Profiting from Asymmetrically Dominated Alternatives: The Case of Online Diamond Pricing

Chunhua Wu and Koray Cosguner*

June 2016

Abstract

The asymmetric dominance effect, first introduced by Huber et al. (1982), has been robustly documented in various lab experiments in the literature. However, the practical validity and significance in a real marketplace has never been verified. In this paper, we empirically test the existence of this effect and, more importantly, quantify its magnitude using a unique panel data set from a major online jewelry market. We estimate a proportional hazard model that is derived from consumer choice primitives, including consumer arrival process, consumer consideration set formation, conditional choice probabilities with embedded asymmetric dominance effect. Our model estimates suggest that in general consumers have low probability of detecting the existence of the dominance relationships in the marketplace; however once they discover, the decoy diamonds significantly increase sales likelihoods of dominant diamonds. We quantify the overall profit impact of asymmetric dominance and find that it contributes about 21.4% of the retailer's gross profit. We also find that the existing decoy pricing in the marketplace improves the retailer's overall gross profit by 19%, compared to a uniform pricing strategy with no dominance relationship. Finally, we explore various strategies that the retailer can adopt to improve its profitability through further utilizing the asymmetric dominance effect. We find that there is a great potential for the retailer to gain additional profits.

Keywords: Asymmetric Dominance Effect, Proportional Hazard Model, Diamond Pricing, Context Dependent Choice

*Chunhua Wu (chunhua.wu@sauder.ubc.ca) is Assistant Professor of Marketing and Behavioral Science at the University of British Columbia. Koray Cosguner (kcosguner@gsu.edu) is Assistant Professor of Marketing at Georgia State University. The authors thank seminar participants at the University of British Columbia, the University of Alberta, University of Colorado Boulder, and the 2014 Marketing Science Conference for their valuable feedbacks.

1 Introduction

Standard rational choice models in economics and marketing are built upon the revealed preference assumption, which implicitly assumes two principles: the principle of regularity (Luce, 1977) and the principle of independence of irrelevant alternatives (hereafter, IIA) (Luce, 1959). In contrast, researchers in consumer behavior have adopted the notion of constructed preference (Bettman et al., 1998) and have extensively documented the effect of context dependence in consumer choices (Simonson, 1989a). The asymmetric dominance (also called the decoy or attraction) effect (Huber et al., 1982), a classic example of context dependent choices, violates the aforementioned two principles. The asymmetric dominance effect (hereafter, AD effect) states that adding an alternative D—which is strictly dominated by A, but not by B—into a choice set accommodating A and B might increase not only the choice probability of A (violation of regularity), but also the relative share of A with respect to B (violation of IIA).

Since its introduction in Huber et al. (1982), the AD effect has been thoroughly examined in consumer behavior research. Past experimental studies have extensively shown the robustness of the effect across dozens of choice domains (Huber and Puto, 1983; Huber et al., 1982; Wedell, 1991; Lehmann and Pan, 1994; Royle et al., 1999). A recent issue of *Journal of Marketing Research* has featured a debate on the boundaries and limits of the AD effect (Frederick et al., 2014; Yang and Lynn, 2014; Simonson, 2014; Huber et al., 2014). Simonson (2014) comments that how likely the asymmetric dominance is perceived is the key that drives the likelihood of replicating the effect, and calls for a systematic study on the drivers of asymmetric dominance perception. In addition, the practical validity and significance of the AD effect in real choice situations has been questioned (Frederick et al., 2014; Yang and Lynn, 2014). In response to these studies, Müller et al. (2014) show that variations in the experimental choice settings might cause the failure to replicate the AD effect. Huber et al. (2014) recognized the lack of practice of the AD effect in today's marketplace. Our research in this paper uniquely contributes to the recent debate, and broadly, the literature, by 1) assuring that the AD effect is significant in a real marketplace; 2) revealing how likely the asymmetric dominance relationships would be perceived by consumers; 3) showing the heterogeneity in the awareness of, and the response to, the asymmetrically dominated alternatives across consumer segments; and moreover, 4) quantifying the profitability impact of utilizing the AD effect in the marketplace.

Despite the many experimental studies documented the effect in the existing literature, surprisingly and to the best of our knowledge, there has been no empirical study from real world practices similar to ours. Moreover, most of the extant research focuses on how decoys affect the choice probabilities of different alternatives, while leaving the potential profitability implications—the practical validity and significance—untouched. Note that this latter effect could only be quantified in empirical studies. There are several potential reasons for the lack of empirical quantification of the AD effect. The first reason is the lack of data in practice, because it is typically difficult to classify a product as a strict decoy in most consumer packaged goods. Consumers usually have heterogeneous preferences over different product attributes such as brand, taste, package size and even package designs, so that the price difference between similar products can be attributed to consumer segmentation, making it hard to define decoy structures among the alternative products. Second, as noted in Huber et al. (1982), unlike in lab experiments where only a few alternatives with limited number of attributes exist, the choice scenarios in real life are much more complex, so that the AD effect may be lessened, simply because it would be harder for consumers to discover the decoy-dominant pairs. In addition, for repeatedly purchased products, added decoys may not significantly change consumers' preferences about the alternatives that exist before the decoy introductions. For example, if consumers develop strong preferences for an existing brand over time, just because a decoy to a competing brand is introduced, consumers would not possibly leave the focal brand and switch to the competing brand. Third, the choice decision has to be salient enough; otherwise, consumers may just make random choices without paying enough attention to the choice alternatives. Finally, it might be quite possible that decoy pricing strategies[1] may not generate a positive profit impact for a firm, which limits the

[1] We use decoy pricing strategy to refer to the practice of creating asymmetric dominance through pricing in the marketplace.

existence of the practice in the real world.

In order to empirically study the existence of the AD effect and quantify its magnitude and profit impact, we need data from a product category that is important for the buyer but not repeatedly purchased; that has products with a few well-defined attributes that consumers uniformly prefer; and that has the decoy pricing patterns in the observed pricing practice. The online diamond market is a highly appropriate case for this purpose: diamonds are commodity-type products that are defined only on a few attributes; consumers uniformly prefer certain diamond attributes; diamond purchases are important but not repeated lifetime decisions; and, more importantly, we do frequently observe decoy pricing patterns in the online diamond market.

