terminated between November 1998 and November 2003 (a period of 5 years after the merger announcement). The merged company primarily terminated brands of former Kia Motors, and one can observe significant changes in the product line. In particular, Kia’s small- to mid-size luxury car line underwent drastic changes, including the elimination of some of its best-selling brands. In addition, terminated brands coincide with low-markup percentage brands in Table 1.6. I view these brand terminations as the merged Hyundai–Kia groups’ differentiated product organization. In other words, a merged firm has an incentive to terminate intra-firm competing brands to maximize profit.

V: Post-Merger Product Quality Improvements

Another potential reason for vehicle price increases is product quality improvement. Although Korean automobile manufactures suffered from a reputation for low quality during the 1980s and early 1990s, today’s automobile consumers (both in Korea and in the United States) generally recognize Korean cars to have undergone substantial quality improvements during the late 1990s to 2000s. Figure 1.7 illustrates that, since 1992, Hyundai Sonata’s price in the United States increased about 8 percent and Hyundai Elantra’s price increased...

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61 This topic relates to endogenous product choices (product positioning). Although I do not model endogenous differentiated-product positioning in this paper, in the conclusion section, I will mention future extensions of this project that would examine the dynamics of product positioning.

62 Hyundai Sonata and Genesis were named Green Car Journal’s Car of The Year in 2011 and 2009.
Table 1.9: Left figure: Bands supplied by Hyundai and Kia Motors in November 1998 (merger announcement month), Right figure: Brands supplied by Hyundai-Kia groups in Nov. 2003 (five years after merger)

<table>
<thead>
<tr>
<th>Class</th>
<th>Brands supplied by Hyundai and Kia Motors in Nov.1998</th>
<th>Brands supplied by Hyundai-Kia groups in Nov.2003</th>
</tr>
</thead>
<tbody>
<tr>
<td>City/Small</td>
<td>Atos</td>
<td></td>
</tr>
<tr>
<td>City/Small</td>
<td>Pride (5)</td>
<td></td>
</tr>
<tr>
<td>Sub-Compact</td>
<td>Accent (12)</td>
<td>Avella (40)</td>
</tr>
<tr>
<td>Sub-Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sub-Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td>Avante (2)</td>
<td>Sephia (8)</td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td>Shuma</td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Size</td>
<td>Sonata (1)</td>
<td>Credos (22)</td>
</tr>
<tr>
<td>Mid-Size</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Size</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mid-Size Luxury</td>
<td>Grandeur (3)</td>
<td>Potentia</td>
</tr>
<tr>
<td>Full-Size Luxury</td>
<td>Dynasty</td>
<td>Enterprise</td>
</tr>
<tr>
<td>Full-Size Luxury</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sports</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sports</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sports</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact SUV/Jeep</td>
<td>(Asia-)Retona</td>
<td></td>
</tr>
<tr>
<td>SUV/Jeep</td>
<td>Gallopper (21)</td>
<td></td>
</tr>
<tr>
<td>Compact Crossover SUV</td>
<td>Sportage (17)</td>
<td></td>
</tr>
<tr>
<td>Crossover SUV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minivan/MPV</td>
<td>Santamo</td>
<td>Carnival (15)</td>
</tr>
<tr>
<td>Minivan/MPV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Compact Minivan/MPV</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A brand name with a strike-through indicates a brand terminated at some point during December 1998 - November 2003.

Parentheses indicate 1991–2010 top 40 sales statuses and rank.

SUV: Sports Utility Vehicle, with off-road driving ability, Minvan = MPV: Multiple Purpose Vehicle

Crossover SUV: Mixture of SUV and MPV

about 11 percent. Given the assumption that competition status in the United States’ automobile market has remained unchanged, one might interpret such price increases as increases in quality. Thus, one could potentially attribute a portion of the price increases in Korea to improvements in product quality. However, such quality improvements cannot be measured as a numerical variable in this research, and are not included in the subsequent analysis in
VI: Post-Merger Changes in Material Costs

An increase in material costs could be a major cause of price increases. Figure 1.10 depicts the inflation-adjusted Importer Price Index during 1991–2010, which roughly measures imported material costs. I observe two spikes, first in 1998 and then during 2008–2009. The spikes are due to the devaluation of the Korean won (in 1998 and 2009) and global material cost increases (in 2008). This figure indicates that increases in material cost could cause rises in vehicle prices during 2008–2009. However, the effects of material cost increases (on vehicle prices) were limited to the 2008–2009 period.

Note that unobserved product characteristics, $\xi_{jt}$’s, are not direct measures of product quality. Rather, $\xi_{jt}$’s are recovered as residuals in equation (1.3), and depend on other products supplied in the market. In general, researchers rarely observe quality improvements in data in numerical forms. A notable exception is Leslie and Jin (2003), wherein restaurant hygiene scores (measures of restaurant qualities) are observed and policy impacts of newly introduced hygiene grade cards are investigated.

Since Korea is not rich in natural resources, Korean manufacturing industries import materials from abroad.
VII: Post-Merger Changes in Supply Side Competition

Change in the forms of supply side competition might contribute to long-run price deviations. The benchmark (conventional) simulation assumes a static Bertrand price competition. However, since the merged Hyundai-Kia group took about 70 percent of the domestic market’s share in Korea, it remains possible that firms engaged in other forms of competition, such as leader-follower or dynamic price competitions. By observing price transitions in each vehicle type category (see Figures 1.6, 1.14, and 1.15), fringe/small-scale firms (GM-Daewoo, Samsung, and Ssangyong Motors) seem to follow Hyundai-Kia group’s prices, especially during 2006–2010. These observations suggest that part of the long-run simulation price discrepancy can be explained by the changes in supply side competition.

In summary, all of the changes described above (and numerous other changes not discussed here) are likely to have occurred simultaneously in the post-merger regime, and thus to have contributed to vehicle prices in Korea. In the next section, I break down the changes in consumer incomes, preferences, marginal costs, and product lines, and investigate their contributions to discrepancies between observed and simulated prices.

1.7 Counterfactuals: Accounting for Long-Run Post-Merger Price Discrepancies, A Partial Contribution Approach

In this section, I account for the long-run price simulation discrepancies by taking into account observed post-merger market conditions in simulations. I realize that post-merger information is not available at the time merger policy decisions are made, and that simulation

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65I observe that fringe (small-scale) firms raised their vehicle prices about 2 to 6 months after the Hyundai-Kia group raised its prices. The Edgeworth price cycle model, suggested by Maskin and Tirole (1998) and empirically analyzed by Noel (2007, 2008, 2009, 2010) and Lewis (working paper) with gasoline industry data, may capture such price movements. In addition, these observations decrease the likelihood of industry-wide collusion, as firms raise prices simultaneously in a situation of perfect collusion. Furthermore, dynamic price competitions, put forth by Rotemberg and Saloner (1986) who suggest high prices during a recession, are not likely to describe this specific industry, since I do not observe high prices during the global recession (2008-2009).

66Such as the abilities of CEOs and effective advertisements through mass media.
results reported here are completely hypothetical. However, these hypothetical simulations enable us to detect the sources of long-run simulated price discrepancies. Detected sources provide useful information for future antitrust policymaking in which antitrust policymakers can debate factors that should be included in post-merger price simulations. Note that the benchmark simulation, which uses only the pre-merger data, relies crucially on the strong assumptions (I-1)-(IV-1). In general, one cannot expect that such strong assumptions will hold after the merger, especially in the long run. In particular, I change the benchmark assumptions by using the following observed (or estimated) post-merger data.

**Using Observed Post-Merger Conditions in Simulations:**

(I-3) Observed post-merger consumer incomes  
(II-3) Observed post-merger consumer preferences  
(III-3) Observed post-merger marginal costs  
(IV-3) Observed post-merger product lines

Herein I take the partial contribution (ceteris paribus) approach. In other words, I investigate contributions of each (I-3)-(IV-3), given other factors fixed to the benchmark simulation assumptions. In this way, I numerically evaluate effects of each (I-3)-(IV-3) separately with the goal of contributing to future horizontal-merger policymaking. In particular, I materialize post-merger information (I-3)-(IV-3) under the following conditions:

**Using Observed Post-Merger Market Conditions in Simulations: Implementations**

(I-4) Applying the 30.9 percent increase in quarter dummy (income proxy)  
(II-4) Substituting the estimated post-merger preference parameters ($\hat{\alpha}, \hat{\beta}, \hat{\sigma}$), with using pre-merger $\xi_{jt}$ values  
(III-4) Applying a uniform 5 percent post-merger marginal cost reduction among Hyundai-Kia group’s brands

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67For example, when I use (II-3), I also apply (I-1), (III-1), and (IV-1) for a post-merger price simulation.
(IV-4) Applying the observed November 2007 product lines, with post-merger $x_{jt}$, $\xi_{jt}$ and $\hat{mc}_{jt}$ values

Note that, in general, changes in consumer preference and supply-side changes in product lines are not separable. Consumer’s preference over unobserved product characteristics $\xi_{jt}$ depends on available products that automobile manufactures determine to supply. To alleviate this non-separability problem, I have chosen the pre-merger $\xi_{jt}$ values used in (II-4) and post-merger $\xi_{jt}$ values used in (IV-4).

1.7.1 A Ceteris Paribus (Partial Contribution) Evaluation in Post-Merger Changes

Table 1.10 lists the results of each partial contribution of the post-merger changes for improving (average of observed long run minus benchmark simulation) price discrepancy, given other changes unapplied. I observe that consumer income increased 30.9 percent after the Hyundai–Kia merger (see Table 1.7). Applying (I-4), which increases average of pre-merger quarter dummies (income proxy) by 30.9 percent, results in a reduction of the outside goods (non-purchase) share and a $933 increase in post-merger aggregate price. (II-4) enables an investigation on the effect of preference change. By substituting the estimated post-merger preferences ($\hat{\alpha}, \hat{\beta}, \hat{\sigma}$), the aggregate price increases by $2,192. The post-merger changes in preference comprise the largest observable source of simulation discrepancy. (III-4), a uniform 5 percent reduction in marginal costs among Hyundai-Kia vehicles, investigates the consequences of post-merger marginal cost improvements from the merger synergy. The simulation results indicate that these marginal cost improvements result in an aggregate increase.

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68I observe that more and more SUVs became available in the post-merger regime. Technically, one can decision-theoretically debate the relationship between consumer preference and choice sets, although such discussions are not within the scope of this research.

69I recognize product lines are endogenously determined given consumer incomes and preferences. I am currently working on another research project that analyzes firms’ endogenous dynamic choices of differentiated products (product lines) given the perfect foresights on consumer income and preferences.

70The uniform 5 percent marginal cost reductions are temporarily assumed. I am currently working on production function estimations and recovering marginal costs using observed wage and rental rate data. Using recovered marginal production costs, I will attempt to investigate the merger synergy effect (TFP improvement) after the Hyundai-Kia merger.
Table 1.10: **Using observed post-merger changes in simulation**: Partial (ceteris paribus) and total contributions on price discrepancies

<table>
<thead>
<tr>
<th>Type of post-merger projection</th>
<th>Partial (or total) contribution for simulated post-merger aggregate prices</th>
<th>Simulated post-merger aggregate price</th>
<th>Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>(I-4): Using only post-merger consumer income change</td>
<td>+933 (25.26%)</td>
<td>$17,674</td>
<td>30.9% increase in average of pre-merger quarter dummies</td>
</tr>
<tr>
<td>(II-4): Using only post-merger consumer preference change</td>
<td>+82,192 (59.36%)</td>
<td>$18,933</td>
<td>Unobserved product characteristics, ξjt’s, unchanged</td>
</tr>
<tr>
<td>(III-4): Using only post-merger marginal costs changes</td>
<td>-499 (-13.52%)</td>
<td>$16,242</td>
<td>Uniform 5% reduction in mcjt’s among Hyundai-Kia vehicles</td>
</tr>
<tr>
<td>(IV-4): Using only post-merger product line changes</td>
<td>$269 (7.31%)</td>
<td>$17,011</td>
<td>Using product lines in Nov. 2007 with recovered post-merger ξjt’s</td>
</tr>
</tbody>
</table>

Using (I-4), (II-4), and (III-4) simultaneously applying (I-4) - (III-4) produces $19,002

1000 won = 1 US dollar exchange rate applied

Simulated prices with benchmark (conventional) assumptions (I-1)-(IV-1) is $16,741

Second column represents changes in comparison with benchmark simulated price

Percentages in the second column indicate contributions to reduce (observed long run minus simulated) price discrepancy = $3,692 (= $20,433 - $16,741). For example (I-4) contributes $933 \times 100 = 25.26\text{ percent.}$

Average of observed long-run (1999–2003) prices = $17,109

Average of observed long-run (2004–2010) prices = $20,433

price reduction of $499\text{.}$ Finally, (IV-4) investigates the impact of product line changes. I substitute the observed November 2007 product lines, their product characteristics (both observable and unobservable), and marginal costs. The result indicates that such product line changes increase the aggregate price by $269. A strong caveat is required for interpreting this number. Given consumer incomes and preferences, the product lines were endogenously determined by firms. As I discussed in the section 6, the merged Hyundai-Kia group avoided intra-firm product competitions, and terminated some intra-firm competing products. Such product-line organization results in the increase in aggregate price. These simulation results

71This result marks a contrast to the marginal cost reduction seen in perfectly substitutable homogeneous goods markets. In a homogeneous product market with Bertrand price competition and given that marginal costs are identical, one expect a 5 percent market price decrease with a 5 percent marginal cost reduction. In a differentiated-product market, the effects of marginal cost reductions are weakened by imperfect substitutions.
indicate that changes in consumer income and preference had a substantial impact on post-merger price hikes, although supply side changes in marginal costs and product lines also had sizable impacts.

More importantly, these post-merger changes in (I-4)-(III-4) can be applied simultaneously\textsuperscript{72}, and such a simulation with simultaneous factor changes may have practical value in antitrust policymaking. With this motive in mind, I simulate post-merger prices using (I-4)-(III-4) simultaneously. The result is a 61.24 percent (\$2,260) discrepancy reduction, and more than half of the discrepancy can be explained by incorporating (I-4)-(III-4). This simulation result from simultaneous post-merger changes indicates that antitrust policymakers can benefit from incorporating potential changes in relevant exogenous\textsuperscript{73} factors into the simulation model\textsuperscript{74}.

Lastly, there remains an unexplained portion of simulation discrepancy. However, note that such post-merger changes as product quality improvements and changes of supply side competition could explain the remaining simulation discrepancy. In particular, unobserved product quality improvements are likely to be the major component. A consensus exists among automobile industry specialists that Korean automobile manufactures improved their product quality throughout the 2000s\textsuperscript{75}. Such quality improvements ideally should be observed and incorporated in simulations. However, product quality improvements are, unfortunately, not numerically observed in this research and thus remain in the unexplained discrepancy.

\textsuperscript{72}Since both (IV-4) and (III-4) change marginal costs, (IV-4) cannot be applied with (III-4).

\textsuperscript{73}Exogenous to the simulation model.

\textsuperscript{74}In this case study, post-merger preference changes play the most significant role in creating long-run simulation discrepancy. However, in other cases such as a horizontal merger in the cereal industry, post-merger supply side changes in marginal cost and product lines could play substantial roles.

\textsuperscript{75}GM-Daewoo Motors and Renault-Samsung Motors had also improved product qualities by introducing General Motors and Renault vehicle based automobile brands. General Motors and Renault Motors were also likely to carry over production technologies.
Figure 1.11: Left figure: Applying post-merger income, Right figure: Applying post-merger preference

Figure 1.12: Left figure: Applying marginal cost reduction, Right figure: Applying post-merger product line

1.8 Conclusion and Future Extensions

This paper demonstrates empirically that the post-merger price simulation method proposed by Nevo (2000, 2001) [32] can offer reasonable performance in predicting short-term post-merger prices, although, in this case study, some of the simulation assumptions changed even in the short term. Nonetheless, using this simulation reveals significant long-run discrepancies between observed and simulated prices. This research also investigates counterfactual simulations, which take into account observed post-merger changes in the market. Counterfactual simulations exemplify that changes in consumer incomes and preferences, and marginal costs can explain the majority of simulation discrepancies. This ex-post evaluation
of simulation performance suggests that, when antitrust policymakers apply the results of post-merger price simulations, they must take into account possible changes in factors that the simulation model takes as exogenous.

One can expand this research in two important directions. The first direction involves modeling supply-side endogenous product positioning\textsuperscript{76}, a currently active research area in the empirical industrial organization literature. Although endogenous product-positioning\textsuperscript{77} serves as an important component of antitrust policymaking, only a limited number of empirical investigations are currently available, especially regarding the dynamics of differentiated-product positioning\textsuperscript{78}. Sweeting (working paper) [40] stands as the pioneering researcher in this area. Due to simple market characteristics, the Korean automobile market is advantageous when it comes to investigating supply-side product choice dynamics.

Investigating Williamson’s trade-off with internationally competing firms serves as the second direction of possible research extension. The core of the antitrust merger debate lies in whether consumer-side welfare-reducing price effects can be compensated for supply-side welfare-increasing productivity gains, when looked at from a perspective of enhancing social surplus. This Williamson trade-off framework becomes extremely challenging considering the existence of firms that engage in both domestic and international competitions, and also invest in quality improvements. The trade-off problem would then become whether one can view welfare losses among domestic consumers (that result from high the post-merger domestic market concentration) as necessary sacrifices for the productivity (and quality) increase (and subsequent welfare gains) of globally operating domestic firms. In particular, the Hyundai–Kia group, which has extracted consumer surplus since the merger, has—at

\textsuperscript{76}E.g.: Such differentiated-product firms as magazine publishers or beer manufacturers dynamically allocate their products on the product space. They organize their product positioning to correspond to changes in costs, government regulations, and consumer tastes. Importantly, the effect of such policy changes as tighter environmental regulations or tax increases depends on how firms react to new market conditions by reallocating their differentiate products. For example, market effects of the currently debated “sugar tax” depend on how quickly food (or soda) manufacturers react to the sugar tax by changing their product lines.

\textsuperscript{77}See Gandhi, Froeb, Tachantz, and Werden (2008) [17] for the theoretical frame work of post-merger differentiated-product space organizations.

\textsuperscript{78}See Draganska, Mazzeo, and Seim (working paper) for their literature review on endogenous product choice by firms.
the same time—heavily invested in quality, design, and manufacturing improvements\textsuperscript{79} and, furthermore, has expanded global sales\textsuperscript{80}. If one takes the social surplus maximizing point of view, post-merger welfare losses among Korean domestic automobile buyers could be offset by Hyundai–Kia group’s global sales expansions, made possible by the improvements in productivity and product quality\textsuperscript{81}. Although I am unable to provide answers to this important social question, my conjecture is that the merger between Hyundai and Kia Motors enhanced Korea’s overall welfare, thanks to the large expansion of exports by the merged Hyundai-Kia group.


\textsuperscript{80}As of December 2010, Hyundai-Kia group is the forth-largest automobile manufacture in the world, following GM, Toyota, and Volkswagen groups.

\textsuperscript{81}Hyundai Motors’ famous “10 years or 100,000 miles” warranty in North America began in 1999, right after the Hyundai-Kia merger.
Appendix 1: Data Construction Details

1.8.1 Categorizations for Estimation and Construction of Instrumental Variables

Based on Berry, Levinsohn, and Pakes (1995) [5], I construct and use following instrumental variables.

(1) Cost shifter = kilogram × (Importer Price Index)
(2) Sum of within same class competing firm products’ size
(3) Sum of within same class competing firm products’ horsepower-per-kilogram
(4) Sum of within same class competing firm products’ kilometer-per-litter

Brand classes are listed on the table 1.11.\(^{82}\)

\(^{82}\)Since SUVs, Crossover-SUVs, and Minivans have complicated classifications, I categorize them into the single category.

\(^{83}\)Berry, Levinsohn, and Pakes (1995) also use the sum of the characteristics of other products offered by the same firm. I do not use such instruments in this research due to concerns about endogenous product characteristic choices.

Table 1.11: Automobile brand classifications by firm

Omitted
Appendix 2: Constructions of Aggregate Prices

In this appendix, I describe the construction of aggregated prices. I use two objective criteria for creating representative prices and denoting $P$ as aggregated price or price by firm, $p$ as observed price, and $q$ as observed sales quantity.

Sales Weighted Prices

The definition of sales weighted prices:

(1-1) Sales weighted aggregate prices

$$P_{aggregate,t} = \sum_{j \in all \ brands \ supplied \ at \ time \ t} \left[ \frac{p_{j,t} \cdot q_{j,t}}{\sum_{j \in all \ brands \ supplied \ at \ time \ t} q_{j,t}} \right]$$

(1-2) Sales weighted prices by firm (ex: Hyundai Motors)

$$P_{Hyundai,t} = \sum_{j \in all \ Hyundai \ brands \ supplied \ at \ time \ t} \left[ \frac{p_{j,t} \cdot q_{j,t}}{\sum_{j \in all \ Hyundai \ brands \ supplied \ at \ time \ t} q_{j,t}} \right]$$

These prices are plotted on 1.9.