We use diamond pricing and sales data from a major online jewelry retailer to achieve our research objectives that fill an important gap in the literature. Modeling the impact of decoy diamonds on the sales of both decoys and dominants requires us to separate the effect of consumer search (Burdett and Judd (1983)) from the AD effect. In order to achieve that, our model starts with individual primitives that include the consumer's arrival process, consideration set formation and choice probabilities conditional on consideration set. The model then aggregates to a diamond-level proportional hazard framework that directly incorporates two critical components: the probability of detecting the decoys and the dominants, which we call the *detection probability*; and the changes in purchasing probabilities once a diamond is discovered as a dominant, which we call the *asymmetric dominance hazard*. The first component captures the likelihood of including pairs of decoy and dominant diamonds in the consideration sets formed by consumers through their diamond search process; while the second component quantifies the AD effect on dominant diamonds' choice probabilities. In most of the lab experiments in the literature, the detection probability component is not emphasized. This is because experimental subjects are perfectly informed, in detail, on the choice alternatives such that they are very unlikely to make "mistakes" in a lab setting. In response to the recent challenge to the robustness of the AD effect, Simonson (2014) comments that "it is not surprising that the AD effect is often not observed when other choice drivers have greater impact and/or when the asymmetric dominance configuration is unlikely to be perceived." This is especially true in real purchase scenarios with numerous potential alternatives, where consumers need to put significant efforts in the search process and the final consideration set may simply not contain alternatives with such decoy–dominant relationship. In addition, consumers might be heterogeneous in these two components (detection probability and asymmetric dominance hazard). In order to capture such heterogeneity, we explore the behavioral differences of consumers in these two components across different diamond price ranges.

We apply our model to this novel diamond data set to examine how each diamond's characteristics, price and the relevant dominance structure would affect its daily sales likelihood. Results suggest that it is relatively more difficult to sell diamonds with larger carats and either very low or very high cut, color and clarity levels. Results also help us quantify how the detection probability and asymmetric dominance hazard change with the dominance structure. The detection probability for decoys is, in general, quite low, especially for diamonds in higher price ranges. However, it increases considerably, as a decoy diamond is priced relatively higher (compared to diamonds sharing the same characteristics) and has more dominants. In addition, we find a significant boost in the asymmetric dominance hazard for a dominant diamond when it is detected, with a stronger effect for high price diamonds. The asymmetric dominance hazard also increases significantly when a dominant is priced relatively lower (compared to diamonds sharing the same characteristics) and has more decoys. Overall, these findings bring real life evidence on the existence of the AD effect.

Our second objective is to quantify the profit impact of AD effect. As noted before, such profitability impact of AD has not been studied in the literature. The direct measurement of AD effect on profit comes from our model estimates in the asymmetric dominance hazard component. We use the model estimates as an input, and compare the differences in the expected profits when we turn on-and-off the AD parameters. Overall, we find that asymmetric dominance effect has contributed 21.4% of the total retailer's gross profit; and the profit contribution is quite even across different diamond price segments. We also investigate the implication of asymmetric dominance on the retailer's pricing strategy. One potential strategy the retailer could use is to introduce "uniform" pricing so that identical diamonds always have the same price, and diamonds with better physical attributes are always priced higher than those with inferior attributes. Note that, under such pricing strategy, there will not be any decoy–dominant relationships. Our policy analysis reveal that the current pricing practice increases the retailer's gross profit by 19.04% compared to a uniform pricing strategy without any dominance structure in the market. The profit impact is mostly driven by diamonds in higher price ranges. As a consequence, our findings suggest that the retailer obtains a significant profit gain from the asymmetric dominance structure introduced in the marketplace, and the current pricing practice is significantly more effective than a uniform pricing strategy.

Finally, we further investigate how the decoys and dominants could be priced in a more effective way to further increase the retailer's gross profit. We manipulate three strategies the retailer might apply: 1) changing the number of listed decoys/dominants; 2) changing the price dispersion for diamonds with the same attributes; 3) changing the baseline decoy/dominant discovery probabilities. Borrowing the terminologies from the literature, we call the first strategy the frequency effect and the second one the range effect (Huber et al., 1982); finally, we name the third strategy the awareness effect. The simulation study indicates that the retailer can gain additional profit from all three polices. The potential profit gain would be the largest if the retailer could manage market-level awareness of decoy pricing in an effective manner. At the optimal level of awareness, the retailer might attain an additional 5.36% gross profit compared to the existing awareness level.

1.1 Relevant Literature

This paper contributes to two streams of the literature: the general consumer behavior literature on context dependent choices and the empirical consumer choice modeling literature in marketing and economics.

Many behavioral studies have shown that changing the choice context by adding new alternatives has some systematic effects on the preferences of choice makers. The first such effect is the similarity effect; Tversky (1972) documented that adding alternatives to a core choice set tends to get a disproportionately larger share from existing similar alternatives. A second context dependence effect is called the compromise effect, as in Simonson (1989a), where adding extreme alternatives that are very strong in some attributes but weak in others to a core choice set might increase the compromised alternatives' shares. Our paper is directly linked to a third context dependence effect, namely the asymmetric dominance effect, as studied in Huber et al. (1982). Huber et al. (1982) reveal that adding asymmetrically dominated alternatives to a core choice set might increase shares of the dominating alternatives. This effect might even be observed after adding a relatively inferior, but not asymmetrically dominated alternative (Huber and Puto, 1983) to the core choice set. Follow-up studies in this domain have investigated the cognitive processes and mechanisms underlying the AD effect, as well as factors inflating or mitigating it (Ratneshwar et al., 1987; Heath et al., 1995). Some studies have aimed to understand which context effects are predominant under which conditions (Mourali et al., 2007; Khan et al., 2011). Our intention in this study is to empirically test whether the AD effect exists in a real-world market and, further, to quantify its magnitude and measure its impact on the profitability of the retailer.

Our study is also closely related to the studies modeling the consumer choice in the economics and marketing literature. Classic multinomial logit and probit models are built upon the revealed preference assumption and, thus, cannot directly account for the above mentioned context dependence effects. Given the extensive documentation on the prevalence of these context effects in the behavioral literature, a few empirical and analytical methods have been developed to incorporate these context effects into the choice models. Tversky (1972) formulated his well-recognized Elimination-By-Aspects (EBA) model to account for the similarity effect. Kamakura and Srivastava (1984) modified the standard multinomial probit model in order to account for the similarity effect by modifying the error structure through incorporating similarity-based error correlations. Kivetz et al. (2004) proposed a choice model that can account for the compromise effect. Orhun (2009) proposed an analytical choice model to study AD and compromise effects under the loss-aversion assumption. The most recent study in this domain is the one by Rooderkerk et al. (2011), in which they proposed an empirical choice model that can incorporate AD, compromise and similarity effects all together. They used a choice-based conjoint data to estimate their proposed model and showed that ignoring these context effects significantly biases the choice model's predictions. Our paper adopts a different approach by proposing a proportional hazard model framework that explicitly accounts for the AD effect in a real product market.

Therefore, the contribution of this paper is twofold. From the academic perspective, this is the first attempt to confirm the existence and quantify the magnitude and profit impact of the AD effect in a real marketplace. From the managerial perspective, our policy analysis provides insights into the profitability implications of the decoy pricing practice. We also show how the retailer could further improve profitability by further utilizing the AD effect.

In the sections that follow, we begin by describing the online diamond industry and the data we use. We then develop our proportional hazard model from individual primitives and discuss the associated estimation procedure. Next, we present our estimation results and discuss the managerial implications based on the policy analysis. Finally, we conclude with a discussion of the potential limitations of our study and directions for future research.

2 Data

2.1 Industry Background

Several retailers have emerged in the online market for diamonds and fine jewelry products in the past two decades. We use a panel data set from one major retailer in this market in the United States. The retailer sells a variety of jewelry products, such as loose diamonds, gemstones, wedding rings, bracelets, necklaces, and earrings, to end consumers. Loose diamonds account for the core part of the business, contributing the majority of the retailer's revenue. According to its annual report, the retailer works with dozens of diamond suppliers worldwide under an "exclusivity" agreement. This agreement requires the suppliers to sell their diamonds only through the retailer's online channel, and not through other competing online and offline channels. To operate in a cost-efficient manner, the retailer uses a drop-shipping business model. The retailer, in most cases, doesn't physically carry inventories of loose diamonds on its own site, but instead purchases the diamonds from its suppliers when consumers place their orders from the retailer's website. Unlike traditional brick-and-mortar stores, where only a limited number of diamonds are available, this drop-shipping model allows the retailer to list tens of thousands of diamonds every day. In this setting, suppliers list their diamonds on the retailer's online channel and establish the wholesale price for each of the listed diamonds. The retailer then adds its own markups to the wholesale prices. According to the retailer's annual report and to media interviews with its managers, the markup is usually fixed at around 18% to 20%.

The retailer's website is designed to allow potential consumers to effectively search loose diamonds based on their physical characteristics such as carat, clarity, color, cut (the 4Cs hereafter), and price. After such search, consumers' consideration sets usually contain multiple decoy diamonds—i.e., diamonds with the same set of physical characteristics (the same grade hereafter) or even inferior characteristics, but with higher prices than their counterparts (the dominants hereafter). We call this observed pricing behavior the decoy pricing strategy.

Since the retailer uses a drop-shipping business model and adds a fixed markup for each diamond, this variation in prices comes from the diamond suppliers.[2] It is possible that charging different prices for diamonds with the same physical characteristics could be the outcome of a market equilibrium. One classical explanation is the consumer search cost (Burdett and Judd, 1983). The decoy diamonds still have a chance to sell because consumers bear a cost to search for and compare diamonds and, thus, may not be fully informed. Thus, the additional profit margin for decoy diamonds might counterbalance the potential demand loss due to their low sales likelihood. We add another possible explanation

[2]It is also possible for the retailer to strategically add different markups for different diamonds. However, according to public sources and media reports, the retailer just adds the same fixed margin for all diamonds.

for such price variation based on the asymmetric dominance theory: strategically pricing the diamonds lower to make them dominants would boost the demand due the AD effect for informed consumers, thus counterbalancing the profit losses from lower prices. Since we do not have information at individual supplier level, the supplier side pricing decisions is not the focus of the paper. Instead, we focus on the demand side and take the observed market price structure as given and estimate the demand for diamonds. We capture the search explanation in the detection probability component and model the AD effect in the asymmetric dominance hazard part.

We acknowledge that the retailer is not strategically pricing to utilize the AD effect, because diamond suppliers introduce the price variation and the asymmetric dominance structure in the market. Nevertheless, consumers would respond to the dominance structure regardless of the source of the variation. Consequently, the dominance structure would still have an impact on the retailer's profitability, which we will demonstrate in our policy analysis. Furthermore, strategic pricing on top of the suppliers' wholesale prices is still an option for the retailer. We explore this potential in our policy analysis.

2.2 Data Description and Dominance Construction

We construct a panel data set of diamonds from this retailer and focus specifically on sales of loose diamonds. We collect the data from the retailer's website through a web crawler for a period from February, 2011 to September, 2011. For each diamond listed during our sample period, we observe the diamond's inherent physical characteristics (mainly the 4Cs and some other attributes such as symmetry and polish) and daily prices until the diamond is no longer listed on the website. We assume that a diamond is sold through the retailer's website on the last day it was listed as available. We believe that this is a reasonable assumption because, as discussed before, the suppliers have an exclusive agreement with the retailer, and thus, the diamonds would not be listed on other online and offline channels along with the retailer's channel. Given that the retailer has a significant share of 5% of the total U.S. market for diamond engagement ring sales, we believe that it is the primary channel for those suppliers—i.e., the exclusive agreement is incentive-compatible.

In our analysis, we focus specifically on round-shaped diamonds with prices ranging between \$2K and \$20K, which account for 36% of the total diamonds sold in this period. If we only look at diamonds priced greater than \$2K, our sample account for 72% of the diamonds. Diamonds in different price ranges might be more attractive to different segments of potential buyers with different budgetary constraints. To examine the potential heterogeneity for the asymmetric dominance effect across different consumer segments, we further divide the diamonds into low-end (\$2K-\$5K), medium-end (\$5K-\$10K) and high-end (\$10K-\$20K) price segments based on each diamond's first-day market price.