Indexed Prices

Index weight are defined as

$$w_{j,period} = \frac{Sales \ quantity \ of \ brand \ j \ in \ a \ specific \ period}{Total \ sales \ quantity \ in \ a \ specific \ period}.$$ 


I define indexed prices as:

(2-1) Indexed aggregate prices

$$P_{aggregate,t} = \sum_{j \in all \ brands \ supplied \ at \ time \ t} p_{j,t} \cdot w_{j,period}$$

(2-2) Indexed prices by firm (ex: Hyundai Motors)

$$P_{Hyundai,t} = \sum_{j \in all \ Hyundai \ brands \ supplied \ at \ time \ t} p_{j,t} \cdot w_{j,period}$$

I plot the indexed prices in Figure 1.13. Unfortunately, the prices have “jumps” at Januaries of 1996, 2001, and 2006, however, long-run post-merger prices are clearly observed.
Appendix 3: Supplemental Figures

In this section, I post supplemental figures which are not posted in the main body of the paper.

Vehicle Price Transitions

Figure 1.14, 1.15, and 1.16 show that vehicle prices categorized by class. There are two notable findings among these figures:

1. Prices did not increase immediately after the Hyundai–Kia merger in November 1998.
2. Prices significantly increased in 2006.

1. is caused by the following reason. In the production function estimations, I observe statistically significant Total Factor Productivity (TFP) improvements. Thus, newly merged Hyundai-Kia group’s plants obtained merger synergy (TFP improvement), and improved (decreased) their marginal costs. Improved marginal cost prevents Hyundai-Kia group from increasing their vehicle prices after the merger.

Figure 1.13: Left Figure: Indexed aggregate price, Right Figure: Indexed prices by firms

Data source: Motor Magazine and Carlife Magazine (prices in Korea)
Appendix 5: Simple Example of Nevo’s Ownership Matrix Method, and Simulation Computation

Example: Two firms and three brands. Firm A supplies goods 1 and 2 and firm B supplies good 3. Profits for each firm are

\[
\Pi_A = (p_1 - mc_1)s_1(p)M + (p_2 - mc_2)s_2(p)M - C_A
\]

\[
\Pi_B = (p_3 - mc_3)s_3(p)M - C_B.
\]

Figure 1.14: Left figure: City-/Small-size car prices, Right figure: Subcompact car prices

Figure 1.15: Left figure: Compact crossover SUV prices, Right figure: Crossover SUV prices
First order necessary conditions are

\[ s_1(p) + (p_1 - m_{c_1}) \frac{\partial s_1(p)}{\partial p_1} + (p_2 - m_{c_2}) \frac{\partial s_2(p)}{\partial p_1} = 0 \]

\[ (p_1 - m_{c_1}) \frac{\partial s_1(p)}{\partial p_2} + s_2(p) + (p_2 - m_{c_2}) \frac{\partial s_2(p)}{\partial p_2} = 0 \]

\[ s_3(p) + (p_3 - m_{c_3}) \frac{\partial s_3(p)}{\partial p_3} = 0 \]

and

\[
\begin{bmatrix}
- \frac{\partial s_1(p)}{\partial p_1} & - \frac{\partial s_1(p)}{\partial p_2} & 0 \\
- \frac{\partial s_2(p)}{\partial p_1} & - \frac{\partial s_2(p)}{\partial p_2} & 0 \\
0 & 0 & - \frac{\partial s_3(p)}{\partial p_3}
\end{bmatrix}
\begin{bmatrix}
p_1 - m_{c_1} \\
p_2 - m_{c_2} \\
p_3 - m_{c_3}
\end{bmatrix}
= \begin{bmatrix}
s_1(p) \\
s_2(p) \\
s_3(p)
\end{bmatrix}.
\]

Then, we obtain

\[
\begin{bmatrix}
p_1 - m_{c_1} \\
p_2 - m_{c_2} \\
p_3 - m_{c_3}
\end{bmatrix}
= \begin{bmatrix}
1 & 1 & 0 \\
1 & 1 & 0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
- \frac{\partial s_1(p)}{\partial p_1} & - \frac{\partial s_2(p)}{\partial p_1} & - \frac{\partial s_3(p)}{\partial p_1} \\
- \frac{\partial s_1(p)}{\partial p_2} & - \frac{\partial s_2(p)}{\partial p_2} & - \frac{\partial s_3(p)}{\partial p_2} \\
- \frac{\partial s_1(p)}{\partial p_3} & - \frac{\partial s_2(p)}{\partial p_3} & - \frac{\partial s_3(p)}{\partial p_3}
\end{bmatrix}^{-1}
\begin{bmatrix}
s_1(p) \\
s_2(p) \\
s_3(p)
\end{bmatrix}.
\]

In the paper, I solve/simulate 18 to 41 dimensional versions of this problem (since the number of supplied automobile brands changes over time, dimensions vary).
# Appendix 6: Sales Rankings

## Table 1.12: Top 40 Sales of Domestically-Produced Automobiles (Korea, 1991-2010)

<table>
<thead>
<tr>
<th>Sales Ranking</th>
<th>Firm</th>
<th>Brand</th>
<th>Classification</th>
<th>Sales Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>Hyundai</td>
<td>Sonata</td>
<td>Mid-Size</td>
<td>2,605,467</td>
</tr>
<tr>
<td>(2)</td>
<td>Hyundai</td>
<td>Avante</td>
<td>Compact</td>
<td>1,611,615</td>
</tr>
<tr>
<td>(3)</td>
<td>Hyundai</td>
<td>Grandeur</td>
<td>Mid-Size Luxury</td>
<td>922,587</td>
</tr>
<tr>
<td>(4)</td>
<td>Daewoo</td>
<td>Matiz</td>
<td>City/Small</td>
<td>695,707</td>
</tr>
<tr>
<td>(5)</td>
<td>Kia</td>
<td>Pride</td>
<td>Sub-Compact</td>
<td>622,416</td>
</tr>
<tr>
<td>(6)</td>
<td>Hyundai</td>
<td>Elantra</td>
<td>Compact</td>
<td>580,596</td>
</tr>
<tr>
<td>(7)</td>
<td>Hyundai</td>
<td>SantaFe</td>
<td>Crossover SUV</td>
<td>580,368</td>
</tr>
<tr>
<td>(8)</td>
<td>Kia</td>
<td>Sonata</td>
<td>Compact</td>
<td>539,333</td>
</tr>
<tr>
<td>(9)</td>
<td>Samsung</td>
<td>SM5</td>
<td>Mid-Size</td>
<td>458,776</td>
</tr>
<tr>
<td>(10)</td>
<td>Hyundai</td>
<td>Excel</td>
<td>Sub-Compact</td>
<td>416,273</td>
</tr>
<tr>
<td>(11)</td>
<td>Daewoo</td>
<td>Tico</td>
<td>City/Small</td>
<td>415,096</td>
</tr>
<tr>
<td>(12)</td>
<td>Hyundai</td>
<td>Accent</td>
<td>Sub-Compact</td>
<td>406,960</td>
</tr>
<tr>
<td>(13)</td>
<td>Daewoo</td>
<td>Prince</td>
<td>Mid-Size Luxury</td>
<td>392,454</td>
</tr>
<tr>
<td>(14)</td>
<td>Kia</td>
<td>Carens</td>
<td>Compact Minivan/MPV</td>
<td>388,042</td>
</tr>
<tr>
<td>(15)</td>
<td>Kia</td>
<td>Carnival</td>
<td>Minivan/MPV</td>
<td>383,575</td>
</tr>
<tr>
<td>(16)</td>
<td>Kia</td>
<td>Morning</td>
<td>Compact</td>
<td>371,513</td>
</tr>
<tr>
<td>(17)</td>
<td>Kia</td>
<td>Sportage</td>
<td>Compact Crossover SUV</td>
<td>345,148</td>
</tr>
<tr>
<td>(18)</td>
<td>Ssangyong</td>
<td>Musso</td>
<td>SUV/Jeep</td>
<td>326,968</td>
</tr>
<tr>
<td>(19)</td>
<td>Kia</td>
<td>Sorento</td>
<td>Crossover SUV</td>
<td>321,001</td>
</tr>
<tr>
<td>(20)</td>
<td>Daewoo</td>
<td>Espero</td>
<td>Mid-Size</td>
<td>306,941</td>
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<tr>
<td>(21)</td>
<td>Hyundai</td>
<td>Galloper</td>
<td>Compact SUV/Jeep</td>
<td>306,596</td>
</tr>
<tr>
<td>(22)</td>
<td>Kia</td>
<td>Credos</td>
<td>Mid-Size</td>
<td>275,058</td>
</tr>
<tr>
<td>(23)</td>
<td>Samsung</td>
<td>SM3</td>
<td>Compact</td>
<td>275,817</td>
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<td>(24)</td>
<td>Samsung</td>
<td>SM520</td>
<td>Mid-Size</td>
<td>272,851</td>
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<td>(25)</td>
<td>Ssangyong</td>
<td>Korando</td>
<td>Compact SUV/Jeep</td>
<td>271,229</td>
</tr>
<tr>
<td>(26)</td>
<td>Hyundai</td>
<td>Tucson</td>
<td>Compact Crossover SUV</td>
<td>255,510</td>
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<tr>
<td>(27)</td>
<td>Hyundai</td>
<td>Verna</td>
<td>Sub-Compact</td>
<td>253,494</td>
</tr>
<tr>
<td>(28)</td>
<td>Daewoo</td>
<td>Nubira</td>
<td>Compact</td>
<td>243,718</td>
</tr>
<tr>
<td>(29)</td>
<td>Daewoo</td>
<td>LeMan</td>
<td>Sub-Compact</td>
<td>238,527</td>
</tr>
<tr>
<td>(30)</td>
<td>Kia</td>
<td>Optima</td>
<td>Mid-Size</td>
<td>218,665</td>
</tr>
<tr>
<td>(31)</td>
<td>Daewoo</td>
<td>Lacetti</td>
<td>Compact</td>
<td>193,286</td>
</tr>
<tr>
<td>(32)</td>
<td>Hyundai</td>
<td>Trajet</td>
<td>Minivan/MPV</td>
<td>191,767</td>
</tr>
<tr>
<td>(33)</td>
<td>Daewoo</td>
<td>Leganza</td>
<td>Mid-Size</td>
<td>189,380</td>
</tr>
<tr>
<td>(34)</td>
<td>Kia</td>
<td>Lotze</td>
<td>Mid-Size</td>
<td>188,236</td>
</tr>
<tr>
<td>(35)</td>
<td>Daewoo</td>
<td>Rezzo</td>
<td>Compact Minivan/MPV</td>
<td>180,463</td>
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<tr>
<td>(36)</td>
<td>Ssangyong</td>
<td>Rexton</td>
<td>Crossover SUV</td>
<td>172,836</td>
</tr>
<tr>
<td>(37)</td>
<td>Daewoo</td>
<td>Lanos</td>
<td>Sub-Compact</td>
<td>166,032</td>
</tr>
<tr>
<td>(38)</td>
<td>Kia</td>
<td>Capital</td>
<td>Compact</td>
<td>153,090</td>
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<tr>
<td>(39)</td>
<td>Hyundai</td>
<td>Equus</td>
<td>Full-Size Luxury</td>
<td>150,171</td>
</tr>
<tr>
<td>(40)</td>
<td>Kia</td>
<td>Avella</td>
<td>Sub-Compact</td>
<td>138,099</td>
</tr>
</tbody>
</table>
Appendix 4: Measuring Merger Synergy by Estimating a Production Function and Recovering Production Marginal Costs

In this appendix, I estimate an automobile-plant-level production function and examine the Hyundai-Kia merger’s synergy. As mentioned in the paper, the direct comparisons of pre- and post-merger marginal costs are difficult because Korean automobile manufactures changed their product lines largely. Alternatively, I directly measure the Total Factor Productivity (henceforth TFP) changes before and after the Hyundai-Kia merger.

Plant Level Data

Production and cost functions are estimated with data from Korean Annual Mining and Manufacturing Survey which contains annual plant level data\(^8^4\). The plant information is summarized in Table 1.13.

Firms’ Cost Minimization Problem

I assume a production function has the Cobb-Douglas form \(Y = f(K, L) = AK^{\alpha_k}L^{\alpha_L}\) where \(Y\) is a value added, \(A\) is a TFP, \(K\) is a value of capital equipment (includes building, structure, machine, vessels and vehicles, etc), and \(L\) is the number of total labor hours.

---

\(^8^4\)The data is available from http://kostat.go.kr. Unfortunately, this dataset does not have plant id indicators. However, because of small number of automobile assembling plants in South Korea, I was able to pin down plants’ identities by matching their province/city locations, plant establishment years, and end/beginning of year number of labors. Xu also use the same survey data (for Electric Motor Industry) to construct his technology diffusion model.

Table 1.13: List of automobile plants in Korea

Omitted

Data Source: Firm websites (ownership), Korea Mining and Manufacturing Survey (location and sampling years), Ward’s Automotive Yearbook (produced vehicle brand)
Given an amount of production $Y$, a firm solves the cost minimization problem

$$\min_{K,L} \{ rK + wL \} \quad \text{s.t.} \quad Y = AK^{\alpha_k}L^{\alpha_l}.$$  

It is trivial that this minimization problem provides the following well-known Cobb-Douglas cost and marginal cost functions

$$C(r, w, Y) = \left( \frac{Y}{A} \right)^{\frac{1}{\alpha_k+\alpha_l}} \cdot \left[ \left( \frac{\alpha_k}{\alpha_l} \right)^{\frac{\alpha_l}{\alpha_k+\alpha_l}} + \left( \frac{\alpha_l}{\alpha_k} \right)^{\frac{\alpha_k}{\alpha_k+\alpha_l}} \right] \cdot r^{\frac{\alpha_k}{\alpha_k+\alpha_l}} \cdot w^{\frac{\alpha_l}{\alpha_k+\alpha_l}}$$

$$MC(r, w, Y) = \frac{1}{\alpha_k + \alpha_l} \cdot \frac{1}{Y} \cdot C(r, w, Y)$$

**Production Function Estimation**

For estimation, we assume the production function is

$$Y_{jTp} = A_j K_{jTp}^{\alpha_k} L_{jTp}^{\alpha_l} \exp(\varepsilon_{jTp})$$

By taking natural logarithm, we have

$$y_{jTp} = a_j + \alpha_k k_{jTp} + \alpha_l l_{jTp} + \varepsilon_{jTp}$$

where I define $y_{jTp} = \log Y_{jTp}$, $a_{jTp} = \log A_j$, $k_{jTp} = \log K_{jTp}$, $l_{jTp} = \log L_{jTp}$. Note that I use firm level heterogeneity term $a_j$ which is different from plant level heterogeneity. It is ideal to estimate both firm and plant level heterogeneities, although the small sample size restricts such possibilities.

Table 1.14 shows estimation results\(^85\). I confirmed significant merger synergy (increase in TFP) after the Hyundai-Kia merger. Potential causes of this merger synergy are (1) technology diffusions among merged Hyundai-Kia group plants, (2) reallocations of capital resources, (3) sharing vehicle parts, and (4) organizational improvements in production systems.

**Loan Rates and Worker Wages**

Table 1.17 contains bank-to-firm loan rates and manufacturing sector worker wage in Korea (hourly wages). Loan rates decreased after the Hyundai-Kia merger, while hourly wages are currently working on organizing plant-level investment data to implement the production function estimation method proposed by Olley-Pakes [34].
Table 1.14: Production function estimation results

(Sample size = 211)  

<table>
<thead>
<tr>
<th></th>
<th>Fixed-effect</th>
<th>Random-effect</th>
<th>Olley-Pakes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hyundai-Kia merger synergy dummy</td>
<td>0.5288425**</td>
<td>0.7764618**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.1629887)</td>
<td>(0.1305422)</td>
<td></td>
</tr>
<tr>
<td>Log of capitals: $k_{jpT}$</td>
<td>0.2493353**</td>
<td>0.2768914**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0686254)</td>
<td>(0.0667296)</td>
<td></td>
</tr>
<tr>
<td>Log of labor hours: $l_{jpT}$</td>
<td>0.7767417**</td>
<td>0.7786819**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.073964 )</td>
<td>(0.0733462)</td>
<td></td>
</tr>
<tr>
<td>Year 1994-1995 dummy</td>
<td>0.1845082</td>
<td>0.1720114</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2199425)</td>
<td>(0.2265514)</td>
<td></td>
</tr>
<tr>
<td>Year 1996-1997 dummy</td>
<td>0.6856387**</td>
<td>0.7152682**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2069489)</td>
<td>(0.2129984)</td>
<td></td>
</tr>
<tr>
<td>Year 1998-1999 dummy</td>
<td>0.0691629</td>
<td>0.0380033</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2149192)</td>
<td>(0.2195961)</td>
<td></td>
</tr>
<tr>
<td>Year 2000-2001 dummy</td>
<td>0.3862698*</td>
<td>0.3009461</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2245226)</td>
<td>(0.2238168)</td>
<td></td>
</tr>
<tr>
<td>Year 2002-2003 dummy</td>
<td>0.9488245**</td>
<td>0.8473274</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2300275)</td>
<td>(0.2310227)</td>
<td></td>
</tr>
<tr>
<td>Year 2004-2005 dummy</td>
<td>0.8188824**</td>
<td>0.716725**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.226336)</td>
<td>(0.2262378)</td>
<td></td>
</tr>
<tr>
<td>Year 2006-2007 dummy</td>
<td>1.413632**</td>
<td>1.443058**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2067615)</td>
<td>(0.2128381)</td>
<td></td>
</tr>
<tr>
<td>Year 2008-2009 dummy</td>
<td>1.276235**</td>
<td>1.307849**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.2081042)</td>
<td>(0.2141733)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-3.818104**</td>
<td>-4.239063**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.5081779)</td>
<td>(0.500086)</td>
<td></td>
</tr>
</tbody>
</table>

Note: Basement years for dummy variables are 1991-1992. Random effect model is rejected by the Hausman test.

have kept increasing.
Figure 1.17: Left figure: Bank-to-firm loan rates in Korea, Right figure: Manufacturing sector hourly wage in Korea

Data Source: Bank of Korea, Statistics Korea (Korea’s national bureaus of statistics)
REFERENCES


CHAPTER 2

Risk- & Regret-Averse Bidders in Sealed-Bid Auctions

2.1 Introduction

In this paper, we propose a risk- & regret-averse model to explain widely-observed overbidding phenomenon across different auction rules. The proposed risk- & regret-averse model nests the canonically-accepted risk-neutral and risk-averse models, and it predicts a revenue ranking that is consistent with experimental observations.

A significant number of experimental auction researchers report that bids observed in sealed-bid auction experiments are higher than predictions from risk-neutral Bayesian Nash Equilibria (BNE). Such experimental phenomena is called overbidding, and observed in first-price auction experiments conducted by Cox, Robertson, and Smith (1982) [9] and Cox, Simth, and Walker (1988) [10]. Scholars have observed many other instances of overbidding. Kagel and Levin (1993) [16] noted observations of overbidding in first-, second-, and third-price auctions. Noussair and Silver (2006) [34] discussed observations of overbidding in all-pay auction experiments.

Based on these experimental observations, researchers have been proposing theoretical and behavioral models to explain overbidding. The literature offers three major explanations, and this research combines these three separate explanations into one structural model. The first explanation, that bidders have a risk-averse preference, remains the best-accepted explanation. Bidders prefer to raise probabilities of winning at the costs of higher payments. Higher payments are associated with higher bids which are more than risk-neutral BNE bids. The second explanation is that bidders have preference for winning, apart from their valuations of goods. Scholars refer to this preference for winning as the Joy of Winning.
(JOE). The third explanation is that bidders are driven by anticipated ex-post regrets. When a bidder loses, and if she is willing to pay the resulting price, the bidder perceives the resulting forgone surplus as a loser regret. On the other side, when a bidder wins, and if she realizes that she overprices, scholars see such overpayment as a winner regret.

2.1.1 Motivation: Discrepancies in Observed Bids and Risk-Averse Model Predictions

To clarify our motivation, herein we compare observed bids in experimental auctions and theoretical predictions from the risk-averse preference model. We demonstrate that the risk-averse model predicts both overbidding (bidding above risk-neutral BNE) and underbidding (bidding below risk-neutral BNE), depending on auction rules. Then, we illustrate discrepancies between observed bids in experiments and risk-averse model predictions.

Figures 1 to 4 depict experiment results in symmetric independent private value first-price, all-pay, third-price, and second-price auctions (listing in the order of figures) from Kagel and Levin (1993) [16] and Noussair and Silver (2006) [34]. In their experiments, bidders’ valuations of auctioned objects are exogenously given (controlled) by experiment administrators, but bidders choose bids by themselves. Valuations are from i.i.d. uniform distributions.