Table 1: Price Regression: ln(price) on diamond attributes and daily dummies

Variable		**Estimate**	**Std. Err.**
Carat	ln(Carat)	1.768	0.0004
Cut	Poor	0.000	
	Good	0.056^{**}	0.0009
	Very Good	0.114^{**}	0.0009
	Ideal	0.180^{**}	0.0009
	Signature Ideal	0.231^{**}	0.0013
Color	J	0.000	
	I	0.141^{**}	0.0004
	H	0.268^{**}	0.0004
	G	0.361^{**}	0.0003
	F	0.455^{**}	0.0003
	E	0.503^{**}	0.0004
	D	0.583^{**}	0.0004
Clarity	SI2	0.000	
	SI1	0.124^{**}	0.0003
	VS2	0.274^{**}	0.0003
	VS1	0.371^{**}	0.0003
	VVS2	0.455^{**}	0.0003
	VVS1	0.544^{**}	0.0003
	IF	0.619^{**}	0.0004
	FL	0.762^{**}	0.0004
	Daily Dummies	included	
Adj. R-squared		0.9997	
Adj. R-squared w/o daily dummies		0.9527	
Adj. R-squared w/ daily separate regressions		0.949–0.966	

Note: Estimates with ** are significant at 0.05 significance level.

Before starting our main analysis, we want to demonstrate the existence of decoy pricing patterns by using some preliminary analysis. First, in order to understand what determines the diamond prices, we run an ordinary least squares regression with daily diamond prices as our dependent variable and inherent characteristics as independent variables to uncover the secret diamond-pricing formula. To control the potential demand effect across different days, we add daily fixed effects. We report the main regression results in Table 1. The adjusted R-squared for the model with 4Cs, along with daily fixed effects, is as high as 99.97%, indicating that, in general, these factors could predict diamond prices well, especially because we have included diamonds in a wide price range. A significant portion of the data variation comes from the daily price levels: a regression without the daily fixed effects yield an adjusted R-squared of 95.27%; when we run separate regression models for each day, the adjusted R-squared varies from 94.92% to 96.57%. In the data, each specific diamond's price might change overtime and on average, each diamond's price changes once in every 21 days conditional on the diamond is unsold. This within-diamond price variation accounts for 1.88% of the total price variation in the sample. If we look at diamonds in the price range of $5K to $10K, then the within-diamond price variation accounts for 19% of the total price variation. To further check the robustness, we run several regressions by incorporating other attributes, such as symmetry and polish, into the main regression model. Overall, the R-squared measure does not improve. Moreover, the effects of these additional variables on the prices are mostly insignificant, and the estimates are small in magnitude compared to the estimates of the 4Cs. For example, the implied price difference contributed by symmetry and polish turns out to be less than 0.5%. Thus, we have strong supporting figures to conclude that the quality of a diamond can be measured very precisely by simply looking at its 4Cs. In other words, a diamond can be characterized as a combination of five characteristics: its 4Cs and price. This is, indeed, quite consistent with industry reports on diamond valuations and articles educating consumers on purchasing diamonds. Even though the variation in diamonds' physical attributes explains a decent portion of the price variation, we still observe significant within-grade and within-day (same 4Cs) price variation [3]. This variation becomes essential for us to characterize the dyadic decoy/dominant relationships among every diamond pair.

By definition, a product D is a decoy to another product A when D is inferior to the dominant product A in at least one attribute, but has no superior attribute. In our specific setting, we define a diamond to be a decoy under two conditions: 1) in terms of 4Cs, D is inferior in at least one attribute to A and has no attribute superior to A's, but has the same price or a higher price than A; and 2) D shares the same 4Cs attributes with A, but is priced higher.[4] Under the above definitions, for any two diamonds on a particular day, we define the relationship between them as follows:

- A dominates B: $A \succ B$
- No dominance: $A \sim B$

Notice that from the strict definition, two diamonds with the same attributes but different prices must have a strict dominance relationship. In real purchase situations, consumers may not care much or even notice the difference if the price gap is not large enough. Thus, we use a conservative approach in our analysis: we define a dominance relationship for two diamonds with the same 4Cs only if the price difference between the two is larger than 5%. If two diamonds have different 4Cs and have a dominance relationship, we use the strict definition. The mean price difference for diamonds of different grades is usually larger than 5%. The conservative 5% rule also helps us to avoid the potential problem of making a

[3] To illustrate the amount of within-grade and with-day price variation, we calculated average of price standard deviation to mean price ratio. The corresponding mean ratio turns out be 0.1, indicating a sufficiently large price variation.

[4] We do not consider the condition in which D is superior in 4Cs, but the high price premium compared to diamond A does not justify the difference in physical attributes (the near-dominance, as discussed in Huber et al. (1982)). There are two reasons for this. First, this is not a strict definition of decoy. Second, it might be significantly more difficult for consumers to detect such dominance relationships since diamonds are not directly comparable, and consumers may not be able to judge whether the price premium justifies the quality difference.

false dominance relationship when the dominated diamond is, indeed, superior in other non-critical attributes such as symmetry and polish. As mentioned before, in a full regression model, the price premium contributed by each of these attributes is generally smaller than 0.5%. So the 5% rule for two diamonds with the same 4Cs should be conservative enough.[5] We next code the dyadic relationship between diamonds A and B as 1 if A dominates B, -1 if B dominates A and 0 otherwise. Every dyadic relationship between all listed diamonds is constructed for each day in our data sample, because the price for the same diamond can change day by day. For a particular diamond, we define the number of diamonds that dominate it as the out-degree and the number of decoys it has as the in-degree.[6] Therefore, as the number of in-degree increases, the diamond is expected to become more attractive, and vice-versa. We check the percentage of the degrees (dyadic dominance) defined based on the two parts in our definition, and find that the first part in which diamonds differ at least in one of the 4C attributes account for 86% of the total degrees.[7] Under our definition of a dominance relationship, a diamond can belong to one of the four categories on a particular day: 1) neither decoy nor dominant, in which both the in-degree and out-degree are 0; 2) strict decoy, with a positive out-degrees and zero in-degrees; 3) strict dominant, with a zero out-degrees and positive in-degrees; and 4) both decoy and dominant, with positive in-degrees and out-degrees. Table 2 shows the count of diamond-days for each category under our conservative 5% rule, along with relationships defined based on part 1) of our decoy definition, and 1% and 10% rules for robustness checks. We observe that most of the diamonds fall into the both decoy and dominant category, a result driven mainly by the significant within-grade price variations. In addition, distribution of the diamonds across the three different rules are quite similar and comparable in magnitude.