First-Price Auction Experiments: Figure 1 summarizes Kagel and Levin (1993) [16]’s first-price auction results and indicates that significant amounts of bids are above risk-neutral BNE in both five- and ten-bidder first-price auction experiments. These experimental results perfectly agree with the theoretical prediction in Riley and Samuelson (1981) [37], in which they proved that risk-averse bidders bid more than risk-neutral BNE. Therefore, the risk-averse preference can predict bidders’ behavior in experimental first-price auctions well.

---

1We explain the details of their datasets in Section 6. We remove extreme outliers such as non-serious bids (close to zero bids). We also normalize their data to [0,1] scale for comparison purposes.

Figure 2.1: Kagel and Levin (1993): Frist-Price Auction Experiments

(a) Frist-Price: Five Bidder Experiment

(b) Frist-Price: Ten Bidder Experiment

Figure 2.2: Noussair and Silver (2006) - (a) Six Bidder All-Pay Experiment (b) Calibrated Risk-Averse BNE

(a) Noussair and Silver (2006) - All-Pay: Six Bidder Experiment

(b) Theoretical Six Bider All-Pay Auction Experiment

**All-Pay Auction Experiments:** Figure 2(a) depicts the results from all-pay auctions from Noussair and Silver (2006) [34]. They experiment with six-bidder all-pay auctions. In theoretical all-pay auctions, the risk-averse preference predicts two different bidding behaviors, depending on bidders’ valuations, as illustrated in Figure 2(b). A risk-averse bidder with a low or middle valuation bids less than risk-neutral BNE to avoid payments caused by the all-pay payment rule when she loses. On the other hand, a risk-averse bidder with an
extremely high valuation tries to secure her winning payoff by increasing her bid and increasing her winning probability. As a result, a risk-averse BNE bidding function single-crosses the risk-neutral one at very high valuation. Therefore, the risk-averse preference predicts underbidding in all-pay auctions, except bidders with extremely high valuations. Figure 2(b) plots the risk-averse BNE. However, Figure 2(a) shows that significant amounts of bids in experiments fall above risk-neutral BNE\(^3\). The estimated bidding function lies above the risk-neutral BNE. To explain this observed overbidding, one needs a risk-loving preference, which is not consistent with other empirical economics findings\(^4\). Since all-pay auctions have such important real-world applications as patent races and political elections, we believe that the risk-averse model’s prediction inability in all-pay auctions poses a significant problem.

**Third-Price Auction Experiments:** Figures 3(a) and 3(c) illustrate third-price auction experiment results with five and ten bidders. Third-price auctions, unlike other auctions, are hypothetical auctions never seen in the real world. However, third-price auction experiments provide useful insights into bidders’ behavior, especially into their risk-averse attitudes. The theoretical risk-averse model prediction is as follows. In third-price auctions, a winner pays the value of third highest bid, and bidders bid higher than their valuations. If a bidder wins, a third-highest bid can be more than her valuation, and her payment can exceed her valuation. Thus, payoffs in third-price auctions can be negative. As a consequence, risk-averse bidders try to avoid negative payoffs by decreasing their bids and lowering probabilities of winning. Therefore, the risk-averse preference predicts underbidding. Figures 3(b) and 3(d) plot the risk-averse BNE\(^5\). By comparing the estimated bidding functions and risk-averse BNE, we observe overbidding among lower valuation bidders in five-bidder experiments and among entire valuation bidders in ten-bidder experiments. If one sticks to the risk-averse framework and strategic interactions, and if one wants to explain these observed overbiddings in third-price auction experiments, one needs to accept the risk-loving preference. This generates two immediate problems. First, the risk-loving preference is not

\(^3\)The estimated bidding function (by absolute minimum distance estimation) has a “jump” around valuation 0.6 to 0.8.

\(^4\)In particular, in the insurance literature, one rarely observes risk-loving behaviors.

\(^5\)The analytic bidding function with the CARA preference is derived in the appendix of Kagel and Levin (1993) [16]. The CARA risk-averse parameter 1.25 is used to create Figures 3(b) and 3(d).
Figure 2.3: Kagel and Levin (1993): Third-Price Auction Experiments Results - Comparisons to Risk-Averse BNEs

(a) Third-Price: Five-Bidder Experiment Result

(b) Theoretical Third-Price Five-Bidder BNE with CARA Risk-Averse Parameter 1.25

(c) Third-Price: Ten-Bidder Experiment Result

(d) Theoretical Third-Price Ten-Bidder BNE with CARA Risk-Averse Parameter 1.25
consistent with empirical literature in economics, because we never observe such empirical
evidences of risk-loving attitudes as negative insurance premiums. Second, bidders in Kagel
and Levin (1993) \cite{16}'s experiments\textsuperscript{6} reveal a risk-averse preference in the first-price auction
experiment. Thus, we have preference inconsistency in bidders’ risk-averse attitudes. As in
the all-pay auction experiment, the risk-averse preference alone cannot explain overbidding
in third-price auctions.

**Second-Price Auction Experiments:** Figure 4 depicts the second-price auction
experiment results. In theory, bidding one’s valuation is a weakly dominant strategy in second-
price auctions regardless of the bidders’ risk-attitudes. However, the experiment results in
Figure 4 demonstrate that bidders tend to bid more than their valuations. Therefore, the
risk-averse preference alone cannot explain the observed overbidding in the second-price auc-
tion experiments\textsuperscript{7,8}.

\textsuperscript{6}They are University of Huston undergraduate and MBA students.
\textsuperscript{7}Researchers have developed such concepts to explain observed overbidding in second-price auction exper-
iments as non-strategic interactions and the existence of spiteful feelings. Among such proposed explanations,
the most well-accepted explanations is the Joy of Winning, where bidders obtain payoffs that are separated
from their valuations. See Cooper and Fang (2008) \cite{8} for an example. We will return to the Joy of Winning
in Section 4.
\textsuperscript{8}We concentrate on the framework of strategic interactions in this research.
These comparisons between experimental results and theoretical predictions illustrate that the risk-averse model alone cannot explain widely-observed overbidding phenomena across different types of auction rules. The risk-averse preference predicts both overbidding and underbidding, depending on specific auction rules. This insufficiency of the risk-averse preference concerns us about reliabilities of auction designs. An auction design with a risk-averse preference model can provide opposite revenue predictions due to the model’s underbidding natures under some auction rules. As a result, such auction designs are likely to be unreliable. To design better auctions in the real world, we need to have a model that consistently explains overbidding phenomenon across a variety of auction rules.

2.1.2 Contributions

Based on the above motivation, we propose risk- & regret-averse model in the rest of this paper. Our model nests canonically accepted risk-neutral and risk-averse preferences in the auction literature. This paper makes two main contributions. First, by numerical calibrations, we qualitatively demonstrate that the risk- & regret-averse model can explain overbidding across a variety of symmetric Independent Private Value (IPV) auction rules. Section 7 reviews the calibration figures. Second, by revenue comparisons, we quantitatively demonstrate that the risk- & regret-averse model predicts a revenue ranking among standard Independent Private Value (IPV) auctions as

\[ \text{all-pay} > \text{first-price} \approx \text{second-price} > \text{third-price}. \]

This ranking drastically contrasts with a prediction based on risk-averse preference, as our model demonstrates the revenue supremacy in all-pay auctions. Table 2.2 in Section 7 summarizes the results of revenue comparisons. This new revenue ranking is consistent

\[^9\text{Revenue computations are based on the uniform valuation distribution and with estimated risk-averse and regret-averse parameters.}\]

\[^{10}\text{With a uniform valuation distribution and with reasonable risk-averse attitudes, the risk-averse preference predicts a revenue ranking as}\]

\[ \text{first-price} > \text{second-price} > \text{third-price} > \text{all-pay}. \]

Programs that compute revenues with risk-averse preference are posted on Yoshimoto’s website.
with the experimental auction literature, especially results from all-pay auction experiments in Noussair and Silver (2006) [34] and Gneezy and Smorodinsky (2006) [22], who report surprisingly large revenues generated in all-pay auction experiments.

### 2.1.3 Literature

Sizable amounts of experimental auction research have analyzed overbidding, and these analyses propose a variety of explanations. Since we have already discussed Kagel and Levin (1993) [16] and Noussair and Silver (2006) [34] with their experimental data, and since we focus on regret-averse attitudes among auction bidders, we here concentrate on the three most-related studies with respect to regret-averse attitudes.

Engelbrecht-Wiggans (1989) [14] is the first theoretical study of bidding that incorporates regret\(^{11}\). Recent papers by Engelbrecht-Wiggans and Kotok (2007) [16] and Filiz-Ozbay and Ozbay (2007) [18] experimentally investigate the effect of feedback policies on bidding behaviors. These studies explain observed overbidding by anticipated ex-post regret. In particular, in Filiz-Ozbay and Ozbay (2007) [18], they experiment with first-price auctions under different post-auction information disclosure environments. Using the reduced-form regressions, they find significant differences in bidding behaviors caused by changes in post-auction information disclosure policies. Bids are significantly higher in the environment where winning bids are publicly announced at the end of each auction, compared to those in a no post-auction information disclosure environment. Based on the reduced form regression results, they assess and verify existences of anticipated regrets under different information disclosure environments. Although we do not discuss differences in information disclosure environments in this paper, we recognize our risk- & regret-averse model is the structural extension of Filiz-Ozbay and Ozbay (2007) in the sense that we statistically verify the significance of regret-averse attitudes in auctions.

We emphasize that we restrict our attention to strategic interactions among bidders. We

---

\(^{11}\)In this research, we use terminologies (1) “Regret”, (2) “Anticipated Regret”, and (3) “Expected Regret” interchangeably. These are all ex-ante evaluations of ex-post regret. Formal definitions of regret are in Section 3.

\(^{12}\)See also Engelbrecht-Wiggans and Kotok (2005) [15]
acknowledge that one may explain the failure to choose a dominant strategy by arguments at a cognitive level, such as imperfect reasoning, or many other behavioral models. We believe such behavioral models are orthogonal to our research. Nevertheless, we view them as adequate explanations of overbidding phenomenon\textsuperscript{13}.

2.1.4 Organization of Paper

We organize this paper as follows. In Section 2, we illustrate bidders’ regret-averse attitudes with the simple first-price auction example. In Section 3, we define the formal models of expected (anticipated) regret. In Section 4, we apply the risk- & regret-averse model to the auction environment. We also propose several testable empirical hypotheses. Section 5 discusses Independent Private Value (IPV) auctions with the risk- & regret-averse model. In Section 6, we structurally estimate model parameters and test empirical hypotheses. In Section 7, we compute calibrations and counterfactual revenue rankings. Section 8 concludes and mentions possible future extensions. A separate Appendix discusses extensions to asymmetric and common-value auctions.

\textsuperscript{13}We are confident that many behavioral models, such as level-K and quantal-response models, remain compatible with our model.
2.2 Regrets: Simple First-Price Auction Example

Before formally introducing definitions, it is worthwhile to cultivate the intuitions behind regrets in auctions. In this section, we consider a simple first-price auction example in which perceptions of regrets naturally emerge.

We consider a fictional auction story. Mrs. Robinson is a big fan of baseball and she participates in an auction where an auctioneer offers a vintage Joe DiMaggio autographed bat. This auction is in the sealed-bid first-price format, and we hypothetically assume valuations among bidders are private, to simplify the explanation. All such information such amounts of winning and losing bids are publicly announced after the auction. Mrs. Robinson evaluates the bat as worth $1,000, and for some equilibrium reasons, that we will intensively investigate throughout this paper, she submits a bid of $800. After such an auction, Mrs. Robinson ex-post experiences one of the following three mutually exclusive events.

**Event 1: Mrs. Robinson wins the auction but she overprices**

It turns out that Mrs. Robinson’s submitted bid ($800) is the highest and she obtains the bat. However, from the public announcement, she ex-post learns that the second-highest bid fell far below her bid, say $600. Then, Mrs. Robinson ex-post realizes that she only needed to bid $(600 + \varepsilon)$ to win the auction, where $\varepsilon$ is a smallest monetary unit. This means she ex-post realizes she overprices the bat to the amount of $800−600 = $200. A regret in this event is defined as the difference between an ex-post best payoff (which could be achievable if Mrs. Robinson knew that the second highest bid was $600 before an auction) and a realized payoff (which Mrs. Robinson actually obtains after the auction). If Mrs. Robinson has the risk-neutral preference, her regret is defined by

$$
\text{ex-post best payoff} - \text{realized winning payoff} = 200,
$$

(2.1)

---

14 Joe DiMaggio (1914–1999), a Hall of Fame baseball player for the New York Yankees.
15 We will relax the private value assumption in online Appendix of this paper.
16 We follow the convention in auction literature. We assume that monetary units are continuous and signals (valuations) are drawn from atom-less distributions. Ties happen with probability measure zero, and we simply ignore $\varepsilon$ in discussions.
which is nothing but the amount Mrs. Robinson had overpriced\(^\text{17}\). Next, if Mrs. Robinson has a risk-averse preference with a CARA \((u(z) = \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha z))\) von Neumann-Morgenstern (henceforth, vNM) payoff function\(^\text{18}\) with a risk-averse parameter \(\alpha\), her regret is similarly defined by the difference between an ex-post best payoff and a realized payoff

\[
\begin{align*}
\left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha(1000 - 600)) \right] - \left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha(1000 - 800)) \right].
\end{align*}
\]

(2.2)

Furthermore, if Mrs. Robinson has not only risk-averse but also regret-averse attitudes, meaning she amplifies a regret (which is the difference between an ex-post best and a realized payoff) with an index function with a regret-averse parameter \(\gamma\), her regret is defined by

\[
\begin{align*}
\left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha(1000 - 600)) \right] - \left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha(1000 - 800)) \right]^{1+\gamma}.
\end{align*}
\]

(2.3)

We call numerical amounts defined by (2.1), (2.2), and (2.3) as \textbf{winner regret} in order to capture a winner’s perception over a forgone payoff caused by an overpayment that could be avoidable\(^\text{19}\).

\textbf{Event 2: Mrs. Robinson loses the auction but she underprices the affordable bat}

It turns out that Mrs. Robinson’s submitted bid ($800) is not the highest and she loses the auction. However, from the public announcement, she ex-post learns that the highest bid is below her valuation (which is $1,000), say the highest bid is $900. Then, Mrs. Robinson ex-post realizes that she underpriced her bid. In other words, if she \textit{had submitted} a bid of $(900 + \varepsilon)$, she \textit{could have won} an auction with a positive payoff. In the manner similar to Event 1, a regret is defined as the difference between an ex-post best payoff (which \textit{could} be achievable if she knew the highest bid \textit{was} $900 before an auction) and a realized losing

\(^{17}\text{Some researchers call this event as “Money Left on a Table.”}\)

\(^{18}\text{We normalize a CARA payoff function so that } u(0) = 0 \text{ and } u'(0) = 1.\)

\(^{19}\text{Note that if } \gamma = 0 \text{ (no regret amplification), (2.3) collapses to (2.2). In addition, if } \alpha \to 0, \text{ (2.2) collapses to (2.1). These nesting properties provide testabilities in risk-averse and regret-averse attitudes. We will explore these testabilities in the empirical sections.}\)
payoff of zero. If Mrs. Robinson has the risk-neutral preference, her regret is defined by

\[ \frac{1000 - 900}{\text{ex-post best payoff}} - \frac{0}{\text{realized losing payoff}} = 100. \tag{2.4} \]

Furthermore, as we saw in Event 1, if Mrs. Robinson has not only a risk-averse preference but also a regret-averse attitude, her regret is defined by

\[
\left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha(1000 - 900)) \right] - \left[ \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha \cdot 0) \right]^{1+\gamma}.
\tag{2.5}
\]

We call numerical amounts defined by (2.4), and (2.5) as loser regret to capture losers’ perceptions over a forgone positive payoff that could be achievable.

**Event 3:** Mrs. Robinson loses the auction and the bat is not affordable to her

It turns out that Mrs. Robinson’s submitted bid ($800) is not the highest and she loses the auction. Furthermore, by the public announcement, she ex-post learns that the highest bid is far above her valuation (which is $1,000), say the highest bid is $1,300. This means she ex-post realizes that the bat is unaffordable to her. Here, unaffordable means that even if she knew the highest bid was $1,300, she would have had no way to obtain a positive payoff. If Mrs. Robinson has the risk-neutral preference, her regret is defined by

\[ \frac{0}{\text{ex-post best payoff}} - \frac{0}{\text{realized losing payoff}} = 0. \tag{2.6} \]

In this event, even if Mrs. Robinson has both risk-averse and regret-averse attitudes, her regret is still zero, because a regret is defined by the difference between an ex-post best payoff and a realized payoff.

Intuitively, the concept of regret numerically converts the perception of “if a person knew the true state” stories. Ex-post best payoffs provide reasonable reference points to describe potentially attainable payoffs that a bidder may consider when she chooses her bid in an action.
2.3 A Decision Model of Anticipated (Expected) Regret

In this section, we define the regret minimizing decision rule proposed by Hayashi [23] that we use throughout this paper. The regret minimization problems nest expected payoff maximization problems.

2.3.1 Definition

The formal definition of the regret minimizing decision rule is described as follows.

**Definition 1**: Regret minimizing decision rule (Hayashi, 2008 [23])

An agent chooses an action $b^*$ with the criterion

$$b^* = \arg \min_{b \in A} \left\{ \int_X \left[ \sup_{b \in A} \left\{ u(\hat{b}, x) \right\} - u(b, x) \right]^{1+\gamma} dG(x) \right\}, \quad (2.7)$$

where $\gamma$ is a regret-averse parameter, $u(\cdot)$ is a vNM function, $A$ is a set of available actions, $X$ is the set of entire states that can be discrete, continuous, or both, and $G(\cdot)$ is the probability measure over a state space.

Notice that we define the integrating object as a homothetic\(^{20}\) index function with a regret-averse parameter $\gamma$. A regret-averse parameter $\gamma$ can be categorized and named by its sign as

$$\begin{align*}
\gamma > 0 : & \quad \text{(i) regret-averse} \\
\gamma = 0 : & \quad \text{(ii) regret-neutral} \iff \text{expected payoff maximization} \\
\gamma < 0 : & \quad \text{(iii) regret-loving}
\end{align*}$$

Three interpretations can explain this parameter. (i) If an agent is regret-averse ($\gamma > 0$), she tends to amplify the difference between an ex-post best payoff she could obtain (which is achievable if she knew a true state is $x$) and a payoff she obtains by choosing action $b$. (ii)

\(^{20}\)Because of a homothetic index function, the regret minimization problem is robust to an affine payoff transformation. A constant part of an affine transformation is canceled out by the subtraction. A multiplication part of an affine transformation can be moved to the outside of minimization problem.
If an agent is regret-neutral \( (\gamma = 0) \), she solves an expected payoff maximization problem, as we explain greater detail shortly. (iii) If an agent is regret-loving \( (\gamma < 0) \), she tends to diminish her regrets\(^{21}\).

Regret minimization problems nest expected payoff maximization problems\(^ {22}\). If \( \gamma = 0 \), the portion of the ex-post best payoff in equation (2.7) becomes a constant, and it can be removed from a minimization problem. More precise, if \( \gamma = 0 \), we can write a regret minimization problem as

\[
\begin{align*}
    b^* & = \argmin_{b \in A} \left\{ \int \sup_{\tilde{b} \in A} \left\{ u(\tilde{b}, x) - u(b, x) \right\} dG(x) \right\} \\
    & = \argmin_{b \in A} \left\{ -\int u(b, x)dG(x) \right\} \\
    & = \argmax_{b \in A} \left\{ \int u(b, x)dG(x) \right\}.
\end{align*}
\]

In the last equality, we change a minus of minimization problem to a maximization problem. The last expression is nothing but an expected payoff maximizing problem. This nesting property has significant empirical implications.

\(^{21}\)We define a regret-loving attitude for purely theoretical purposes, and we view it is unrealistic to assume such attitudes.

\(^{22}\)If states are discrete, it also nests Savage (1951) [38]'s minmax regret decision rule. As \( \gamma \to \infty \), the regret decision rule gradually emphasizes a state that provides a maximum regret and eventually becomes Savage’s minmax criterion in the limit.
2.4 Auction Games with Risk- & Regret-averse Bidders and Empirical Hypotheses

One can straightforwardly apply the concept of regret to the auction environment by specifying a state space to be a signal (valuation) space. In this section, we define the Bayesian Nash Equilibrium (henceforth BNE) equilibrium concept with regret minimizing criterion in symmetric Independent Private-Value (henceforth IPV) auctions\(^{23}\). We also introduce testable empirical (behavioral) hypotheses that we test in the empirical application sections.