[5] In the robustness section, we also check the model estimates based on the dyadic relationships defined on 4Cs, symmetry and polish. Results are qualitatively very similar and the model with classification based on 4Cs outperform the alternative model based on the BIC criteria.

[6] A diamond can have positive in-degrees and out-degrees at the same time.

[7] In the robustness section, we also check for model estimates using dominance relationships defined only by this first component of the definition. Results are qualitatively very similar, and the model with decoy characterization based on both definitions has a higher BIC value.

Table 2: Count of Diamond-Day Observations for Each Diamond Type

Diamond Type	**Definition 1**	**1% rule**	**5% rule**	**10% rule**
Neither decoy nor dominant	34,657	23,976	27,077	30,812
Strict decoy	461,131	333,058	404,283	442,231
Strict dominant	380,423	295,779	340,456	367,735
Both decoy and dominant	1,840,614	2,064,012	1,945,009	1,876,047

Table 3 further summarizes in-degrees and out-degrees for diamonds in our sample. From this table, we also see that there is some heterogeneity in the distribution of decoys across low-($2K-$5K), medium-($5K-$10K) and high-price ($10K-$20K) segment diamonds. Each diamond has a median of 10, 5 and 5 decoys in the low-, medium-, and high-price segments respectively. The number of diamonds supplied in each segment—with the low-end segment having the highest number—probably drives this pattern.[8] It is also possible that the suppliers might be allocating their decoy diamonds in a strategic manner across diamonds of different price ranges, based on the intensity of the within segment competition, and the magnitude of the search and the AD effect across these different price segments.

Table 3: Diamond In-degrees and Out-degrees Across Price Ranges

In-degrees and Out-degrees	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Median in-degrees	10.0	5.0	5.0	7.0
Mean in-degrees	31.2	13.1	11.8	21.4
Median out-degrees	13.0	5.0	5.0	8.0
Mean out-degrees	37.6	13.9	11.8	25.1

2.3 Data Evidence on AD Effect

The existence of price dispersion and dominance relationships among physically identical diamonds could potentially be explained by classic consumer search theory (Burdett and Judd, 1983; Hong and Shum, 2006). In this section, we discuss data evidences that may not be explained by solely consumer search, instead might be suggestive of the AD effect.

[8]The mean in-degrees and mean out-degrees are not exactly the same. This is because we construct the relationship based on all the diamonds in the market, but we choose the diamonds in the 2K-20K range as the focus of analysis. Some of the dyadic relationships are truncated in the sample.

We first provide some statistics on how the diamond sales likelihood is affected by which of the four dominance types it belongs to. Table 4 describes the percentage of diamonds sold in the total diamond-day observations according to different types of diamonds. Each cell is calculated as follows: for example, take the strict decoys in 2K-5K range, there are in total 150,784 diamond-day observations that belongs to this category, and 2,213 were sold. Thus, the sale probability in this cell becomes 1.47%. This table suggests that it is easier to sell medium-end diamonds (2.49% of medium-priced ones are sold) compared to low-end (1.93%) and high-end diamonds (1.94%).

Table 4: Daily Percentage of Diamonds Sold Across Price Ranges

Diamond Type	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Neither decoy nor dominant	2.42%	1.88%	1.54%	1.96%
Strict decoy	1.47%	2.07%	1.57%	1.68%
Strict dominant	2.59%	2.72%	2.13%	2.53%
Both decoy and dominant	1.88%	2.52%	2.00%	2.08%
Total	1.93%	2.49%	1.94%	2.07%

More importantly, Table 4 shows that being a strict decoy decreases the diamond sale percentages for all the segments (average 1.68%), while being a strict dominant would consistently increase the diamond sales probability (average 2.53%), compared to diamonds that belong to the "neither decoy nor dominant" (1.96%) and "both decoy and dominant" (2.08%) conditions. Qualitatively, such patterns could be explained by the consumer search story: strict decoys are significantly less likely to sell compared to the "neither" condition is because of the possibility that the decoy diamond has a dominant being included together in the consideration set. A rational consumer would have a zero probability of purchasing this decoy diamond once the relationship is discovered. Yet the the sale probability is not zero because consumers have search costs, and may not be able to examine all the potential diamond options and discover a diamond being dominated. For strict dominants, under random consumer search, they should have similar probabilities of being included in the consideration set as diamonds in the neither condition, and slightly more sale probabilities because of their relative price advantages. The fact that they have on average a significant 30% larger sale probability could be suggestive of effects beyond pure consumer search: if it is purely search effect, the supplier could price, say 10% lower for the diamonds in the "neither" condition to make them dominants and increase the demand by 30%. Even in the extreme case that the costs of the diamonds are zero, a simple expected profit calculation would yield a higher level of profit ($1.3 \times 0.9 > 1.0$) for the supplier. We attribute this significant sales impact to the potential AD effect: once a dominant enters into a consumer's consideration set with its corresponding decoys, the consumer is likely to perceive the dominant as more attractive, and this increases the dominant's sale likelihood by a significant magnitude.

Second, we further develop a formal statistical method to test whether the price dispersion is purely driven by consumer search. We show the details of our test in Web Appendix A. The intuition is that under pure consumer search story without AD effect, a supplier would price to maximize the expected profit of each individual diamond, and thus identical diamonds with different prices would generate the same optimal expected profit in equilibrium. However, with the AD effect, suppliers need to consider the price optimization beyond each individual diamond, because decoys would serve as "loss-leaders" that help generate higher expected profits from their dominants. And consequently, one would expect the profit contribution from dominants to be higher than that from decoys. Under the hypothesis of no AD effect, we can utilize the rich price and sales information in our data to recover the cost c_{jt} of each diamond from the optimality of the suppliers. c_{jt} should be approximately the same for diamonds with identical physical attributes, and should be exactly the same for the same sku across days. However, under the AD effect, since the demand of high price decoys are more price elastic, the calculated costs c_{jt} would increase with the relative price level. Testing of the pure search effect thus equals testing of whether recovered c_{jt} is correlated with a diamond's relative price (compared to the average price of diamonds with same physical attributes). We test this using cross-diamond variations in our Test I and within-diamond variations in our Test II. The results are provided in Table A1 in the Web Appendix consistently reject the null hypothesis of a pure consumer search explanation across all three price segments. All the coefficients of the relative price index are positive and significant, and thus are directionally consistent with our AD effect hypothesis. Further, the coefficient estimates are larger in the high price segments, suggesting that the potential AD effect would be strongest in the high price segment.