2.4.1 General Auction Settings

One unit of the indivisible object is being sold via a specific rule of sealed-bid auctions, for example, first-price or all-pay\(^{24}\). We assume the existence of symmetric equilibria with no reservation price. There are \(n\) bidders participating in an auction. Each bidder \(i = 1, \ldots, n\) receives a signal (valuation) \(x_i\), where \(x_i \in [0, \bar{x}]\), and \(\bar{x}\) is an upper bound of signals which can be normalized to one. Let \(F : [0, \bar{x}] \rightarrow [0, 1]\) be the continuously differentiable cumulative distribution function and \(f : [0, \bar{x}] \rightarrow \mathbb{R}_+\) be its derivative. Signals are i.i.d. and valuations are private. We here focus on a symmetric equilibrium with a continuously differentiable and strictly increasing bidding function denoted by \(\beta : [0, \bar{x}] \rightarrow \mathbb{R}_+\). We denote bidder \(i\)'s signal as \(x_i\), and also denote the vector of opponents’ signals as \(x_{-i} = (x_1, \ldots, x_{i-1}, x_{i+1}, \ldots, x_n)\).

The payoff for bidder \(i\) (given her own choice of bid \(b_i\) with her realized signal \(x_i\) and given that her opponents employ a bidding strategy \(\beta\) with their realized signals \(x_{-i}\)) is denoted by a vNM function \(u(b_i, x_i, x_{-i}|\beta)\). For the simplicity of mathematical notations, we drop subscripts of bidder \(i\)'s signal and her bid by denoting \(x = x_i\) and bid \(b = b_i\).

\(^{23}\)We relax symmetry and private-value assumptions in online Appendix of this paper. Extensions to asymmetric and common-value auctions straightforward.

\(^{24}\)Since Krishna (2002) is a standard reference in the auction literature, we try to follow his notations closely.
2.4.2 Equilibrium Concepts

We now introduce the BNE concept in auctions with the regret minimizing criterion.

**Definition 2**: Symmetric BNE with Regret Minimizing Criterion

A symmetric Bayesian Nash Equilibrium (BNE) strategy is a monotone increasing and continuously differentiable bidding function $\beta$ that satisfies

$$
\beta(x) = \arg\min_{b \in A} \left\{ E_{x-i} \left[ \sup_{\tilde{b} \in A} \left\{ u(\tilde{b}, x, x_{-i} | \beta) \right\} - u(b, x, x_{-i} | \beta) \right] \right\}^{1+\gamma} \tag{2.8}
$$

for all $i \in (1, \ldots, n)$ and for any $x \in [0, \bar{x}]$, where $A$ is a bid space that is common to all bidders and $u(\cdot, \cdot, \cdot | \cdot)$ is a vNM function.

Here, we apply the standard symmetric auction BNE interpretations. Given other bidders employ an equilibrium strategy $\beta$, bidder $i$ minimizes her expected regret by optimally choosing her bid $b$, and her optimal choice $b$ coincides with $\beta(x)$. As we have seen in the previous section (equation (2.8)), if we assume regret-neutrality $\gamma = 0$, the equation (2.8) collapses to a standard auction expected payoff maximizing BNE. In this sense, our auction BNE with the regret minimizing criterion nests the standard auction literature. Next, we explore the intuitions behind this BNE.

2.4.3 Understanding Regret Minimizing BNE

In the standard auction theory, one derives a BNE bidding function by solving an expected payoff maximizing first-order condition. The beauty of theoretical auction literature is that composing parts of such a first order condition usually have clear economic interpretations. Researchers usually interpret these as marginal benefit and marginal cost of increasing bids. In this subsection, we first review marginal benefit and cost analysis in an expected payoff maximizing first-price private-value auction, which may appear trivial but holds great importance in fostering the intuitions behind regret. Then, we examine a regret minimizing first-order condition that one can also interpret as marginal benefit and cost.
2.4.3.1 Marginal Benefit and Marginal Cost in Expected Payoff Maximization

In a private-value first-price auction expected payoff maximization problem, the expected payoff (EP) for bidder $i$ (given her signal $x$ and bid $b$, and given other bidders employ a strategy $\beta$ with their signals $x_{-i}$) is written as

$$EP(b, x|\beta) = u(x - b) \cdot E_{x_{-i}}[ALLOC(b, x_{-i}|\beta)]$$

where $u(\cdot)$ is a vNM function and $ALLOC(b, x_{-i}|\beta)$ is a binary allocation function. The first order condition of an expected payoff maximization problem is

$$u'(x - b) \cdot \frac{dE_{x_{-i}}[ALLOC(b, x_{-i}|\beta)]}{db} = -u'(x - b) \cdot E_{x_{-i}}[ALLOC(b, x_{-i}|\beta)].$$

We intentionally keep negative signs on the RHS for consistency in interpretation. A bidder $i$ is choosing her optimal bid to equate her expected marginal benefit (LHS, an increase in winning probability) and marginal cost (RHS, an increase in payment) to maximize her expected payoffs.

2.4.3.2 Marginal Benefit and Marginal Cost Interpretations of Regret Minimization

Such expected marginal benefit/cost interpretation is carried over to regret minimization problems. Define a Regret function $R(\cdot, \cdot|\cdot)$, a winner Regret function $WR(\cdot, \cdot|\cdot)$, and a loser Regret function $LR(\cdot, \cdot|\cdot)$ as

$$R(b, x, x_{-i}|\beta) \equiv \left[ \sup_{\tilde{b} \in A} \left\{ u(\tilde{b}, x, x_{-i}|\beta) \right\} - u(b, x, x_{-i}|\beta) \right]^{1+\gamma}$$

$$WR(b, x, x_{-i}|\beta) \equiv 1_w \cdot R(b, x, x_{-i}|\beta)$$

$$LR(b, x, x_{-i}|\beta) \equiv 1_l \cdot R(b, x, x_{-i}|\beta)$$

where $1_w$ and $1_l$ are binary winning and losing indicators such that

$$1_w = \begin{cases} 1 & \text{if bidder } i \text{ wins} \\ 0 & \text{else} \end{cases} \quad \text{and} \quad 1_l = \begin{cases} 1 & \text{if bidder } i \text{ loses} \\ 0 & \text{else} \end{cases}.$$ 

Since an object auctioned is indivisible, winning and losing are mutually exclusive events. Using this mutual exclusivity, we can decompose a regret function as

$$R(b, x, x_{-i}|\beta) = WR(b, x, x_{-i}|\beta) + LR(b, x, x_{-i}|\beta).$$
Then, one can rewrite the Definition 2 (equation (2.8)) as

$$\beta(x) = \arg\min_{b \in A} \left\{ E_{x_{-i}} [R(b, x, x_{-i}|\beta)] \right\}$$

$$= \arg\min_{b \in A} \left\{ E_{x_{-i}} [WR(b, x, x_{-i}|\beta)] + E_{x_{-i}} [LR(b, x, x_{-i}|\beta)] \right\}.$$ 

One can take a derivative to minimize her expected regret and, thus, solve following first order condition equation,

$$\text{MELR}(b_i, x|\beta) = -\text{MEWR}(b_i, x|\beta)$$

where

$$\text{MELR}(b_i, x|\beta) \equiv \frac{d}{db} E_{x_{-i}} [LR(b, x, x_{-i}|\beta)] \quad \text{and} \quad \text{MEWR}(b_i, x|\beta) \equiv \frac{d}{db} E_{x_{-i}} [WR(b, x, x_{-i}|\beta)]$$

represent Marginal Expected Winner Regret (MEWR) and Marginal Expected Loser Regret (MELR) functions. Note that these expected benefits and costs are for the sake of minimizing regrets. By slightly increasing her bid, a bidder can reduce her expected loser regret (regret caused by underpricing) while she increases her expected winner regret (regret caused by overpricing). In equilibrium, such marginal benefit and cost are equated. Using above notations, we can rewrite the definition of BNE with regret criterion in the following concise way.

**Definition 3**: Symmetric BNE with Regret Criterion (Marginal Benefit and Cost Notation)

A symmetric Bayesian Nash Equilibrium (BNE) strategy is a monotone increasing and continuously differentiable bidding function $\beta$ that solves

$$\text{MELR}(\beta(x_i), x_i|\beta) = -\text{MEWR}(\beta(x_i), x_i|\beta) \quad (2.12)$$

for all $i \in (1, \ldots, n)$ and any $x_i \in [0, \bar{x}]$.

In the case of regret-neutrality $\gamma = 0$, the equation (2.12) collapses to a usual (expected payoff maximizing) standard auction’s first order condition. In particular, in the case of first-price auction, the equation (2.12) becomes (2.10).
2.4.4 Empirical Hypotheses

Based on the theoretical definition above, we now consider empirics with the regret BNE concept. Although the theoretical definition provides us with the solid benchmark, sizable experimental literatures suggest the necessity of modifications to explain empirical phenomena. In this subsection, we introduce empirical hypotheses suggested by the experimental auction literature. Before moving to the detail of each hypothesis, we would like to emphasize that our hypothesis tests are structural, which means we jointly test hypotheses without making strong assumptions such as the risk-neutrality\(^{25}\).

2.4.4.1 Relaxing the Symmetry between Winner and Loser Regrets

The first empirical modification comes from the question about the symmetry between winner and loser regrets. In real-world auctions, bidders may or may not perceive winner and loser regrets equally, and one should empirically test the symmetry in regrets. In addition, Filiz-Ozbay and Ozbay (2007) \cite{18} report asymmetry in regret-averse attitudes with their experimental private-value first-price auction data in the reduced form fashions\(^{26}\). Motivated by their findings, we modify the definition of BNE to make the asymmetry in regret-averse attitudes testable.

**Definition 4 : BNE with Winner and Loser Regrets**

A symmetric Bayesian Nash Equilibrium strategy is a monotone increasing and continuous bidding function \(\beta\) that satisfies

\[
\beta(x) = \arg\min_{b \in A} \left\{ E_{x-i} \left[ \sup_{\tilde{b} \in A} \left\{ u(\tilde{b}, x, x_{-i}|\beta) \right\} - u(b, x, x_{-i}|\beta) \right] \right\}^{1+\gamma_w+1+\gamma_l} \tag{2.13}
\]

\(^{25}\)In reduced form analysis, making strong assumptions before testing hypotheses is often inevitable. For example, an experimental researcher may claim that some experimental phenomena are statistically significant given the assumption of bidders’ risk-neutrality. The problem is that such a claimed conclusion depends on the assumption of risk-neutrality. Structural estimation researchers warn that such a conclusion suffers from “the Double-Hypotheses Problem,” meaning that a testing result in one hypothesis depends on the assumption of another hypothesis. It is worth noting that seminal experimental auction papers such as Kagel and Levin (1993) \cite{16} and Filiz-Ozbay and Ozbay (2007) \cite{18} are avoiding such problems by carefully designing their experiments.

\(^{26}\)We recognize our hypotheses are structurally testing and verifying Filiz-Ozbay and Ozbay (2007) \cite{18}’s experimental findings.
where $1_w$ and $1_l$ are winning and losing indicator defined in the equation (2.11), $\gamma_w$ is a winner-regret parameter, and $\gamma_l$ is a losing-regret parameter.

The difference between equation (2.8) and (2.13) is that a regret is amplified by $1 + \gamma$ in equation (2.8), while it is amplified by $1 + \gamma_w \cdot 1_w + \gamma_l \cdot 1_l$ in equation (2.13). The equation (2.13) literally means that bidders in auctions may perceive their regrets in winning and losing events differently, in terms of the regret amplification with homothetic index function. Definition 4 provides an advantage in that symmetry in regret becomes testable by Hypothesis 2 below. Based on Definition 4, we now propose several empirically testable hypotheses that we will investigate in empirical sections. The first hypothesis tests the existence of bidders’ regret-averse attitudes.

**Hypothesis 1 : Expected Utility Maximization**

\[
H_{1n} : \gamma_w + \gamma_l = 0 \quad \text{(Bidders are Expected Payoff Maximizer)}
\]

\[
H_{1a} : \gamma_w + \gamma_l > 0 \quad \text{(Bidders are Regret Minimizer)}
\]

Hypothesis 1 is the amenity of the nesting property of the regret minimization problem. Next, we propose the second hypothesis for the asymmetry of regret-averse attitudes as we define in the equation (2.13).

**Hypothesis 2 Symmetricity in Regret-Averse Attitude**

\[
H_{2n} : \gamma_w = \gamma_l \quad \text{(Symmetric Regret)}
\]

\[
H_{2a} : \gamma_w \neq \gamma_l \quad \text{(Asymmetric Regret)}
\]

The third hypothesis is testing the risk neutrality by investigating the concavity parameter in a payoff function $u(\cdot)$.

**Hypothesis 3 : Risk-Neutrality**

\[\text{We assume an object auctioned is indivisible, so winning and losing status are mutual exclusive.}\]

\[\text{In empirical sections, bidders in various experiments reveal significant loser regrets ($\gamma_l > 0$, statistically), while we cannot reject $\gamma_w = 0$.}\]
If we choose a CARA \( v(x) = \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha x) \)

\[ H_{3n} : \alpha = 0 \quad \text{(Risk-Neutral)} \]
\[ H_{3a} : \alpha > 0 \quad \text{(Risk-Averse)} \]

2.4.4.2 Joy of Winning

The well-known overbidding phenomenon in second-price sealed-bid auctions motivates the next hypothesis. Experimental auction literature reports that bidders in private-value second-price auction experiments typically bid higher than their valuations, despite the strategy to bid their valuations serves as a weakly dominant strategy with the expected payoff maximizing criterion (as we will see soon, bidding their valuations also serves as a weakly dominant strategy with the regret minimizing criterion). Based on such experimental observations, experimental and empirical researchers takes stances of either (1) assuming a Joy of Winning\(^{30}\) with perfectly rational bidders or (2) consider bounded-rationality models\(^{31}\). In this paper, we take the stance of (1). Nevertheless, we do believe our regret minimizing model is compatible with the literature derived from (2). Here, we would like to clarify the following point; we include a Joy of Winning parameter not to serve as a trivial explanation of overbidding across a variety of auctions, but rather to verify the fact that regret-averse attitudes still play important roles in explaining overbidding phenomena even after we include the Joy of Winning. In the empirical section of this paper, we will statistically verify existences of both regret-averse attitudes and Joy of Winning. The following is the definition of Joy of Winning.

**Definition 5 : Joy of Winning**

\(^{29}\)We choose not CRRA but CARA payoff function to deal with negative payoffs in third-price and all-pay auctions. Note that the CARA payoff function \( v(x) = \frac{1}{\alpha} - \frac{1}{\alpha} \exp(-\alpha x) \) gradually become linear as \( \alpha \to 0 \). In the limit, \( v(x) \) becomes a 45 degree line.

\(^{30}\)For example, see Ertac, Hortascu, and Roberts (2010) [13]. Some experimental researchers reports the existence of “spite,” which is observationally equivalent to Joy of Winning under many circumstances.

\(^{31}\)For example, the logit distribution based quantile response model (McKelvey and Palfrey (1995) [30]) and the cognitive hierarchy model (Camerer, Ho, and Chong (2004) [5]). We strongly believe these models are compatible with our regret minimizing criterion.
The payoff function takes a form of

\[ u(b_i, x, x_{-i}\beta) = \begin{cases} 
  v(x - P(b, x_{-i}|\beta) + J) & : \text{if bidder } i \text{ wins} \\
  v(-P(b, x_{-i}|\beta)) & : \text{if bidder } i \text{ loses}
\end{cases} \]

where \( v(\cdot) \) is a vNM function, \( J \) is the Joy of Winning parameter, and \( P(b, x_{-i}|\beta) \) is a payment function that depends on an auction’s rule.

The advantage of this specific form of payoff function is that one can interpret the Joy of Winning in monetary terms. We now propose the fourth hypothesis to test the existence of the Joy of Winning in the bidders’ payoff function.

**Hypothesis 4 : Existence of the Joy of Winning**

\[ H_{ln} : J = 0 \text{ (No Joy of Winning)} \]
\[ H_{la} : J > 0 \text{ (Joy of Winning)} \]

We test Hypotheses 1–4 in the empirical sections of this paper.

### 2.5 Symmetric Private-Value Auctions

In this section, we investigate equilibrium characteristics of the risk- & regret-averse model among symmetric Independent Private Value (IPV) auctions. We explore this section in the order of second-price, first-price, all-pay, and third-price auctions\(^{32}\).

In the remaining sections of this paper, we use the simplified notation \( \beta_1 = \beta(y_1) \) and \( \beta_2 = \beta(y_2) \) where \( y_1 \) and \( y_2 \) are the highest and the second-highest signals among bidders excluding bidder \( i \). In addition, we use the terminology “affordable” to describe a situation in which a bidder can win an auction with a positive payoff. In a similar manner, we define “unaffordable” as a situation in which it is impossible for a bidder to obtain a positive payoff. In addition, a generic payoff function \( v(z) \) can be normalized as \( v(0) = 0 \), although we do not use such normalization to foster readers’ intuitions. Moreover, we use the notation I, II, III, and AP to indicate First-, Second-, Third-, and All-Pay auctions.

\(^{32}\)Third-price auctions are discussed in Appendix, as not all of readers are interested in third-price auctions.
2.5.1 Second-Price Auction (SPA)

We start with a second-price auction since one can easily derive the equilibrium bidding function by (weakly-) dominant strategy eliminations. Payoffs in a second-price auction is specified by

\[
u(b, x, x_i|\beta) = \begin{cases} 
v(x - \beta_1 + J) & \text{if } \beta_1 < b \text{ (win)} \\
v(0) & \text{if } b < \beta_1 \text{ (lose)}
\end{cases}
\]

where \(\beta_1\) is a highest bid among bidders excluding bidder \(i\) (note that we use the short-hand notations of \(b = b_i\) and \(x = x_i\)). Even with the regret minimizing criterion, a second-price auction keeps the simple equilibrium bidding function.

**Proposition 1** In a second-price auction, a symmetric equilibrium bidding function \(\beta^{II}\) is

\[
\beta^{II}(x) = x + J
\]

for all \(x \in [0, \bar{x}]\).

We can intuitively prove this proposition with Figure 2.6. The horizontal axis measures an amount of the highest of other bids, \(\beta_1\), and the vertical axis measures amounts of ex-post best and realized payoffs. In Figure 2.6, the left (right) figure represents a case in which a bidder bids lower (higher) than \(x + J\). The central figure represents a case in which a bidder bids \(x + J\). We define regrets as the subtraction of thin-dashed line (which is realized payoffs) from thick-dashed line (which is ex-post-best payoffs). As we see, regrets in the central figure (in which regrets are zero over the entire region) weakly dominates those in the other two figures, in which regrets are positive in some regions\(^{33}\).

\(^{33}\)We borrow and modify these fascinating second-price auction figures from Martin J. Osborne’s undergraduate textbook “An Introduction to Game Theory.”
2.5.2 First-Price Auction (FPA)

We investigate regrets in a first-price auction. Since a winner pays her bid in a first-price auction, payoffs are specified by

\[
  u(b, x, x - i | \beta) = \begin{cases} 
    v(x - b + J) & \text{if } \beta_1 < b \\
    v(0) & \text{if } b < \beta_1
  \end{cases}
\]

(2.14)

where \( \beta_1 = \beta(y_1) \) and \( y_1 = \max \{x - i\} \) is the highest signal among bidders excluding bidder \( i \). We can define winner and loser regrets in the following ways, as discussed in Section 2.

**FPA Winner Regret:**

\[
  \text{WR}^I(b, x, x - i | \beta) = \left[ \frac{v(x - \beta_1 + J) - v(x - b + J)}{\text{ex-post best payoff} - \text{realized payoff}} \right]^{1+\gamma_w} 
\]

(2.15)

Winner regret in a first-price auction occurs in a situation in which a bid win an auction but she overprices. In such a situation, an ex-post best payoff is attained by bidding \( \beta_1 \).

**FPA Loser Regret:**

\[
  \text{LR}^I(b, x, x - i | \beta) = \begin{cases} 
    0 & \text{if } \beta_1 > x + J \\
    \frac{v(0) - v(0)}{\text{ex-post best payoff} - \text{realized payoff}} & \text{if } b < \beta_1 < x + J
  \end{cases}
\]

(2.16)
The first row of equation (2.16) describes a situation in which the highest of other bids is above her valuation plus Joy of Winning \((x + J)\), thus, an object is unaffordable to her. In this situation, she has no regret. The second row of equation (2.16) is a case in which an object is affordable to her but she underprices and cannot obtain it.

In a first-price auction, expected regret takes a form

\[
E_{x_i}[R_I^1(b, x, x_i|\beta)] = E_{x_i}[WR_I^1(b, x, x_i|\beta)] + E_{x_i}[LR_I^1(b, x, x_i|\beta)] 
\]

(2.17)

where

\[
E_{x_i}[WR_I^1(b, x, x_i|\beta)] = \int_{\beta(0)}^{b} [v(x - \beta_1 + J) - v(x - b + J)]^{1+\gamma_w} h_1(\beta_1) d\beta_1 
\]

(2.18)

\[
E_{x_i}[LR_I^1(b, x, x_i|\beta)] = \int_{b}^{x+J} [v(x - \beta_1 + J) - v(0)]^{1+\gamma_l} h_1(\beta_1) d\beta_1 
\]

(2.19)

where \(h_1(\cdot)\) is the unconditional density of \(\beta_1\). Note that, in the RHS of equation (2.18) and (2.19), we take integral over other bidders’ bids\(^{34}\) to calculate expected regret. This is equivalent to taking the integral over other bidders’ signals after the changes of variable manipulations. By calculating the first order condition of (2.17) with respect to \(b\), and by substituting the symmetric equilibrium condition \(b = \beta(x)\), we obtain the following proposition (see the derivation in Appendix).

**Proposition 2** *Symmetric IPV First-Price Auction Equilibrium*

The symmetric equilibrium bidding function \(\beta^I\) satisfies

\[
MELR^I(\beta^I(x), x|\beta^I) = -MEWR^I(\beta^I(x), x|\beta^I)
\]

for all \(x \in [0, \bar{x}]\), where the precise form of the equation is

\[
[v(x - \beta^I(x) + J) - v(0)]^{1+\gamma_w} g_1(x) \\
= (1 + \gamma_w) v'(x - \beta^I(x) + J) \frac{d\beta^I(x)}{dx} \int_{0}^{x} [v(x - \beta^I(y_1) + J) - v(x - \beta^I(x) + J)]^{\gamma_w} g_1(y_1) dy_1.
\]

The immediate consequence of Proposition 2 is the weak monotonicity property of \(\beta^I\).

**Corollary 1** If \(\gamma_w, \gamma_l \geq 0\) and \(v(\cdot)\) satisfies \(v'(\cdot) > 0\), \(\beta^I\) is weakly monotone increasing.

\(^{34}\)Since this is a first-price auction with i.i.d. valuations, only the highest of the other bidders’ bids matters to bidder \(i\)’s payoffs and regrets.
By manipulating the equation in Proposition 2, we obtain \( \frac{d\beta^i(x)}{dx} \geq 0 \).

**Case 1** If \( \gamma_w = \gamma_l = 0 \) (regret-neutral), \( J = 0 \) (no joy of winning), and \( v(z) = z \) (risk-neutral) the equation in proposition 2 becomes

\[
\beta^i(x) = x - \frac{\int_0^x F(x)^{n-1} dx}{F(x)^{n-1}}
\]

which is the well-known risk-neutral BNE in a first-price auction.

### 2.5.3 All-Pay Auction (APA)

Next, we direct our attention to all-pay auctions that describe irretrievable costs such as research and development (R & D) patent races, political elections, and lobbying activities. Since a bidder has to pay her bid regardless of winning or losing, payoffs in an all-pay auction are specified as

\[
u(b, x, x_{-i}| Bet) = \begin{cases} 
v(x - b + J) & \text{if } \beta_1 < b \\
v(-b) & \text{if } b < \beta_1 \end{cases}
\]

We can define winner and loser regret in the following ways.

**APA Winner Regret**

\[
WR^{AP}(b, x, x_{-i}| Bet) = \left( \frac{v(x - \beta_1 + J) - v(x - b + J)}{v(x - \beta_1 + J) - v(-b)} \right)^{1+\gamma_w} \quad \text{if } \beta_1 < b.
\] (2.20)

The above equation is bidder \( i \)'s regret over overpricing when she wins. The winner regret in an all-pay auction is identical to that in a first-price auction. The ex-post best payoff is attained by bidding \( \beta_1 \).

**APA Loser Regret**

\[
LR^{AP}(b, x, x_{-i}| Bet) = \begin{cases} 
v(x - \beta_1 + J) & \text{if } \beta_1 > b \text{ and } \beta_1 < x + J \quad \text{(Type A)} \\
v(0) & \text{if } \beta_1 > b \text{ and } \beta_1 > x + J \quad \text{(Type B)} \end{cases}
\]

There are two types of loser regrets in an all-pay auction. The first row is the case in which bidder \( i \) loses an auction although she ex-post realizes she can afford an object. By the
all-pay auction rule, she incurs her bid \( b \). The second row is the case in which bidder \( i \) loses an all-pay auction and she ex-post realizes an object is unaffordable to her, and she wastes her payment of \( b \). In this case, since an object is unaffordable, bidding zero is her ex-post best action. To simplify discussion, we name the loser regrets in the first and second rows as Type A and Type B. Also, we denote Type A and Type B all-pay loser-regret functions as \( LR_{\text{typeA}}(\cdot, \cdot, \cdot|\cdot) \) and \( LR_{\text{typeB}}(\cdot, \cdot, \cdot|\cdot) \). Given that other bidders employ a bidding strategy \( \beta \), expected regret in an all-pay auction takes a form

\[ E_{x-i}[R_{\text{AP}}(b, x, x-i|\beta)] = E_{x-i}[WR_{\text{AP}}(b, x, \beta)] + E_{x-i}[LR_{\text{typeA}}(b, x, x-i|\beta)] + E_{x-i}[LR_{\text{typeB}}(b, x, x-i|\beta)] \]  \hspace{1cm} (2.22)

where

\[ E_{x-i}[WR_{\text{AP}}(b, x, x-i|\beta)] = \int_{\beta(0)}^{b} [v(x - \beta_1 + J) - v(x - b + J)]^{1+\gamma} h_1(\beta_1) d\beta_1 \]  \hspace{1cm} (2.25)

\[ E_{x-i}[LR_{\text{typeA}}(b, x, x-i|\beta)] = \int_{b}^{x+J} [v(x - \beta_1 + J) - v(-b)]^{1+\gamma} h_1(\beta_1) d\beta_1 \]  \hspace{1cm} (2.26)

\[ E_{x-i}[LR_{\text{typeB}}(b, x, x-i|\beta)] = \int_{x+J}^{\beta(\bar{x})} [v(0) - v(-b)]^{1+\gamma} h_1(\beta_1) d\beta_1 \]  \hspace{1cm} (2.27)

where \( h_1(\cdot) \) is the density of \( \beta_1 \) and \( \bar{x} \) is the highest possible signal. In the right hand sides of the above equations, integrals are taken over the highest of the other bidders’ bids, \( \beta_1 \). These integrals are equivalent to integrals other bidders’ signals after the changes of variable manipulations. Taking the derivative of (2.22) with respect to \( b \) and substituting the symmetric equilibrium condition \( b = \beta(x) \) provide the following proposition (see the derivation in Appendix).

**Proposition 3 All-Pay Auction Symmetric Equilibrium**

In an IPV all-pay auction, a symmetric equilibrium bidding function \( \beta_{\text{AP}} \) satisfies

\[ \text{MELR}_{\text{typeA}}(\beta_{\text{AP}}(x), x|\beta_{\text{AP}}) = -\text{MEWR}_{\text{AP}}(\beta_{\text{AP}}(x), x|\beta_{\text{AP}}) \]  \hspace{1cm} (2.28)

\[ -\text{MELR}_{\text{typeB}}(\beta_{\text{AP}}(x), x|\beta_{\text{AP}}) \]  \hspace{1cm} (2.29)
for all \( x \in [0, \bar{x}] \), where the precise form of the equation is
\[
- [v(x - \beta_{AP}(x) + J) - v(-\beta_{AP}(x))]^{1+\gamma} g_1(x) \frac{1}{d\beta_{AP}(x)}
\]
\[
+(1 + \gamma) v'(\beta_{AP}(x)) \int_x^{\beta_{AP}^{-1}(x+J)} [v(x - \beta_{AP}(y_1) + J) - v(-\beta_{AP}(x))] \gamma g_1(y_1) dy_1
\]
\[
= -(1 + \gamma_w) v'(x - \beta_{AP}(x) + J) \int_0^x [v(x - \beta_{AP}(y_1) + J) - v(x - \beta_{AP}(x) + J)] \gamma_w g_1(y_1) dy_1
\]
\[
-(1 + \gamma) v'(-\beta_{AP}(x))[v(0) - v(-\beta_{AP}(x))] \gamma [1 - G_1(\beta_{AP}^{-1}(x+J))].
\]

The immediate consequence of the above proposition is the weak monotonicity of \( \beta_{AP} \).

**Corollary 2** If \( \gamma_w, \gamma_l \geq 0 \) and \( v(\cdot) \) satisfies \( v'(\cdot) > 0 \), \( \beta_{AP} \) is weakly monotone increasing.

(proof) By manipulating the equation in Proposition 3, we obtain \( \frac{d\beta_{AP}(x)}{dx} \geq 0 \).

**Case 2** If \( \gamma_w = \gamma_l = 0 \) (regret-neutral), \( J = 0 \) (no joy of winning), and \( v(z) = z \) (risk-neutral) the equation in proposition 3 becomes
\[
\beta_{AP}(x) = \int_0^x y_1 \cdot g_1(y_1) dy_1
\]
which is the well-known risk-neutral BNE in an all-pay auction.
2.6 Regrets in Independent Private Value Auctions: Experimental Evidence

In this section, we structurally estimate regret and other parameters with experimental auction data. We first illustrate the dataset from the laboratory auction experiments. Second, we explain the structural estimation that is based on the widely used method proposed by Hotz and Miller (1993)[15] in the empirical industrial organization literature. Third, we report estimation results. Fourth, we test hypotheses 1–4 to review the significance of regrets.

2.6.1 Datasets

Kagel and Levin (1993)

The first dataset of Independent Private-Value (IPV) auctions is provided by Kagel and Levin (1993)[16]. Since we have plotted their experimental results in Figures 1, 3, and 4 in the introductory section (Section 1), we here shortly summarize their experiments, and readers who are interested in details are recommended to read the paper. In their series of auction experiments, they conducted first-, second-, and third-price auction experiments with two different number of bidders, five and ten. In each experiment, valuations are drawn from the uniform distribution $U[0, 28.3]$. Since a bidder in a third-price auction can incur negative payments, the participation fee of 10 dollars were given to experiment participants before entering laboratory. Results of auctions are plotted in the introduction section (Section 1). Polynomial function estimations with order six to twelve with strict monotonicity restriction functions are also plotted.

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35 We appreciate John Kagel’s and Dan Levin’s generosity in providing the dataset for this project.
36 In this research, we delete (1) the initial 4 rounds of experiments to eliminate the learning effects and (2) the final 2 rounds to eliminate the certain effects. We also exclude such outliers as bidding more than own valuations in first-price auctions and bidding irrationally high bids in third-price auctions with small valuations.
37 The unit in their experiments is the dollar. In experimental auctions, if Bob (hypothetical name) is assigned a valuation of 25.42 dollars in a specific round of the auction experiment, and he won the first-price auction with his bid of 15.00 dollars, then he receives 25.24 - 15.00 = 10.24 dollars.
38 For details about the strict monotonicity restriction in estimation, see Chernozhukov, Fernandez-Val, and Galichon (2009) [7].
Noussair and Silver (2006)

The second dataset of IPV auctions is provided by Noussair and Silver (2006) [34], in which they implement all-pay auction experiments\(^\text{39}\). Noussair and Silver (2006)’s data are not used in our estimation, although they are used in comparison analysis (in Section 7). Noussair and Silver focus their research on all-pay auctions with six-bidders. Signals (valuations) are independently drawn from \(U[0, 1000]\)^{40}. Since monetary gains generated by all-pay auctions can be negative, 20 dollars of participation fee were provided at the begging of the experiment^{41}. Figure 2 in introductory section (Section 1) lists the results. We used polynomial of order twelve with the strict monotonicity restriction to estimate the bidding function.
2.6.2 Estimation Method

Our estimation is based on the Hotz and Miller (1993)[15] method\(^{42}\), which is widely used in the empirical industrial organization literature. The econometric method proposed by Hotz and Miller (1993) has an advantage in that we can avoid computations to solve out equilibrium policy functions. Policy functions are biding functions in our auction setting. To the best of our knowledge, this paper is the first application of the Hotz and Miller (1993) method to experimental auction data. Here, we summarize the estimation procedure with first-, second-, and third-price auction data from Kagel and Levin (1993) [16] \(^{4344}\). The estimation takes five steps:

**Step 1:**
We assume that the estimated bidding functions converge to the true equilibrium bidding functions. Then, we estimate the equilibrium bidding functions with high order polynomials, \(\hat{\beta}_I^{I,5}, \hat{\beta}_I^{I,10}, \hat{\beta}_I^{II,5}, \hat{\beta}_I^{II,10}, \hat{\beta}_I^{III,5}, \) and \(\hat{\beta}_I^{III,10}\). Note that these estimated biding functions are already plotted in Figures 1, 3, and 4 in the introductory section (Section 1).

**Step 2:**
We substitute estimated equilibrium bidding functions into the first-order conditions in Propositions 1, 2, and 4. We denote a first order condition function as \(\phi\). We interpret the first-order conditions as follows; bidders minimize their expected regret given that other bidders in experiments employ an estimated bidding function as an equilibrium bidding function.

---

\(^{42}\)We thank Charles Noussair and Jonathon Silver for providing the dataset for this project. Since all-pay auctions have such important applications as research and development races, their experimental results have important implications in real world contest designs.

\(^{40}\)Noussair and Silver (2006) used their own experimental monetary unit of 1000 = 4 dollars.

\(^{41}\)Of interest, most of the participants left the experiment with fewer than 20 dollars. This means that participants, on average, lost money during series of all-pay auctions experiments.

\(^{42}\)The empirical auction estimation method proposed by Guerre, Perrigne, Vuong (2000, 2009) also motivated our research.

\(^{43}\)Yoshimoto (2011)[41] describes in detail the estimation method with experimental auction data.

\(^{44}\)We use data from Nousair and Silver (2006) [34] for comparison purposes in the next section, and they are not used in estimation.
Step 3:

We assume bidders in auction experiments are homogeneous. However, they make mean zero optimization errors when they chose bids (or solve first-order conditions),

$$\phi(x, b|\hat{\beta}; \theta) + \varepsilon = 0,$$

where $E[\varepsilon|x] = 0^{45}$. We use the first order conditions as moment conditions, and estimate structural parameters. Denoting the vector of parameters $\theta = (\gamma_w, \gamma_l, \alpha, J)$. In addition, $\phi^K_{n=L}(x^K_{n=L,i}, b^K_{n=L,i}|\beta^K_{n=L}; \theta)$ represents a first-order condition in format $K$ auction with $n = L$ bidders with observed data $(x^K_{n=L,i}, b^K_{n=L,i})$, given an equilibrium strategy $\hat{\beta}^K_{n=L}$. The vector moment function $\Phi$ is constructed as

$$\Phi = \begin{bmatrix}
(N^I_{n=5})^{-1} \sum_{i=1}^{N^I_{n=5}} \phi^I_{n=5} \left( x^I_{n=5,i}, b^I_{n=5,i}|\hat{\beta}^I_{n=5}; \theta \right) \\
(N^I_{n=10})^{-1} \sum_{i=1}^{N^I_{n=10}} \phi^I_{n=10} \left( x^I_{n=10,i}, b^I_{n=10,i}|\hat{\beta}^I_{n=10}; \theta \right) \\
(N^{II}_{n=5})^{-1} \sum_{i=1}^{N^{II}_{n=5}} \phi^{II}_{n=5} \left( x^{II}_{n=5,i}, b^{II}_{n=5,i}|\hat{\beta}^{II}_{n=5}; \theta \right) \\
(N^{II}_{n=10})^{-1} \sum_{i=1}^{N^{II}_{n=10}} \phi^{II}_{n=10} \left( x^{II}_{n=10,i}, b^{II}_{n=10,i}|\hat{\beta}^{II}_{n=10}; \theta \right) \\
(N^{III}_{n=5})^{-1} \sum_{i=1}^{N^{III}_{n=5}} \phi^{III}_{n=5} \left( x^{III}_{n=5,i}, b^{III}_{n=5,i}|\hat{\beta}^{III}_{n=5}; \theta \right) \\
(N^{III}_{n=10})^{-1} \sum_{i=1}^{N^{III}_{n=10}} \phi^{III}_{n=10} \left( x^{III}_{n=10,i}, b^{III}_{n=10,i}|\hat{\beta}^{III}_{n=10}; \theta \right)
\end{bmatrix}$$

where $N^I_{n=5}$, $N^I_{n=10}$, $N^{II}_{n=5}$, $N^{II}_{n=10}$, $N^{III}_{n=5}$, and $N^{III}_{n=10}$ denotes number of observations in first-, second-, and third-auction experiments$^{46}$. We call the above object as pseudo-GMM moment.

$^{45}$Using first-order conditions as moment conditions is a commonly applied method in the Macro literature. Hansen and Singleton (1982) use the Euler condition, which is a dynamic optimization first order condition, as a GMM moment condition.

$^{46}$This object is not a conventional Generalize Method of Moment (GMM) moment vector, since each element of the moment vector consists with the summation across a specific type of auction experiment. This unusual moment condition setting is due to the construction of the dataset. We do not observe bidders’ identity across different types (rules) of auction experiments. For this reason, the standard GMM variance formula cannot be used in this research. See details in Yoshimoto (2011) [41].
Step 4:
We apply the pseudo-GMM estimation to obtain the estimate of $\theta$, 

$$\hat{\theta} = \arg \min_\theta \{ \Phi' V^{-1} \Phi \}$$

where $V$ is the diagonal variance matrix obtained by a similar way as two-step GMM estimation method\textsuperscript{47}.

Step 5:
Bootstraps are implemented to obtain confidence interval of parameter $\theta$

\textsuperscript{47}Note that we are unable to recover off-diagonal elements of $V$, since the dataset does not track identities across different types of auction experiments.
Table 2.1: Estimated parameters and bootstrapped confidence intervals

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>(95% confidence interval)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$: Risk-Averse (CARA)</td>
<td>0.1624</td>
<td>(0.3459, 0.0001)</td>
</tr>
<tr>
<td>$\gamma_w$: Winner-Regret</td>
<td>0.1329</td>
<td>(0.2941, 0.0000)</td>
</tr>
<tr>
<td>$\gamma_l$: Loser-Regret</td>
<td>0.4912</td>
<td>(0.7539, 0.2383)</td>
</tr>
<tr>
<td>$J$: Joy of Winning</td>
<td>0.9386</td>
<td>(0.0792, 0.0121)</td>
</tr>
</tbody>
</table>

2.6.3 Estimation Results and Hypothesis Tests

We use the CARA payoff function $u(z) = \frac{1}{\alpha}[1 - \exp(-\alpha \cdot z)]$ and the index regret functions in our estimation. In the estimation, we use the scale of $U[0, 28.3]$ dollars, which is the scale used in Kagel and Levin (1993)[16]'s experiments, and normalizations are not applied. Estimation results are shown in Table 3.2. We interpret these estimates by hypothesis tests in the next subsection.

2.6.4 Hypothesis Testings

We analyze each hypothesis step-by-step with interpretation of bidders’ behaviors.

Hypothesis 1: Regret-Averse Attitude

The sum of the winner and loser regret-averse parameters is significantly larger than zero\(^{49}\).\(^{49}\)

\(^{48}\)In estimation and bootstrap, we put the restrictions $\alpha > 0$, $\gamma_w \geq 0$, and $\gamma_l \geq 0$ in the minimizing algorithm. We put these restrictions into matlab constrained minimization subroutines. These restrictions come from the common sense of real-world observations as we exclude the possibilities of risk-loving and regret-loving agents. Bootstrapped parameters $\hat{\alpha}$ and $\hat{\gamma}_w$, computed by minimization algorithm with non-negative restriction, tend to stack in zeros. This is why we have lower 5 percent of the bootstrapped quantile is 0.0000.

\(^{49}\)We implement bootstraps 843 times to obtain the bootstrapped distribution of $(\hat{\alpha}_w + \hat{\alpha}_l)$. The lower 2.5 percent quantile is 0.2914.
and the non-existence of regret-averse attitudes is rejected. In other words, there exist regret-averse attitudes among bidders in Kagel and Levin (1993)[16]’s experiments.

**Hypothesis 2: Symmetry in Winner and Loser Regret-Averse Attitudes**

The difference between loser and winner regret-averse parameters is significantly larger than zero\(^{50}\). This means that bidders avoid loser regrets more than they avoid winner regrets. Note that this testing result is consistent with findings reported by Filiz-Ozbay and Ozbay (2007) [18].

**Hypothesis 3: Risk-Averse Attitude**

The CARA risk-averse parameter \(\alpha\) is not significantly different from 0, which means bidders in Kagel-Levin (1993) experiments do not significantly exhibit risk-averse attitudes. This result meets expectations since bidders in third-price auctions behave opposite to the risk-averse preference theory’s prediction.

**Hypothesis 4: Joy of Winning**

Joy of Winning parameter \(J\) is significantly larger than 0, indicating that bidders in the experiment obtain payoffs from their winning status. We are not surprised by this testing result, considering that overbidding in the second-price auctions is commonly observed in the experimental auction literature.

These results from the hypothesis tests indicate the following conclusions. The loser regret-averse attitude, rather than risk-averse attitude, caused the overbidding observed across Independent Private Value (IPV) auctions. Bidders in Kagel and Levin (1993) auction experiments try to avoid their loser regrets, the avoidance of losing attainable positive payoffs. Compared to loser regret, winner regret plays a relatively small role when bidders make their bid choices. In addition, unlike the conventional theoretical and experimental auction literature, a risk-averse attitude does not have significant impact in the explanation of overbidding. Rather, bidders’ risk-averse attitudes are close to risk-neutral. This insignificance of risk-averse attitude is expected because of the contradictions between observed overbidding in experiments and theoretical predictions in third-price and all-pay auctions.