Third, the extent to which consumer search and asymmetric dominance affect the sales likelihood may be impacted by the overall dominance structure, for example, the percentage of diamonds belonging to the strict decoy, and strict dominant types. We run regressions to check these relationships. In the results reported in Table 5, we use the daily percentage sales share of decoys (total number of decoys sold divided by total number of diamonds sold on a given day) and dominants across the low, medium and high price segments as the dependent variables. We use segment dummies and percentage of strict decoys and strict dominants as independent variables. Results show that percentage of strict decoys significantly increases the decoy sales share; while percentage of strict dominants significantly increases the dominants sales share but decreases the decoy sales share. The decoy sales share regression is consistent with search story: having relatively more decoys compared to dominants would reduce the likelihood that decoys are discovered (with their dominants) from search. In terms of the dominant sales share regression, the elasticity of percentage of dominants on sales share is significantly larger than 1 (1.97), suggesting that adding additional dominants would extract disproportionally larger sales share from other diamonds, which is another supporting evidence of the AD effect.

Table 5: Diamond Sales Share Regression

Variable	Decoy Sales Share		Dominant Sales Share	
	Estimate	Std. Err.	Estimate	Std. Err.
Intercept	0.023	0.026	−0.048	0.040
Medium Segment(5K-10K)	0.006	0.016	−0.082**	0.025
High Segment(10K-20K)	−0.008	0.021	−0.086**	0.032
% Decoys	0.899**	0.198	0.161	0.301
% Dominants	−0.312**	0.155	1.972**	0.236
Adj. R-squared	0.118		0.117	

Note: Estimates with ** are significant at 0.05 level.

To sum up, our simple data analysis yields the following results: 1) diamond prices can be characterized by the 4Cs with high precision; 2) there is still price dispersion for diamonds with identical physical attributes; 3) the likelihood of a diamond purchase depends on whether it is a decoy and/or a dominant diamond; and 4) there are suggestive evidences of search and AD effect. Therefore, a careful investigation of the decoy phenomenon through a deliberately developed econometric model is required. We achieve this in the next section.

3 Model

As previously discussed, observed diamond sales are determined by two major drivers: the consumer search process and the AD effect. Quantifying the AD effect requires us to separate its impact from the consumer search process. This itself is a challenging task in empirical applications. Some recent studies have achieved the purpose by utilizing various limited information related to the consumer search, such as aggregate product search data revealed on Amazon.com (Kim et al., 2010), observed consumer consideration sets (Honka, 2014; Honka and Chintagunta, 2015), and the amount of time consumers spent (Pinna and Seiler, 2016). Unlike these papers discussed, we do not observe any information related to consumer search behavior. Thus, our inference has to be at the aggregate level. We take a different approach, and achieve the purpose in three stages. First, we start with individual consumer primitives including the arrival process, consideration set formation and conditional choice probabilities, and we discuss how an aggregate level hazard model could be derived. Second, we show in detail how the asymmetric dominance effect can be embedded inside the consumer choice probability function and why our specification could serve as a test for the AD effect. Third, we discuss in detail how we specify the model that could be estimated using observed data variables. Finally, we discuss how the model could be identified.

3.1 Derivation of Aggregate Hazard from Individual Primitives

We assume potential diamond buyers arrive at random times to the retailer's website. In each specific time τ (can be a millisecond), we assume at most one consumer would be making a diamond purchase decision. A representative consumer i, arriving at time τ_i, searches from the retailer's website to form the consideration set, and then decides whether to purchase one diamond that maximizes her utility in the consideration set or not to purchase anything. In terms of search, we assume independence across diamonds, that is the probability a particular diamond is included is independent of any other diamonds being included or not.[9] We denote the consumer's consideration set as M_i, and the super set containing all the possible consideration sets as $\mathbb{M}$.

We define the conditional choice probability of consumer i choosing a particular diamond j from her consideration set M_i, given j has not been sold before τ_i, as $s_i(j|M_i)$ (we will discuss in detail about this component in the following subsection). The expected sale probability of diamond j at time τ_i is thus the sum of the choice probabilities over all the possible consideration sets:

$$\omega_j(\tau_i) = \sum_{M_i \in \mathbb{M}} Pr(M_i) \times s_i(j|M_i). \tag{1}$$

This consumer and diamond specific choice probability $\omega_j(\tau_i)$ equals the sales hazard of diamond j at time τ_i. This is the case because it is the conditional probability that diamond j will be sold at time point τ_i conditional on it has not been sold till that time point, and the consumer i is the only one that decides whether j would be purchased at this particular time.

We now derive the aggregate level sales hazard for diamond j at discrete time day t. We assume n_t potential consumers arrive randomly during day t, and each consumer can be represented by consumer i. By definition in survival analysis, we know the survival function

[9] This assumption holds under simultaneous search but not sequential search.

for diamond j at end of day t, $S_j(t)$ is defined as:

$$S_j(t) = e^{-H_j(t)}, \tag{2}$$

where $H_j(t) = \int_0^t \omega_j(\tau_i)d\tau$ is the cumulative hazard function.

We use $Ph_j(t)$ to denote the hazard in the discrete time for diamond j on day t:

$$\begin{aligned} Ph_j(t) &= \frac{S_j(t-1) - S_j(t)}{S_j(t-1)} \\ &= 1 - e^{-(H_j(t)-H_j(t-1))} \\ &= 1 - e^{-h_j(t)}, \end{aligned} \tag{3}$$

where $h_j(t) = n_t\omega_j(\tau_i)$, and the corresponding survival function is $S_j(t) = \Pi_{k=1}^t e^{-h_j(k)}$.

Denote the total number of days since diamond j is on market to the end of our observation period as T_j, and the day diamond j is sold since its introduction as T_j^s. Given J diamonds in the data set, the total likelihood we use for estimation can be represented as:

$$L = \Pi_{j=1}^J \left\{ \left[I(T_j^s \leq T_j)(1 - e^{-h_j(T_j^s)})\Pi_{t=1}^{T_j^s-1} e^{-h_j(t)} \right] \times \left[I(T_j^s > T_j)\Pi_{t=1}^{T_j} e^{-h_j(t)} \right] \right\}. \tag{4}$$

3.2 Asymmetric Dominance in Hazard Specification

The key component in our derivation is $h_j(t) = n_t\omega_j(\tau_i)$. While n_t could be approximated by time variant variables that capture daily demand fluctuations, the $\omega_j(\tau_i)$ component requires a more detailed discussion.

For a specific diamond j, we can classify diamonds into three mutually exclusive and collectively exhaustive types based on their relationships to j: the set of C_j^o contains diamonds that are neither dominants nor decoys to j; the set C_j^{out} contains all diamonds that are dominants of j; and finally the set C_j^{in} represents the collection of j's decoys. Denote M_{ij}^o the set of diamonds from C_j^o that are in i's consideration set, and similarly M_{ij}^{out} and M_{ij}^{in}

the sets of diamonds (in i's consideration set) that are from j's dominants set (C_j^{out}) and decoys set (C_j^{in}), respectively. Denote $\mathbb{M}_j^o$, $\mathbb{M}_j^{out}$, and $\mathbb{M}_j^{in}$ as the super sets of M_{ij}^o, M_{ij}^{out} and M_{ij}^{in}, respectively. Now we can express consumer i's consideration set M_i as a combination of j, M_{ij}^o, M_{ij}^{out} and M_{ij}^{in}, and define the choice probability $s_i(j|M_i)$ accordingly[10]:

$$s_i(j|M_i) = \begin{cases} 0, & \text{if } j \notin M_i \\ s_i(j|j \cup M_{ij}^o), & \text{if } j \in M_i \ \& \ M_{ij}^{out} = \varnothing \ \& \ M_{ij}^{in} = \varnothing \\ 0, & \text{if } j \in M_i \ \& \ M_{ij}^{out} \neq \varnothing \\ s_i(j|j \cup M_{ij}^o \cup M_{ij}^{in}), & \text{if } j \in M_i \ \& \ M_{ij}^{in} \neq \varnothing \ \& \ M_{ij}^{out} = \varnothing. \end{cases} \tag{5}$$

In the above equation, j has a choice probability of zero in the first case simply because it is not in the consideration set. The choice probability is also zero in the third case, because we assume consumers are rational, and once a dominant is included in the choice set, the inferior decoy option j will never be purchased. Also notice that in the last case, consumer will only choose an option from the subset $j \cup M_{ij}^o$, but not from M_{ij}^{in}, because diamonds in M_{ij}^{in} are inferior to option j and a rational consumer would not buy those decoys. In other words, the effective choice set becomes the same as the second case. If there is no context effect, $s_i(j|j \cup M_{ij}^o) = s_i(j|j \cup M_{ij}^o \cup M_{ij}^{in})$; while if there is the AD effect, we would expect the presence of diamonds from M_{ij}^{in} to increase the attractiveness and thus the choice share of diamond j. We denote the relationship as follows:

$$s_i(j|j \cup M_{ij}^o \cup M_{ij}^{in}) = s_i(j|j \cup M_{ij}^o) \times q_i(j, M_{ij}^o, M_{ij}^{in}), \tag{6}$$

where $q_i(j|.)$ is a scalar that affects the choice probability of option j, and is a function of dominance relationships in the choice set. Note that, $q_i(j|.) = 1$ if there is no AD effect; $q_i(j|.) > 1$ if there is.

We now aggregate the choice probability over the choice sets to derive the diamond level hazard. Based on our random search assumption, we would have $Pr(j| \cup M_{ij}^o \cup M_{ij}^{in}) = Pr(j)Pr(M_{ij}^o)Pr(M_{ij}^{in})$ and so on. Thus, we can derive following based on equation (1).

[10] The functional form of $s_i(j|M_i)$ could be very general. Given we do not have individual level data, we do not specify it in the paper. A natural choice could be the multinomial logit model.

$$
\begin{aligned}
\omega_j(\tau_i) = & \sum_{M_i \in \mathbb{M}} Pr(M_i) \times s_i(j|M_i) \\
= & \sum_{M_{ij}^o \in \mathbb{M}_j^o} Pr(M_i = j \cup M_{ij}^o) s_i(j|j \cup M_{ij}^o) + \\
& \sum_{M_{ij}^o \in \mathbb{M}_j^o} \sum_{M_{ij}^{in} \in \mathbb{M}_j^{in}} Pr(M_i = j \cup M_{ij}^o \cup M_{ij}^{in}) s_i(j|j \cup M_{ij}^o \cup M_{ij}^{in}) \\
= & Pr(j \in M_i \ \& \ M_{ij}^{in} = \varnothing \ \& \ M_{ij}^{out} = \varnothing) \sum_{M_{ij}^o \in \mathbb{M}_j^o} Pr(M_{ij}^o \in M_i) s_i(j|j \cup M_{ij}^o) + \\
& Pr(j \in M_i \ \& \ M_{ij}^{out} = \varnothing) \sum_{M_{ij}^o \in \mathbb{M}_j^o} Pr(M_{ij}^o \in M_i) s_i(j|j \cup M_{ij}^o) \sum_{M_{ij}^{in} \in \mathbb{M}_j^{in}, M_{ij}^{in} \neq \varnothing} Pr(M_{ij}^{in} \in M_i) q_i(j, M_{ij}^o, M_{ij}^{in}) \\
= & Pr(j \in M_i \ \& \ M_{ij}^{in} = \varnothing \ \& \ M_{ij}^{out} = \varnothing) s_i(j|j, \mathbb{M}_j^o) + \\
& Pr(j \in M_i \ \& \ M_{ij}^{out} = \varnothing) s_i(j|j, \mathbb{M}_j^o) Pr(M_{ij}^{in} \neq \varnothing) q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in}), \\
= & Pr(j \in M_i) s_i(j|j, \mathbb{M}_j^o) \left[Pr(M_{ij}^{in} = \varnothing) Pr(M_{ij}^{out} = \varnothing) + Pr(M_{ij}^{in} \neq \varnothing) Pr(M_{ij}^{out} = \varnothing) q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in}) \right],
\end{aligned} \tag{7}
$$

where $s_i(j|j, \mathbb{M}_j^o) = \sum_{M_{ij}^o \in \mathbb{M}_j^o} Pr(M_{ij}^o \in M_i) s_i(j|j \cup M_{ij}^o)$. Denote $q_i(j|M_{ij}^o, \mathbb{M}_j^{in}) = \sum_{M_{ij}^{in} \in \mathbb{M}_j^{in}, M_{ij}^{in} \neq \varnothing} Pr(M_{ij}^{in} \in M_i) q_i(j, M_{ij}^o, M_{ij}^{in}) / Pr(M_{ij}^{in} \neq \varnothing)$, we have

$$
q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in}) = \sum_{M_{ij}^o \in \mathbb{M}_j^o} Pr(M_{ij}^o \in M_i) s_i(j|j \cup M_{ij}^o) q_i(j, M_{ij}^o, \mathbb{M}_j^{in}) / s_i(j|j, \mathbb{M}_j^o).
$$