\(^{50}\) We compute the bootstrapped distribution of \(\hat{\alpha}_l - \hat{\alpha}_w\). The lower 2.5 percent quantile is 0.0903.
2.7 Counterfactual Analysis: Calibrations and Revenue Rankings

In this section, we calibrate (approximate) equilibrium bidding functions and compute a seller’s expected revenues in Independent Private Value (IPV) first-, second-, third-, and all-pay auctions. Then, we construct revenue rankings. Throughout this section, we use the estimated parameters in Table 3.2.

2.7.1 Calibrating Equilibrium Bidding Functions

In order to compute the seller’s expected revenues, we need to obtain equilibrium bidding functions for each auction format. We apply the calibration (approximation) method with the parameters listed in Table 3.2. Bajari (2001) [2] proposed the methodology used in this section, and we follow his method. The calibration procedures are as follows:

Step 1:
we prepare a high order polynomial function with the strict monotonicity assumption to approximate equilibrium bidding functions. We denote arbitrary coefficients of the Kth order polynomial as \( a = (a_0, a_1, \ldots, a_K) \). In addition, we denote the polynomial function as

\[
f_k(x; a) = a_0 + a_1 x + a_2 x^2 + \cdots + a_k x^k \quad \text{(approximating an equilibrium bidding function)}.
\]

Step 2:
We assume valuations are drawn from \( U[0, \bar{x}] \), and we define \( G+1 \) grid on the \([0, \bar{x}]\).

Step 3:
We plug estimated parameters \( \hat{\theta} = (\hat{\alpha}, \hat{\gamma}_w, \hat{\gamma}_l, \hat{J}) \) in Table 3.2, and a polynomial (which approximates an equilibrium bidding function) into a first-order condition equation \( \phi \). Then, we evaluate first order condition values at each grid with values of \((x_g, f_k(x_g; a))\) where \( g \) indexes grids.

Step 4:

51 We use 6th to 10th order polynomials in the calibration computation. For all-pay auctions, we exceptionally use 18th order polynomials.

52 We set up \( G = 1,000 \). Computation time significantly increases if one uses a larger number of grids such as \( G = 5,000 \) or 10,000.
Computing a following minimizing object, which is the summation of first order condition values at each grid point,

$$\sum_{g=0}^{G} \phi(x_g, f_K(x_g; \hat{a})) | f_k(a); \hat{\theta}).$$

**Step 5:**

We minimize the above object with respect to coefficients of polynomial, $a$. This means that we search over the coefficients $a = (a_1, a_2, \ldots, a_K)$ of arbitrary polynomial function $f_K(x; a)$, in order to find an equilibrium bidding function that fits a first order condition $\phi$.

**Step 6:**

We draw random numbers from the uniform distribution $U[0, \bar{x}]$, and compute an expected revenue using the calibrated bidding function in Step 5.

### 2.7.2 Calibration Results and Revenue Rankings

Figures 2.8, 2.9 and 2.10 depict calibration results with observed bids in experiments.

Figure 2.8 illustrates that, with our risk- & regret-averse criterion, overbidding happens in first- and second-price auctions. Figure 2.9, which contains the calibration results of third-price auctions, illustrates that bidders overbid in the area of low valuations (in the case of five bidders) and in the entire area of valuations (in the case of ten bidders). Such overbidding in third-price auctions is not expected if one adheres to the risk-averse preference. In Figure 2.10, we see the substantial overbidding in all-pay auctions among bidders who have high valuations. The strong loser regret, the avoidance of losing potentially positive payoffs when bidders have high valuations, causes this overbidding in all-pay auctions. As every bidder pays the amount of her bid, the overbidding in all-pay auctions has significant effects on revenues.

Table 2.2 contains calibrated revenues generated with the bidder valuation distribution of $U[0, 28.3]$, as used in Kagel and Levin (1993) [16]. For comparison purposes, we also denote average of observed revenues in their experiments\(^{53}\). Furthermore, in order to make

\(^{53}\)In order to remove learning and certain effects, we removed data from initial 4 rounds and final 2 rounds
comparisons with other reported revenues in the literature, we normalize the revenues by simply dividing them by 28.3. Table 2.2 confirms that the all-pay auction provides highest revenue in both five- and ten-bidder auctions. The all-pay auction supremacy in revenues has been reported in earlier experiments conducted by Noussair and Silver (2006) [34] and from the dataset provided by Kagel and Levin (1993) [16]. Also, outliers, such as non-serious bids (bidding equal or close to zero), are removed.
Figure 2.9: Third-Price Auction Calibrations

(a) Third-Price Calibration: Five Bidders 
(b) Third-Price Calibration: with Ten Bidder

Figure 2.10: All-Pay Auction Calibrations

(a) All-Pay Calibration: Five Bidders 
(b) All-Pay Calibration: with Ten Bidder

Gneezy and Smorodinsky (2006) [22]. We believe our result structurally confirms their experimental findings. For five-bidder auctions, the calibrated revenue ranking is

\[
R^\text{AP}_{\text{v&ra}} > R^\text{I}_{\text{v&ra}} > R^\text{II}_{\text{v&ra}} > R^\text{III}_{\text{v&ra}} \quad \text{(case of } n = 5) \]
Table 2.2: Expected Revenue in Independent Private Value Auctions with Five and Ten Bidders

<table>
<thead>
<tr>
<th>Five Bidder Auctions (N=5)</th>
<th>Expected revenue risk- &amp; regret-averse</th>
<th>Theoretical expected revenue: risk-averse</th>
<th>Theoretical expected revenue: risk-neutral</th>
<th>Average of observed revenue in experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>First-Price (I)</td>
<td>0.7124</td>
<td>0.7636</td>
<td>0.6666</td>
<td>0.7425</td>
</tr>
<tr>
<td>Second-Price (II)</td>
<td>0.6998</td>
<td>0.6666</td>
<td>0.6666</td>
<td>0.6879</td>
</tr>
<tr>
<td>Third-Price (III)</td>
<td>0.6459</td>
<td>0.6530</td>
<td>0.6666</td>
<td>0.6492</td>
</tr>
<tr>
<td>All-Pay (AP)</td>
<td>0.7592</td>
<td>0.6402</td>
<td>0.6666</td>
<td>N.A.</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ten Bidder Auctions (N = 10)</th>
<th>Expected revenue risk- &amp; regret-averse</th>
<th>Theoretical expected revenue: risk-averse</th>
<th>Theoretical expected revenue: risk-neutral</th>
<th>Average of observed revenue in experiment</th>
</tr>
</thead>
<tbody>
<tr>
<td>First-Price (I)</td>
<td>0.8309</td>
<td>0.8613</td>
<td>0.8181</td>
<td>0.8312</td>
</tr>
<tr>
<td>Second-Price (II)</td>
<td>0.8523</td>
<td>0.8181</td>
<td>0.8181</td>
<td>0.8215</td>
</tr>
<tr>
<td>Third-Price (III)</td>
<td>0.8244</td>
<td>0.7676</td>
<td>0.8181</td>
<td>0.8378</td>
</tr>
<tr>
<td>All-Pay (AP)</td>
<td>0.9030</td>
<td>0.6779</td>
<td>0.8181</td>
<td>N.A.</td>
</tr>
</tbody>
</table>

Note: We first compute all revenue calculations with the $U[0, 28.3]$ distribution as in Kagel and Levin (1993), and then normalize them by dividing by 28.3.

Risk-averse revenues are calculated with CARA risk-averse parameter = 1.25.

that agrees with observed revenues in experiments\(^{54}\). For ten-bidder auctions, our numerical calibration results demonstrate that

$$R_{vrkra}^{AP} > R_{vrkra}^{II} > R_{vrkra}^{I} > R_{vrkra}^{III} \quad \text{(case of } n = 10).$$

This ten-bidder revenue ranking does not perfectly agree with the experimentally observed revenues in Kagel and Levin (1993) \(^{16}\). However, differences among experimentally observed revenues in ten-bidder auctions are quite small.

Last, our risk- & regret-averse model contrasts to the risk-averse model in all-pay auction revenues. With a uniform distribution\(^{55}\), the risk-averse preference model predicts (also

\(^{54}\)Due to the absence of all-pay auction experiments in Kagel and Levin (1993) \(^{16}\), we cannot compare calibrated all-pay auction revenues with observed revenue in experiments. For the reference value of revenue, Noussair and Silver (2006) \(^{34}\) report that the average revenues in their six bidder (N=6) all-pay auction experiments was 1.0855. This means that bidders in the all-pay auction experiments, on average, obtained negative payment gains. Note that participation fees compensated for such negative gains.

\(^{55}\)In general, revenue rankings depend on valuation distributions. We restrict our research to uniform
computed in Table 2.2) a revenue ranking of

\[ R_{ra}^{I} > R_{ra}^{II} > R_{ra}^{III} > R_{ra}^{AP}, \]

and all-pay auctions generate the worst revenues. Such revenue predictions based on risk-averse preference are inconsistent with findings in experiments, as noted in the introductory section (Section 1).

### 2.8 Conclusions and Extensions

In this research, we propose and investigate the risk- & regret-averse model that nests the risk-averse and risk-neutral preference models. We found that the loser regret-averse attitude, rather than risk-averse attitude, caused the overbidding observed across Independent Private Value (IPV) auction experiments. The proposed model contributes to the literature in both qualitative and quantitative ways. In the qualitative sense, the model generates overbidding across a wide class of auctions. In the quantitative sense, the model confirms the revenue supremacy in all-pay auctions. These qualitative and quantitative results contrast with the risk-averse preference model that predicts underbidding in some auctions.

There are asymmetric and common-value extensions of this research (see the online Appendix for the derivations of first-order conditions). The experimental auction literature reports several interesting findings that may fit our risk- & regret-averse model. First, Chernomaz (2011) [6] reports the observance of overbidding in his asymmetric first-price auction experiments. Note that, in his experiment, weak bidders (whose valuation distribution is stochastically dominated by those of other bidders and who are more likely to lose) overbid more aggressively than other types of bidders do, even after accounting for risk aversions. Second, there is the well-known “winners’ curse” problem in the experimental common-value auction literature. Kagel and Levin (1986) [26] report that bidders in common-value auction experiments overbid, and winners tend to receive negative payoffs.\(^{56}\) Motivated by these experiments, distributions that are commonly assumed in the experimental auction literature.

\(^{56}\)Note that the risk-averse model has mixed predictions in common-value auctions. If a bidder exhibits the risk-averse preference, she (1) increases her bid to secure her winning status, while (2) decreasing her bid
perimental results, we are currently investigating the implications of our risk- & regret-averse model in asymmetric and common-value auctions.

to avoid a risk in stochastic common value. (1) and (2) work in opposite ways, and researchers in general cannot predict over- or under-bidding in common value auctions. See also Holt and Sherman (2000) [24] for the notable exception.
Appendix A: Derivations of First Order Necessary Conditions

First-Price Auction

In a first-price auction, a bidder \(i\) who has a signal \(x\) solves her regret minimization problem, which is

\[
b^* = \arg\min_{b \in \mathbb{R}_+} \left\{ E_{x_{-i}}[R^1_i(b, x, x_{-i}|\beta)] \right\}
\]

where

\[
E_{x_{-i}}[R^1_i(b, x, x_{-i}|\beta)] = E_{x_{-i}}[WR^1_i(b, x, x_{-i}|\beta)] + E_{x_{-i}}[LR^1_i(b, x, x_{-i}|\beta)]
\]

\[
= \int_{\beta(0)}^b [v(x - \beta_1 + J) - v(x - b + J)]^{1+\gamma_1} h_1(\beta_1) d\beta_1
\]

\[
+ \int_b^{x+J} [v(x - \beta_1 + J) - v(0)]^{1+\gamma_1} h_1(\beta_1) d\beta_1
\]

where \(h_1(\cdot)\) is an unconditional density function of \(\beta_1\), a highest bid among other bidders. By taking derivative with respect to \(b\), we obtain

\[
(1 + \gamma_1)v'(x - b + J) \int_{\beta(0)}^b [v(x - \beta_1 + J) - v(x - b + J)]^{\gamma_1} h_1(\beta_1) d\beta_1
\]

\[
- [v(x - b + J) - v(0)]^{1+\gamma_1} h_1(b) = 0
\]

Next, we change variables. Since other bidders employ an equilibrium bidding strategy \(\beta\), we have the relation \(\beta_1 = \beta(y_1)\) and \(d\beta_1 = \beta'(y_1)dy_1\). Also \(h_1(\cdot)\) is derived by (where \(H_1\) is the distribution function of \(\beta_1\))

\[
h_1(\beta_1) = \frac{dH_1(\beta_1)}{d\beta_1} = \frac{dH_1(\beta_1)}{dy_1} \frac{dy_1}{d\beta_1} = \frac{dF(y_1)^{n-1}}{dy_1} \frac{1}{\beta'(y_1)}
\]

where we use the relation (assuming \(B_1\) is a random variable of \(\beta_1\))

\[
H_1(\beta_1) = H_1(\beta(y_1)) = \Pr(B_1 < \beta(y_1)) = \Pr(\beta^{-1}(B_1) < y_1) = F(y_1)^{n-1}.
\]
An integrating region changes from $\beta(0) \leftrightarrow b$ to $0 \leftrightarrow \beta^{-1}(b)$. By substituting and canceling out, we obtain

\[
(1 + \gamma_w) v'(x - b + J) \int_0^{\beta^{-1}(b)} \left[ v(x - \beta(y_1) + J) - v(x - b + J) \right]^\gamma_w \frac{n}{(n-1)f(y_1)F(y_1)^{n-2}(y_1)} dy_1 = g_1(y_1)
\]

where

\[
[g_1(y_1) = g_1(\beta^{-1}(b))]
\]

\[
= g_1(\beta^{-1}(b))
\]

\[
- [v(x - b + J) - v(0)]^{1 + \gamma_w} \frac{(n-1)f(\beta^{-1}(b))F(\beta^{-1}(b))^{n-2}}{\beta'(\beta^{-1}(b))} = 0
\]

By replacing $(n-1)f(\cdot)F(\cdot)$ by $g_1(\cdot)$ and substituting $b = \beta(x)$, we obtain the equation in proposition 2.

**All-Pay Auction**

In an all-pay auction, a bidder $i$ who has a signal $x$ solves her regret minimization problem, which is

\[
b^* = \arg \min_{b \in \mathbb{R}_+} \left\{ E_{x_{-i}}[R^{AP}(b, x, x_{-i}|\beta)] \right\}
\]

where

\[
E_{x_{-i}}[R^{AP}(b, x, x_{-i}|\beta)] = E_{x_{-i}}[WR^{AP}(b, x, x_{-i}|\beta)] + E_{x_{-i}}[LR^{AP}_{TypeA}(b, x, x_{-i}|\beta)] + E_{x_{-i}}[LR^{AP}_{TypeB}(b, x, x_{-i}|\beta)]
\]

\[
= \int_{\beta(0)}^{\beta(\beta(x))} \left[ v(x - \beta + J) - v(x - b + J) \right]^{1 + \gamma_w} h_1(\beta_1) d\beta_1
\]

\[
+ \int_{\beta(0)}^{\beta(x)} \left[ v(x - \beta + J) - v(-b) \right]^{1 + \gamma_w} h_1(\beta_1) d\beta_1
\]

\[
+ \int_{x+J}^{\beta(\beta(x))} \left[ v(0) - v(-b) \right]^{1 + \gamma_w} h_1(\beta_1) d\beta_1
\]

\[
= \int_{\beta(0)}^{\beta(\beta(x))} \left[ v(x - \beta + J) - v(x - b + J) \right]^{1 + \gamma_w} h_1(\beta_1) d\beta_1
\]

\[
- \int_{x+J}^{\beta(x)} \left[ v(x - \beta + J) - v(-b) \right]^{1 + \gamma_w} h_1(\beta_1) d\beta_1
\]

\[
+ \left[ v(0) - v(-b) \right]^{1 + \gamma_w} \int_{x+J}^{\beta(\beta(x))} h_1(\beta_1) d\beta_1
\]

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where \( h_1(\cdot) \) is an unconditional density of \( \beta_1 \), a highest bid among other bidders. By taking derivative with respect to \( b \), we obtain

\[
(1 + \gamma_w)v'(x - b + J) \int_{\beta(0)}^{b} \left[ v(x - \beta_1 + J) - v(x - b + J) \right] \gamma_w \ h_1(\beta_1) d\beta_1 \tag{2.30}
\]

\[
- [v(x - b + J) - v(-b)]^{1+\gamma} h_1(b) \tag{2.31}
\]

\[
+(1 + \gamma_l)v'(-b) \int_{b}^{\beta(x)} \left[ v(x - \beta_1 + J) - v(-b) \right] \gamma_l h_1(\beta_1) d\beta_1 \tag{2.32}
\]

\[
+(1 + \gamma_l)v'(-b) [v(0) - v(-b)]^{\gamma_l} \int_{x+J}^{\beta(x)} h_1(\beta_1) d\beta_1 = 0 \tag{2.33}
\]

Next, we change variables\(^{57}\). Since other bidders employ an equilibrium bidding strategy \( \beta \), we have the relation \( \beta_1 = \beta(y_1) \) and \( d\beta_1 = \beta'(y_1)dy_1 \). Also \( h_1(\cdot) \) is derived by (where \( H_1 \) is the distribution function of \( \beta_1 \))

\[
h_1(\beta_1) = \frac{dH_1(\beta_1)}{d\beta_1} = \frac{dH_1(\beta_1)}{dy_1} \frac{dy_1}{d\beta_1} = \frac{dF(y_1)^{n-1}}{dy_1} \frac{1}{\beta'(y_1)},
\]

where we use the relation (assuming \( B_1 \) is a random variable of \( \beta_1 \))

\[
H_1(\beta_1) = H_1(\beta(y_1)) = \Pr(B_1 < \beta(y_1))
\]

\[
= \Pr(\beta^{-1}(B_1) < y_1) = F(y_1)^{n-1}.
\]

Similarly, \( H_1(x + J) \) is derived by (assuming \( Y_1 \) is a random variable of \( y_1 \))

\[
H_1(x + J) = \Pr(B_1 < x + J) = \Pr(\beta^{-1}(B_1) < \beta^{-1}(x + J))
\]

\[
= \Pr(Y_1 < \beta^{-1}(x + J)) = F(\beta^{-1}(x + J))^{n-1}.
\]

Also, integrating region changes from \( \beta(0) \leftrightarrow b \) to \( 0 \leftrightarrow \beta^{-1}(b) \) for the first integral and \( b \leftrightarrow x + J \) to \( \beta^{-1}(b) \leftrightarrow \beta^{-1}(x + J) \) for the second integral. By substituting and canceling,

\(^{57}\)The change of variables discussion here is almost identical to the case of first-price auction first order condition derivation.
Finally, we obtain.

\[
(1 + \gamma_w) v'(x - b - J) \int_0^{\beta^{-1}(b)} [v(x - \beta(y_1) + J) - v(x - b + J)]^{\gamma_w} (n - 1) f(y_1) F(y_1)^{n-2} dy_1 \\
- [v(x - b + J) - v(-b)]^{1+\gamma_w} (n - 1) f(\beta^{-1}(b)) F(\beta^{-1}(b))^{n-2} \frac{1}{\beta'(\beta^{-1}(b))} \bigg|_{y_1=\beta_1(y_1)} \\
+ (1 + \gamma_l) v'(-b) \int_{\beta^{-1}(b)}^{\beta^{-1}(x+J)} [v(x - \beta(y_1) + J) - v(-b)]^{\gamma_l} (n - 1) f(y_1) F(y_1)^{n-2} dy_1 \\
+ (1 + \gamma_l) v'(-b) [v(0) - v(-b)]^{\gamma_l} [1 - F(\beta^{-1}(x + J))]^{n-1} = 0
\]

Furthermore, by introducing short hand notations \( g_1(\cdot) = (n - 1) f(\cdot) F(\cdot)^{n-1} \) and \( G_1(\cdot) = F(\cdot)^{n-1} \), and by arranging, we have

\[
(1 + \gamma_w) v'(x - b - J) \int_0^{\beta^{-1}(b)} [v(x - \beta(y_1) + J) - v(x - b + J)]^{\gamma_w} g_1(y_1) dy_1 \\
- [v(x - b + J) - v(-b)]^{1+\gamma_w} g_1(\beta^{-1}(b)) \frac{1}{\beta'(\beta^{-1}(b))} + (1 + \gamma_l) v'(-b) \int_{\beta^{-1}(b)}^{\beta^{-1}(x+J)} [v(x - \beta(y_1) + J) - v(-b)]^{\gamma_l} g_1(y_1) dy_1 \\
+ (1 + \gamma_l) v'(-b) [v(0) - v(-b)]^{\gamma_l} (1 - G_1(\beta^{-1}(x + J))) = 0.
\]

By substituting \( b = \beta(x) \), we obtain the equation in Proposition 3.

### 2.8.1 Third-Price Auction (TPA)

Finally, we analyze a third-price auction which is originally proposed for the theoretical investigation purposes. Although a third-price auction only exists in theoretical and experimental environments, it gives us interesting equilibrium analysis. Since a winner pays a third highest bid, payoffs in the third-price auction are specified by

\[
u(b, x, x_{-i}|\beta) = \begin{cases} v(x - \beta_2 + J) & \text{if } \beta_1 < b \hspace{1cm} \text{win} \\ v(0) & \text{if } b < \beta_1 \hspace{1cm} \text{lose} \end{cases}
\]

where \( \beta_2 = \beta(y_2) \) and \( y_2 \) is the second highest signal among \( x_{-i} \). We can define winning and loser regret in the following manners.

---

58 This subsection can be skipped if a reader is not interested in a third-price auction.

59 More generally, a \( k \)-th price auction where \( k = 1, 2, 3, 4, 5, 6, \ldots, n - 1, n \) are investigated by Monderer and Tennenholtz (2000) [31].
TPA Winner Regret

\[
WR^{III}(b, x, x_{-i}|\beta) = \begin{cases} 
  v(x - \beta_2 + J) - v(x - \beta_2 + J) & \text{if } \beta_1 < b \text{ and } \beta_2 < x + J \\
  v(0) - v(x - \beta_2 + J) & \text{if } \beta_1 < b \text{ and } \beta_2 > x + J \\
  0 & \text{if } \beta_1 > b \text{ and } \beta_2 < x + J \\
  0 & \text{if } \beta_1 > b \text{ and } \beta_2 > x + J
\end{cases}
\]

(2.34)

The first row is an affordable case in which a bidder \(i\) wins an auction. The payment, second highest bid among others, is less than her valuation plus joy of winning \((x + J)\). In this case, she has no regret since her ex-post best payoff is already attained. The second row is a winner regret which is specific to a third-price auction. It is an unaffordable case in which a bidder \(i\) wins auction but payment (which is \(\beta_2\)) exceeds \(x + J\). In such a case, losing an auction is ex-post optimal to her and ex-post best payoff is \(v(0)\).

TPA Loser Regret

\[
LR^{III}(b, x, x_{-i}|\beta) = \begin{cases} 
  v(x - \beta_2 + J) - v(0) & \text{if } \beta_1 > b \text{ and } \beta_2 < x + J \\
  v(0) - v(0) & \text{if } \beta_1 > b \text{ and } \beta_2 > x + J \\
  0 & \text{if } \beta_1 < b \text{ and } \beta_2 < x + J \\
  0 & \text{if } \beta_1 < b \text{ and } \beta_2 > x + J
\end{cases}
\]

(2.35)

The first row is the case of underpricing in which a bidder loses but she can obtain an object with a positive payoff. In this case, ex-post-best payoff is attained by bidding \(\beta_2\). The second row is the case in which a bidder loses and an object is unaffordable to her afterall. Given other bidders employ bidding function \(\beta\), expected regret in a third-price auction takes a form

\[
E_{x_{-i}}[R^{III}(b, x, x_{-i}|\beta)] = E_{x_{-i}}[WR^{III}(b, x, x_{-i}|\beta)] + E_{x_{-i}}[LR^{III}(b, x, x_{-i}|\beta)]
\]

(2.36)

where

\[
E_{x_{-i}}[WR^{III}(b, x, x_{-i}|\beta)] = \int_{x+J}^{b} \int_{\beta_2}^{b} [v(0) - v(x - \beta_2 + J)]^{1+\gamma} h_{1,2}(\beta_1, \beta_2) \partial \beta_1 \partial \beta_2
\]

\[
E_{x_{-i}}[LR^{III}(b, x, x_{-i}|\beta)] = \int_{\beta(0)}^{x+J} \int_{\beta(0)}^{\beta(x)} [v(x - \beta_2 + J) - v(0)]^{1+\gamma} h_{1,2}(\beta_1, \beta_2) \partial \beta_1 \partial \beta_2
\]

and \(h_{1,2}(\beta_1, \beta_2)\) is the joint distribution of \(\beta_1\) and \(\beta_2\). Taking derivative of equation (2.36) and substituting the symmetric equilibrium condition \(b = \beta(x)\) provide the following proposition.
Proposition 4 Symmetric Third-Price Auction Equilibrium

In the IPV third-price auction, the symmetric equilibrium bidding function $\beta_{III}$ satisfies

$$\text{MELR}_{III}(\beta_{III}(x), x|\beta_{III}) = -\text{MEWR}_{III}(\beta_{III}(x), x|\beta_{III})$$

for all $x \in [0, \bar{x}]^{60}$, where the precise form of the equation is

$$\int_{0}^{\beta_{III,-1}(x+J)} [v(x - \beta_{III}(y_2) + J) - v(0)]^{1+\gamma} f(y_2) F(y_2)^n - \beta_2 \partial y_2$$

$$= \int_{\beta_{III,-1}(x+J)}^{x} [v(0) - v(x - \beta_{III}(y_2) + J)]^{1+\gamma} f(y_2) F(y_2)^n - \beta_2 \partial y_2$$

Case 3 If $\gamma_w = \gamma_l = 0$ (regret-neutral), $J = 0$ (no joy of winner), and $v(z) = z$ (risk-neutral) the equation in proposition 4 becomes

$$\beta_{III}(x) = x + \frac{1}{n - 2} F(x)$$

which is the well-known risk-neutral BNE in an third-price auction.

Third-Price Auction

In a third-price auction, a bidder $i$ who has a signal $x$ solves her regret minimization problem, which is

$$b^* = \arg\min_{b \in \mathbb{R}^+} \left\{ E_{x_i}[R_{III}(b, x, x_{-i}|\beta)] \right\}$$

where

$$E_{x_i}[R_{III}(b, x, x_{-i}|\beta)] = E_{x_i}[W_{III}(b, x, x_{-i}|\beta)] + E_{x_i}[L_{III}(b, x, x_{-i}|\beta)]$$

$$= \int_{x+J}^{b} \int_{\beta_{2}}^{b} [v(0) - v(x - \beta_{2} + J)]^{1+\gamma} \ h_{1,2}(\beta_{1}, \beta_{2}) \ \partial \beta_{1} \partial \beta_{2}$$

$$+ \int_{\beta(0)}^{x+J} \int_{b}^{\beta(2)} [v(x - \beta_{2} + J) - v(0)]^{1+\gamma} \ h_{1,2}(\beta_{1}, \beta_{2}) \ \partial \beta_{1} \partial \beta_{2}$$

where $h_{1,2}(\cdot, \cdot)$ is an unconditional joint density of $\beta_1$ and $\beta_2$, a highest and a second highest bid among other bidders. Decomposing a joint density function as $h_{1,2}(\beta_{1}, \beta_{2}) = \frac{\partial \beta_{1}}{\partial \beta_{2}} \ h_{1,2}(\beta_{1}, \beta_{2})$
\[ h_{1|2}(\beta_1|\beta_2)h_2(\beta_2), \] we obtain and by arranging

\[
= \int_{x+J}^{b} [v(0) - v(x - \beta_2 + J)]^{1+\gamma_w} \left[ \int_{\beta_2}^{b} h_{1|2}(\beta_1|\beta_2) \partial \beta_1 \right] h_2(\beta_2) \partial \beta_2
\]

integrating

\[
+ \int_{\beta(0)}^{x+J} [v(x - \beta_2 + J) - v(0)]^{1+\gamma} \left[ \int_{b}^{\beta(\bar{x})} h_{1|2}(\beta_1|\beta_2) \partial \beta_1 \right] h_2(\beta_2) \partial \beta_2
\]

integrating

\[
= \int_{x+J}^{b} [v(0) - v(x - \beta_2 + J)]^{1+\gamma_w} \left[ H_{1|2}(b|\beta_2) - H_{1|2}(\beta_2|\beta_2) \right] h_2(\beta_2) \partial \beta_2
\]

\[
+ \int_{\beta(0)}^{x+J} [v(x - \beta_2 + J) - v(0)]^{1+\gamma} \left[ 1 - H_{1|2}(b|\beta_2) \right] h_2(\beta_2) \partial \beta_2.
\]

next, by taking derivative with respect to \( b \), we obtain

\[
\int_{x+J}^{b} [v(0) - v(x - \beta_2 + J)]^{1+\gamma_w} \left[ h_{1|2}(b|\beta_2)h_2(\beta_2) \partial \beta_2 \right]
\]

\[= h_{2|1}(\beta_2|b)h_1(b) \]

\[
- \int_{\beta(0)}^{x+J} [v(x - \beta_2 + J) - v(0)]^{1+\gamma} \left[ h_{1|2}(b|\beta_2)h_2(\beta_2) \partial \beta_2 \right] = 0.
\]

Now, by manipulating a conditional density function as \( h_{1|2}(b|\beta_2)h_2(\beta_2) = h_{1,2}(b, \beta_2) = h_{2|1}(\beta_2|b)h_1(b) \), we have

\[
\int_{x+J}^{b} [v(0) - v(x - \beta_2 + J)]^{1+\gamma_w} h_{2|1}(\beta_2|b) \partial \beta_2
\]

cancel out

\[
- \int_{\beta(0)}^{x+J} [v(x - \beta_2 + J) - v(0)]^{1+\gamma} h_{2|1}(\beta_2|b) \partial \beta_2 = 0.
\]

cancel out

Next, we change variables. Since other bidders employ bidding function \( \beta \), we have the relation \( \beta_2 = \beta(y_2) \) and \( \partial \beta_2 = \beta'(y_2) \partial y_2 \). Also, \( h_{2|1}(\cdot) \) is derived by (where denoting \( H_{2|1}(\cdot|\cdot) \) is a corresponding conditional distribution function)

\[
h_{2|1}(\beta_2|b) = \frac{\partial H_{2|1}(\beta_2|b)}{\partial \beta_2} = \frac{\partial H_{2|1}(\beta_2|b)}{\partial y_2} \frac{\partial y_2}{\partial \beta_2} = \frac{\partial F_{2|1}(y_2|\beta^{-1}(b))}{\partial y_2} \frac{1}{\frac{\partial \beta}{\partial y_2}} = \frac{1}{F(\beta^{-1}(b))^{n-2}} \beta'(y_2)
\]

\[
= (n-2) \frac{f(y_2) F(y_2)^{n-3}}{F(\beta^{-1}(b))^{n-2}} \beta'(y_2).
\]
where we use the relation (denoting $B_2$ as a random variable of $\beta_2$)

$$
H_{2|1}(\beta_2|b) = \Pr(B_2 < \beta_2|b) = \Pr(B_2 < \beta(y_2)|b) = \Pr(\beta^{-1}(B_2) < y_2|\beta^{-1}(b)) = F_{2|1}(y_2|\beta^{-1}(b)).
$$

Integrating regions change from $x + J \leftrightarrow b$ to $\beta^{-1}(x + J) \leftrightarrow \beta^{-1}(b)$ for the first integral and from $\beta(0) \leftrightarrow x + J$ to $0 \leftrightarrow \beta^{-1}(x + J)$ for the second integral. By substituting, we obtain

$$
\int_{\beta^{-1}(x+J)}^{\beta^{-1}(b)} [v(0) - v(x - \beta(y_2) + J)]^{1+\gamma_w} \frac{(n-2)f(y_2)F(y_2)^{n-3}}{F(\beta^{-1}(b))^{n-2}} \frac{1}{\beta'(y_2)} \beta'(y_2) \partial y_2

- \int_{0}^{\beta^{-1}(x+J)} [v(x - \beta(y_2) + J) - v(0)]^{1+\gamma_l} \frac{(n-2)f(y_2)F(y_2)^{n-3}}{F(\beta^{-1}(b))^{n-2}} \frac{1}{\beta'(y_2)} \beta'(y_2) \partial y_2 = 0
$$

By canceling outs, we have

$$
\int_{\beta^{-1}(x+J)}^{\beta^{-1}(b)} [v(0) - v(x - \beta(y_2) + J)]^{1+\gamma_w} f(y_2)F(y_2)^{n-3} \partial y_2

= \text{marginal expected winner regret} = \text{MEWR}^{\gamma}(b,x|\beta)

- \int_{0}^{\beta^{-1}(x+J)} [v(x - \beta(y_2) + J) - v(0)]^{1+\gamma_l} f(y_2)F(y_2)^{n-3} \partial y_2 = 0.

= \text{marginal expected loser regret} = \text{MELR}^{\gamma}(b,x|\beta)
$$

By substituting $b = \beta(x)$, we obtain the equation in Proposition 4.
REFERENCES


CHAPTER 3

Structural Estimations Using Experimental Auction Data: An Approach in the Absence of Closed-Form Bidding Functions

3.1 Introduction

Over the last fifty years, researchers have contributed to the development of auction science. Along with the theoretical auction literature developments initiated by Vickrey (1961) [23], the experimental auction literature has come to test, support, and also refute the theoretical predictions of auction science. Now more than ever, experimental auction researchers conduct various types of auction experiments.

The traditional approach in experimental auction literature is simple: researchers make comparisons between theoretical predictions and bidding behaviors observed in experiments. To make such comparison possible, researchers first carefully design experimental environments (designing such auction environments as signal distributions and auction rules) in which they can find closed-form equilibrium bidding functions and conduct auction experiments.¹ This tradition finds its origin in the fact that closed-form equilibrium bidding functions are not generally available in auction science.

Consequently, the experimental auction literature relies heavily on what I refer to as closed-form bidding function approach: experimental researchers exploit a limited number of classes (of payoff functions, signal distributions, and auction rules) from which researchers can derive closed-form equilibrium bidding functions. Once experiments are done, researchers

¹For example, Kagel and Levin (1993) [16]
apply simple estimation methods, such as linear regressions, to estimate coefficients of closed-form equilibrium bidding functions.

The crucial limitation of this approach is that closed-form equilibrium bidding functions are not always available. In fact, researchers can find numerous combinations of bidders’ preferences, signal distributions, and auction rules that do not provide closed-form equilibrium bidding functions.\textsuperscript{2} As a natural consequence, experimental researchers inevitably design their experiments in which they can obtain closed-from equilibrium bidding functions, although such experimental environment do not closely replicate auctions held in the real-world.\textsuperscript{4} In addition, as the field of behavioral economics evolves, researchers are desiring to use more and more behavioral preferences with flexible preference parameters. However, most behavioral preferences do not provide closed-form equilibrium bidding functions and prevent researchers from analyses based on equilibrium bids.

To solve the issues with such limitations, I propose an estimator characterized by (1) the absence of closed-form equilibrium bidding functions to estimate preference parameters and (2) an applicability to a large variety of auction environments (including any variety of signal distributions; various risk-averse preferences; and independent-, common-, and affiliated-value auctions).

In forming my estimation method, I take the advantage of fundamental nature in experimental auctions: researchers observe signals in experiments.\textsuperscript{5} This observability enables researchers to estimate equilibrium bidding functions. Specifically, I use the two-step estimation method widely used in empirical industrial organization literature. My method is as follows: Step 1: I non-parametrically estimate equilibrium bidding functions with experimental auction data. Step 2: I input estimated equilibrium bidding functions into bidders’ payoff-maximizing first-order conditions and apply the Generalized Method of Mo-

\textsuperscript{2}For instance, if bidders exhibit the Constant Absolute Risk-Averse (CARA) preference, closed-from equilibrium bidding functions are not analytically solvable in first- and all-pay auctions.

\textsuperscript{3}The CARA preference has an advantage to mitigate income-level heterogeneity problems among bidders.

\textsuperscript{4}The representative assumptions assumed in experiments that does not replicate auctions in real world is uniform signal distribution. Without uniformity in signals, researchers usually cannot obtain closed-form equilibrium bidding functions, although many empirical auction analyses show that signal distributions in real world auctions are not uniform.

\textsuperscript{5}In contrast, researchers do not observe signals in empirical auctions.
ment (GMM) estimator, using first order conditions as moments. Standard deviations are obtained by bootstraps.

To demonstrate the usefulness of my estimator, I apply it to an asymmetric auction experiment dataset provided by Chernomaz (working paper) [7]. In asymmetric auctions, it is known that closed-form equilibrium bidding functions are generally not available for use with risk-averse preferences. By using this dataset, I structurally estimate a Constant Absolute Risk-Averse (CARA) parameter present among bidders.

The benefits of structural estimations are enormous. By simulations with estimated preference parameters, researchers have opportunities to implement various types of counterfactuals that they could not have afforded financially in their original experiments. For example, after estimating a risk-averse preference parameter, researchers can simulate hypothetical auctions in which the number of bidders are different from their limited original experimental settings. By doing so, researchers can compare expected revenues across many different numbers of bidders.6

As such, this is organized in the following way: In Section 2, I explain the two-step estimation method using experimental auction data. In Section 3, I apply my estimation method to the dataset from asymmetric auction experiments. In Section 4, I explore potential applications and future extensions.

3.2 Estimation Method

The methodology here is based on Hotz and Miller’s (1993) [15] two-step estimation method that is widely used in empirical industrial organization.7 Also, my method is the straightforward extension of auction estimation methods proposed by Guerre, Perrigne, and Vuong (2000, 2009) [10] [11] in which non-parametric estimation methods are used for empirical

6Other potential examples of structural simulations include: (1) Evaluating revenue changes caused by the introductions of reservation prices. (2) Evaluating the impact of collusive behaviors. (3) Evaluating revenue changes caused by changing auction formats/rules.


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The contribution of Hotz and Miller (1993) [15] is that researchers are not required to solve out equilibrium policy functions in games (equivalent to equilibrium bidding functions in auctions). Note that researchers cannot generally expect to have closed-form policy functions. If researchers desire to solve equilibrium policy functions, they have to employ intensive numerical computations. Rather, Hotz and Miller (1993) [15] suggest that researchers nonparametrically estimate equilibrium policy functions (bidding functions) with observed data, then substitute estimated policy functions into the generalized method of moment (or maximum likelihood) estimators. The comparison between estimation methods is depicted in Figure 1. The rest of this section explains how Hotz and Miller’s two-step estimation method works with experimental auction data.

For the simplicity of explanation, I explain a independent private value first-price auction experiment. A researcher observes the dataset from experimental auctions

\[ \left\{ \left( x_{i,r,A}, b_{i,r,A} \right), \left( x_{i,r,B}, b_{i,r,B} \right) \right\}_{i=1}^{N} \]  

where \( r \in \{1, 2, \ldots, R\} \) is an auction round index, \( i \in \{1, \ldots, N\} \) is a bidder index, \( \{A, B\} \) are different auction treatments. In addition, \( x_{i,r,A} \) (\( x_{i,r,B} \)) is a private value that is exogenously assigned to bidder \( i \) in treatment \( A \) (in treatment \( B \)), and \( b_{i,r,A} \) (\( b_{i,r,B} \)) are bids which she endogenously chooses in treatment \( A \) (in treatment \( B \)). Note that \( x_{i,r,A} \) can be.

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8 The difference between Guerre, Perrigne, and Vuong (2000, 2009) [10] [11] and this research should be clearly mentioned. Guerre, Perrigne, and Vuong (2000, 2009) non-parametrically use empirical bid data to recover signal distributions and utility functions. On the other hand, this research uses experimental signal and bid data to recover preference parameters.


10 The estimation framework in this paper is easily applied to affiliated- and common-Value environments.

11 The number of treatments can be larger than two.

12 Typical examples of treatments are different number of bidders. For example, in Kagel and Levin (1993) [16] experiment, treatments are, \( A \): auction with five bidders (small markets), \( B \): auction with ten bidders (large markets) with \( x_{i,r,A} = x_{i,r,B} \). At each round of their experiments, bidders simultaneously submit bids in both five-bidders and ten-bidders markets, holding their signals (valuations) fixed in each round. Numerous other treatments can be applied, for example, \( A \): first-price auction with no participation fee, \( B \): first-price auction with participation fee. It is important to emphasize that in my formation bidder \( i \) in experimental auction round \( r \) could receive different signals across treatments.
equal to \( x_{i,r,B} \).

A bidder in an experiment solves her expected payoff maximization problems in both treatment with von-Neumann-Morgenstern (vNM) payoff function \( u(\cdot | \theta) \) where \( \theta \) is a preference parameter. Our ultimate goal is obtaining the estimate of preference parameter \( \theta \). Bidder \( i \)'s optimization problems at experimental round \( r \) is written as follows.

\[
\begin{align*}
    b_{i,r,A} &= \arg \max_{b_A} \{ u(x_{i,r,A} - b_A | \theta) \cdot H_A(b_A | \beta_A) \} \quad \text{(Treatment A)} \\
    b_{i,r,B} &= \arg \max_{b_B} \{ u(x_{i,r,B} - b_B | \theta) \cdot H_B(b_B | \beta_B) \} \quad \text{(Treatment B)}
\end{align*}
\]

where \( H_A(b_A | \beta_A) \) represents the probability of winning in treatment \( A \) when bidder \( i \) submits a bid \( b_A \), and given other bidders employ equilibrium bidding strategy \( \beta_A \). \( H_B(b_{i,r,B} | \beta_B) \) is defined similarly. By taking derivatives with respect to \( b_A \) and \( b_B \), we can obtain the first-

---

13In this research, I assume bidders in experiment have homogeneous preference. Heterogeneities are introduced through optimization errors, as I will explain soon.
order condition equations,

\[-u'(x_{i,r,A} - b_{i,r,A}|\theta) \cdot H_A(b_{i,r,A}|\beta_A) + u(x_{i,r,A} - b_{i,r,A}|\theta) \cdot h_A(b_{i,r,A}|\beta_A) = 0 \quad (3.1)\]

\[-u'(x_{i,r,B} - b_{i,r,B}|\theta) \cdot H_B(b_{i,r,B}|\beta_B) + u(x_{i,r,B} - b_{i,r,B}|\theta) \cdot h_B(b_{i,r,B}|\beta_B) = 0, \quad (3.2)\]

where \( h_A(b_{i,r,A}|\beta_A) = \left[ \frac{d}{db} H_A(b_{i,r,A}|\beta_A) \right]_{b_A=b_{i,r,A}} \) and \( h_B(b_{i,r,B}|\beta_B) \) is defined similarly. Note that we have not yet substituted the symmetric equilibrium conditions \( b_{i,r,A} = \beta_A(x_{i,r}) \) and \( b_{i,r,B} = \beta_A(x_{i,r}) \) into equation (3.1) and (3.2), rather making the following assumption.

**Assumption 1** Bidders in experiment make conditionally mean zero optimization error \( \{\varepsilon_{i,r,A}, \varepsilon_{i,r,B}\} \) that are additive to first-order conditions,

\[ E[\varepsilon_{i,r,A}|x_{i,r,A}] = E[\varepsilon_{i,r,B}|x_{i,r,B}] = 0. \]

This assumption implies that bidder \( i \) cannot perfectly choose her optimal bids and she makes additive errors when she evaluates her first-order conditions.\(^{14,15}\) Next, based on Hotz and Miller (1993) \(^{15}\), I nonparametrically (or semi-nonparametrically) estimate equilibrium bidding functions \( \hat{\beta}_A \) and \( \hat{\beta}_B \) with the following assumptions.\(^{16}\)

**Assumption 2** As \( N \to \infty \) and \( r \to \infty \), estimated bidding functions uniformly converge to the equilibrium bidding functions,

\[ \hat{\beta}_A \to \beta_A \quad \text{and} \quad \hat{\beta}_B \to \beta_B. \]

Under Assumption 1 and 2, we can construct a moment vector \( z_{i,r} \) by replacing \( \beta_A \) by \( \hat{\beta}_A \) and \( \beta_B \) by \( \hat{\beta}_B \),

\[ z_{i,r,A} = \begin{bmatrix} -u'(x_{i,r,A} - b_{i,r,A}|\theta) \cdot H_A(b_{i,r,A}|\hat{\beta}_A) + u(x_{i,r,A} - b_{i,r,A}|\theta) \cdot h_A(b_{i,r,A}|\hat{\beta}_A) \\ -u'(x_{i,r,B} - b_{i,r,B}|\theta) \cdot H_B(b_{i,r,B}|\hat{\beta}_B) + u(x_{i,r,B} - b_{i,r,B}|\theta) \cdot h_B(b_{i,r,B}|\hat{\beta}_B) \end{bmatrix} \]

\[ z_{i,r,B} = \begin{bmatrix} \varepsilon_{i,r,A} \\ \varepsilon_{i,r,B} \end{bmatrix} \]

\(^{14}\)Note that \( \varepsilon_{i,r,A} \) and \( \varepsilon_{i,r,B} \) could be correlated.

\(^{15}\)To the best of my knowledge, additive errors in first-order conditions has its origin in Hansen and Singleton (1982) \(^{14}\). In their estimation with rational expectation model, they used Euler equations, that is of course first order conditions, as moment conditions.

\(^{16}\)In practice, to obtain estimated equilibrium bidding functions \( \hat{\beta}_A \) and \( \hat{\beta}_B \), I apply higher order polynomial function to fit experimental dataset \( \{(x_{i,r,A}, b_{i,r,A}), (x_{i,r,B}, b_{i,r,B})\}_{i=1}^{N} \) with strict monotonicity assumptions in equilibrium bidding functions. I numerically observe that even sixth or seventh order polynomial function fits experimental data quite well.
The rest of estimation follows the conventional Two-Step Generalized Method of Moment (TSGMM) procedure. We numerically solve the minimization problem

\[ \hat{\theta}_{1st} = \arg \min_{\theta} \{ M' \cdot I_2 \cdot M \} \quad \text{where} \quad M = \sum_{r=1}^{R} \sum_{i=1}^{N} z_{i,r} \]

and \( I_2 \) is the two-by-two identity matrix, and

\[ \hat{\theta}_{TSGMM} = \arg \min_{\theta} \{ M' \cdot W^{-1} \cdot M \} \quad \text{where} \quad W = \frac{1}{RN} \sum_{r=1}^{R} \sum_{i=1}^{N} \hat{z}_{i,r}(\hat{\theta}_{1st}) \hat{z}_{i,r}(\hat{\theta}_{1st})' \]

We use bootstraps to obtain standard deviations.\(^{17}\) In the next section, we will see the application of this estimator using the dataset from asymmetric independent private value first-price auction experiment.

### 3.3 Application: Asymmetric Auctions with Risk-Averse Bidders

In this section, I apply the proposed estimator to independent private value asymmetric first-price auction dataset provided by Chernomaz (working paper) \(^{7}\) in which drastic overbidding phenomenon is observed.\(^{18}\) Despite the fact that no auction is perfectly symmetric\(^{19}\) in the real-world, and implications from asymmetric auction experiments are beneficial to design real-world auctions, asymmetric auction experiments are rarely conducted.\(^{20}\) The primal reason is that researchers cannot generally obtain closed-form equilibrium bidding in asymmetric auctions.\(^{21}\) In Chernomaz’s experiment, bidders are categorized as weak and strong bidders, as weak bidders’ signal distribution is stochastically dominated by strong bidders’ one. In this section, I aim to structurally explain such observed overbidding can be explained by risk-averse preference with statistical test. The null hypothesis here is that

\(^{17}\)The standard GMM variance-covariance matrix formula cannot be used here as it does not capture variance in the first step.

\(^{18}\)Overbidding phenomenon is that bidders in auction experiments tend to bid more than risk-neutral Bayesian Nash equilibrium. Overbidding phenomenon is observed in almost all auction experiments. See the survey of Kagel (1995) \(^{9}\) for details.

\(^{19}\)Here, I mean symmetric in terms of signal distributions.


\(^{21}\)Under the assumption of risk-neutral bidders, uniform signal distributions, and un-common supports of signals, Plum (1992) \(^{22}\) derived the formula of closed-from equilibrium bidding for asymmetric auctions. However, once researchers introduce risk-averse preferences, equilibrium bidding functions are not analytically solvable.
bidders in the experiment are risk-neutral. The alternative is that they are risk-averse. I assume bidders have the Constant Absolute Risk-Averse (CARA) payoff function that includes risk-neutral preference as special case. Then, I estimate risk-averse parameters and structurally test the risk-neutrality among bidders. Finally, by utilizing estimated risk-averse parameter, I counterfactually simulate expected inefficiencies.

3.3.1 Experimental Setting

The experiment was conducted in the following way. At the beginning of auction round $r$, three bidders (out of thirty participants in experiment) are randomly matched to form a group. I hypothetically index randomly matched group members as bidder $i$, $j$, and $k$. Bidders independently draw valuations from the uniform distribution denoting $x_{i,r}, x_{j,r}, x_{k,r} \sim F(x) = \frac{1}{\bar{x}}x = U[0, \bar{x}]$ where $\bar{x} = $ $4$ In a first stage of round $r$, three bidders play a three-player symmetric first-price auction and submit their bids of $\{(b_{i,r,1st}, b_{j,r,1st}, b_{k,r,1st})\}$. The result of first round auction is not revealed at this point. Then bidders move to a second stage. In the second stage, two of three bidders are randomly matched and form a subgroup. Such a subgroup is named as strong and the meaning of this naming will be clear soon. Without loss of generality, I hypothetically assume bidder $j$ and $k$ are matched to form a subgroup. The valuation for a subgroup is renewed as $x_{\text{strong},r} = \max\{x_{j,r}, x_{k,r}\}$. Note that by order statistics, we can view $x_{\text{strong},r} \sim G(x) = F^2(x) = \frac{1}{\bar{x}^2}x^2$ where $x \in [0, \bar{x}]$. I interchangeably use the convenient terminology “weak” and “strong” to express bidder types in second stage, as bidder $i$’s signal distribution is stochastically dominated by subgroup’s one. Then, player $i$ (weak bidder) and subgroup (strong bidder) play a two-player asymmetric first-price auction and submit their bid $\{(b_{i,r,2nd}, b_{\text{strong},r,2nd})\}$. After a second stage, all results but identities of bidders, including winning and loosing bid amounts in both first and second stage, are publicly announced. Plot 3.2 and 3.3 shows row data with risk-neutral bidding functions. Not that players play three-bidder symmetric auctions in first stages then play two-bidder asymmetric auctions in second stages. Notice that in both first and second

\[^{22}\text{Using the CARA payoff function has its advantage in eliminating income effects. Note that researchers cannot control income levels among experimental participants.}\]
stage, players exhibit drastic overbidding, bidding more than risk-neutral Bayesian Nash equilibrium. Thus, risk-neutral hypothesis seems to be unreasonable, although researchers have to structurally test to reject it.
3.3.2 Hypotheses and Moment Conditions

I assume bidders have a Constant Absolute Risk-Averse (CARA) preference with von-Neumann Morgenstern function $u(z) = \frac{1}{\theta} \{1 - \exp(-\theta \cdot z)\}$. As $\theta \to \infty$, $u(z)$ becomes the risk-neutral payoff function of $u(z) = z$.\(^{23}\) The statistical hypotheses I test here are

\[
H_0 : \ \theta = 0 \quad \text{(Bidders are risk-neutral)} \\
H_a : \ \theta > 0 \quad \text{(Bidders are risk-averse)}
\]

3.3.2.1 Optimization problem in First Stages

In a first-stage, bidder $i$ solves the standard symmetric first-price auction optimization problem of

\[
b_{i,r,1st} = \arg\max_b \left\{ u(x_{i,r} - b) \cdot H_{1st}(b_{i,1st} | \hat{\beta}_{1st}) \right\}
\]

where where $\hat{\beta}_{1st}$ the estimated equilibrium bidding function and

\[
H_{1st}(b_{i,1st} | \hat{\beta}_{1st}) = F^2(\hat{\beta}_{1st}^{-1}(b_{i,1st})) = \frac{1}{\theta^2} \cdot \left( \hat{\beta}_{1st}^{-1}(b_{i,1st}) \right)^2
\]

as signals come from uniform distribution. Bidder $i$’s first-order necessary condition in a first stage is expressed as

\[
z_{i,r,1st} = -u'(x_{i,r,1st} - b_{i,r,1st} | \theta) \cdot H_{1st}(b_{i,r,1st} | \hat{\beta}_{1st}) + u(x_{i,r,1st} - b_{i,r,1st} | \theta) \cdot h_{1st}(b_{i,r,1st} | \hat{\beta}_{1st}) = \varepsilon_{i,r,1st},
\]

where

\[
h_{1st}(b_{i,r,1st} | \hat{\beta}_{1st}) = \frac{d}{db_{i,1st}} H_{1st}(b_{i,1st} | \hat{\beta}_{1st}) = \frac{d}{db_{i,1st}} F^2(\hat{\beta}_{1st}^{-1}(b_{i,1st})) = \frac{2 \cdot f(\hat{\beta}_{1st}^{-1}(b_{i,1st})) \cdot F(\hat{\beta}_{1st}^{-1}(b_{i,1st}))}{\hat{\beta}_{1st}'(\hat{\beta}_{1st}^{-1}(b_{i,1st}))}
\]

Bidder $j$ and $k$’s first-order condition follows similarly.

3.3.2.2 Optimization problem in Second Stages

In a second stage, bidder $i$ (weak bidder) and subgroup’s (strong bidder) optimization problems become

\[
b_{\text{weak},r,2nd} = \arg\max_b \left\{ u(x_{\text{weak},r} - b) \cdot H_{\text{weak},2nd}(b_{\text{weak},r,2nd} | \hat{\beta}_{\text{strong},2nd}) \right\} \quad \text{(for weak bidders)}
\]

\[
b_{\text{strong},r,2nd} = \arg\max_b \left\{ u(x_{\text{strong},r} - b) \cdot H_{\text{strong},2nd}(b_{\text{strong},r,2nd} | \hat{\beta}_{\text{weak},2nd}) \right\} \quad \text{(for strong bidders)}
\]

\(^{23}\)Also, note that $u'(0) = 1.$
where $\hat{\beta}_{weak,2nd}$ is the estimated bidding function using weak (non-group or single) bidders' bids, $\hat{\beta}_{strong,2nd}$ is the estimated bidding function using strong (subgroup) bids and

$$H_{weak,2nd}(b_{weak,r,2nd}|\hat{\beta}_{strong,2nd}) = G(\hat{\beta}_{strong,2nd}^{-1}(b_{strong,r,2nd})) = \frac{1}{x^2} \left[ \hat{\beta}_{strong,2nd}^{-1}(b_{strong,r,2nd}) \right]^2$$

$$H_{strong,2nd}(b_{strong,r,2nd}|\hat{\beta}_{weak,2nd}) = F(\hat{\beta}_{weak,2nd}^{-1}(b_{strong,r,2nd})) = \frac{1}{x} \hat{\beta}_{weak,2nd}^{-1}(b_{strong,r,2nd})$$

First order necessary conditions are

$$z_{weak,r,2nd} = -u'(x_{weak,r} - b_{weak,r,2nd}|\theta) \cdot H_{weak,2nd}(b_{weak,r,2nd}|\hat{\beta}_{strong,2nd})$$

$$+ u(x_{weak,r} - b_{weak,r,2nd}|\theta) \cdot h_{weak,2nd}(b_{weak,r,2nd}|\hat{\beta}_{strong,2nd})$$

$$= \varepsilon_{weak,r,1st}$$

for weak bidders and

$$z_{strong,r,2nd} = -u'(x_{strong,r} - b_{strong,r,2nd}|\theta) \cdot H_{strong,2nd}(b_{strong,r,2nd}|\hat{\beta}_{weak,2nd})$$

$$+ u(x_{strong,r} - b_{strong,r,2nd}|\theta) \cdot h_{strong,2nd}(b_{strong,r,2nd}|\hat{\beta}_{weak,2nd})$$

$$= \varepsilon_{weak,r,1st}$$

for strong bidders, where

$$h_{weak,2nd}(b_{weak,r,2nd}|\hat{\beta}_{strong,2nd}) = \frac{d}{db_{weak,r,2nd}} H_{weak,2nd}(b_{weak,r,2nd}|\hat{\beta}_{strong,2nd})$$

$$= \frac{g(\hat{\beta}_{strong,2nd}^{-1}(b_{weak,r,2nd}))}{\hat{\beta}_{strong,2nd}'(\beta_{strong,2nd}^{-1}(b_{weak,r,2nd}))}$$

$$h_{strong,2nd}(b_{strong,r,2nd}|\hat{\beta}_{weak,2nd}) = \frac{d}{db_{strong,r,2nd}} H_{strong,2nd}(b_{strong,r,2nd}|\hat{\beta}_{weak,2nd})$$

$$= \frac{f(\hat{\beta}_{weak,2nd}^{-1}(b_{strong,r,2nd}))}{\hat{\beta}_{weak,2nd}'(\beta_{weak,2nd}^{-1}(b_{strong,r,2nd}))}.$$ 

### 3.3.2.3 Moment

Now, I construct a moment vector based on first-order conditions above. The moment is

$$\begin{bmatrix}
  z_{i,r,1st}(x_{i,r}, b_{i,r,1st}|\theta) \\
  z_{weak,r,2nd}(x_{weak,r}, b_{weak,r,2nd}|\theta) \\
  z_{j,r}(x_{j,r,1st}, b_{j,r,1st}|\theta) \\
  z_{strong,r,2nd}(x_{strong,r,2nd}, b_{strong,r,2nd}|\theta)
\end{bmatrix}.$$
### Table 3.1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Sample</th>
<th>Number of Bidders</th>
<th>Number of Total Rounds</th>
<th>Mean of 1st Stage Bids</th>
<th>Mean of 2nd Stage Bids</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weak Bidders</td>
<td>315</td>
<td>15</td>
<td>21</td>
<td>$7.300</td>
</tr>
<tr>
<td>Strong Bidders</td>
<td>315</td>
<td>15</td>
<td>21</td>
<td>$9.552</td>
</tr>
</tbody>
</table>

### Table 3.2: Estimation Results

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
<th>Bootstrapped 95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>CARA Parameter: $\theta$</td>
<td>0.5328</td>
<td>(0.6569, 0.3956)</td>
</tr>
</tbody>
</table>

The moment above is used to estimate the CARA risk-averse parameter $\theta$ among weak-bidders. This moment is special in the sense that we do not track bidders identities and relying on the assumptions that bidders.\(^{24}\) For this reason, off-diagonal elements of GMM weight matrix is fixed to zero.

#### 3.3.3 Descriptive Statistics and Estimation Result

The descriptive statistics are listed on Table 3.1. Note that due to the valuation update rule, strong bidders on average has higher valuations (and on average they bid higher). The table shows the estimation results. Note that by the signal updating rule in the second stage, strong bidders on average has higher signals and higher bids. The table 3.2 shows that for both weak and strong bidders risk-neutral hypotheses are rejected with 95% confidence interval.

\(^{24}\)If researchers desire to track bidders identities, alternative constructions of moments are possible. Such moments include

$$
\begin{bmatrix}
z_{i,r,1st}(x_{i,r}, b_{i,r,1st}|\theta_{\text{weak}}) \\
z_{\text{weak},r,2nd}(x_{i,r}, b_{\text{weak},r,2nd}|\theta_{\text{weak}})
\end{bmatrix}
$$

and

$$
\begin{bmatrix}
z_{j,r,1st}(x_{j,r,1st}, b_{j,r,1st}|\theta_{\text{strong}}) \\
z_{\text{strong},r,2nd}(x_{\text{strong},r,2nd}, b_{\text{strong},r,2nd}|\theta_{\text{strong}})
\end{bmatrix}.
$$
Figure 3.4: Left figure: Calibrated Equilibrium Bidding Function for Weak Bidders, Right figure: Calibrated Equilibrium Bidding Function for Weak Strong Bidders

Table 3.3: Expected Revenues and Expected Efficiencies

<table>
<thead>
<tr>
<th>Preference</th>
<th>Parameter</th>
<th>Expected Revenue</th>
<th>Inefficient Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>CARA Risk-Averse</td>
<td>$\hat{\theta} = 0.5328$ (estimated)</td>
<td>$10.7290$</td>
<td>3.94%</td>
</tr>
<tr>
<td>Risk-Neutral</td>
<td>$\theta = 0.0001$ (assumed)</td>
<td>$7.8945$</td>
<td>8.83%</td>
</tr>
</tbody>
</table>

3.3.4 Counterfactual Simulations

Next, I calibrate equilibrium bidding functions with estimated parameters and show that risk-averse preference model can explain overbidding in asymmetric auctions. Figure 3.4 shows that calibrated (with estimated risk-averse parameter) bidding functions closely replicate the estimated bidding functions. In addition, calibrated bidding functions are above risk-neutral ones, indicating that risk-averse preference model can explain observed overbidding phenomena in asymmetric auctions. Last, I simulate expected revenues and make comparisons between risk-neutral and risk-averse models. As I have numerically shown that the risk-averse preference generates overbidding, I obtained the higher revenue by using

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25 I used the calibrated bidding functions to compute expected revenues. 10,000 signals are drawn for both weak and strong types.
the estimated risk-averse parameter. Also, simulation shows that percentage of inefficient allocation decreases from 3.94% to 8.83% and indicating inefficient allocation problems are mitigated with risk-averse bidders. I would like to emphasize that these counterfactual simulations are not possible without structural models.

3.4 Conclusion

In this paper, I proposed a structural estimation method using experimental auction data. I clarified the estimation method by which researchers can obtain estimates of structural parameters in the absence of closed-form equilibrium bidding functions. I also exemplified the estimation procedures used to obtain a CARA risk-averse parameter in asymmetric auctions. Although I restricted the scope of my research to private-value auctions in this paper, the method is also easily applied to affiliated- and common-value auctions. In addition, I encourage behavioral researchers to use this method to estimate behavioral parameters by using datasets from auction experiments that closely replicate auctions in real world.
References