Here $q_i(j|M_{ij}^o, \mathbb{M}_j^{in})$ is the average of $q_i(j, M_{ij}^o, M_{ij}^{in})$ weighted by the probability of having M_{ij}^{in}; and $q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in})$ is the average of $q_i(j|M_{ij}^o, \mathbb{M}_j^{in})$ weighted by the probability of having M_{ij}^o. Thus the final $q_i(j|M_{ij}^o, \mathbb{M}_j^{in})$ is the average of all the $q_i(j|.)$ weighted by the probability of all the possible combination of M_{ij}^{in} and M_{ij}^o. Note that, the random search assumption is used in the derivation of the above equation (7) starting from the second equal line.

Now equation (7) tells us that the aggregate sales hazard in the continuous time can be decomposed to the sum of two components: 1) the probability that no dominance-decoy relations are included in the consideration set times the aggregate choice probability over all the no dominants–no decoys sets (the baseline choice probability); and 2) the probability that a diamond's decoys but not dominants are included in the consideration set times the baseline choice probability times an additional aggregate term q that depends on the diamond dominance relationship structure. From consumer choice theory, we know that for each specific consideration set, $q_i(j|M_{ij}^o, M_{ij}^{in}) \geq 1$, i.e., it can not be the case that adding dominated options into the choice set would reduce the choice share of a dominant. When this q function aggregates to the market level, it is a weighted average of all the consideration set level q s. Thus, the aggregate $q_i(j|\mathbb{M}_j^o, \mathbb{M}_j^{in}) \geq 1$. As $q_i(j|M_{ij}^o, M_{ij}^{in})$ captures the potential AD effect at individual choice level, testing whether $q_i(j|\mathbb{M}_j^o, \mathbb{M}_j^{in}) > 1$ equals testing whether on average the AD effect exists in individual choices, i.e. whether $\mathbb{E}q_i(j|M_{ij}^o, M_{ij}^{in}) > 1$.

We now discuss a few properties of the model. First, given the aggregate nature of the data, our model is also aggregated overall individual search and choice primitives. The unit of our analysis is each diamond, which is different from classic choice models defined on brand or product shares. Second, in terms of how to model the AD effect conditional on choice set, we choose to put a scalar function $q_{ij}(.)$ on the dominant when the dominance relationship is discovered. The original Huber et al. (1982) paper states that the presence of decoys will not only increase the choice probability of the dominant, but also the relative share of the dominant compared to the non-dominant. When $q_{ij}(.) > 1$, our specification becomes consistent with the AD theory. Of course, it would be ideal to separately model the AD impact on the dominant and each non-dominant option. However, since our identification relies on the relative share of dominants to non-dominants, we are not able to achieve that. Third, we have used a representative consumer i in our derivation. It is quite possible that consumers are heterogeneous, and their choice preferences would not be independent of their search process, i.e., the $Pr(.)$, $s(.)$ and $q(.)$ functions are not independent. Given the nature of the data, we are not able to model such interdependence. In other words, the selection problem is not explicitly modeled. The central estimates of detection and AD effect could be viewed as the market average effect. Nevertheless, we estimate different parameters across different price segments, which captures some part of the consumer heterogeneity.

3.3 Functional Form Specification

We now discuss the details of the functional form we use to model the hazard component $h_j(t)$ at discrete time, based on equation (7).

$$\begin{aligned} h_j(t) =& n_t \omega_j(\tau_i) \\ =& n_t Pr(j \in M_i) s_i(j|j, \mathbb{M}_j^o) \times \\ & \left[Pr(M_{ij}^{in} = \varnothing) Pr(M_{ij}^{out} = \varnothing) + Pr(M_{ij}^{in} \neq \varnothing) Pr(M_{ij}^{out} = \varnothing) q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in}) \right] \\ =& h_0(t) \times \psi_j(Z_t, X_j, W_{jt}, p_{jt}, \tilde{p}_{jt}) \times \phi_j(N_{jt}, \tilde{p}_{jt}), \end{aligned} \tag{8}$$

In the specification above, the first component $h_0(t)$ corresponds to the baseline hazard that could potentially depend on time t; the second component $\psi_j(.)$ controls for the variation due to observed diamond attributes as well as daily demand fluctuations; and the third component $\phi_j(N_{jt}, \tilde{p}_{jt})$ corresponds to the most critical part in our model, i.e., the probability of diamond dominance detection and the aggregate level AD effect.

Details of the variables used are as follows: for a diamond j, we use X_j to denote its physical attributes, p_{jt} to denote its price in day t and $\tilde{p}_{jt}$ to denote its relative price compared to prices of other same grade diamonds. We define a grade as a unique combination of the 4Cs and use $\bar{p}_{jt}$ to represent the average price for all diamonds for the grade that diamond j belongs to. The relative price measurement $\tilde{p}_{jt}$ is defined as $\tilde{p}_{jt} = (p_{jt} - \bar{p}_{jt})/\bar{p}_{jt}$. We use Z_t to denote variables capturing the daily demand differences; and W_{jt} to denote variables summarizing the competitiveness and attractiveness of the grade that diamond j belongs to. We define $N_{jt} = \left[N_{jt}^{in}, N_{jt}^{out}\right]$ as the decoy-dominant relationship, where N_{jt}^{in} denotes the number of in-degrees (number of decoys diamond j has in day t), and N_{jt}^{out} denotes the number of out-degrees (the number of diamonds dominating diamond j in day t). For a complete list of variables and their descriptions, see Table 6.

We assume that the baseline hazard is a function of a constant and the number of days the corresponding diamond is on the market: $h_0(t) = \exp(\lambda_0 + \lambda_1 \ln t)$. We model the second

Table 6: List of Variables Used in Model Estimation

	Variable Name	Description
Z_t	Google search	Daily Google search trends index of diamond-related keywords
	Weekday dummies	Dummy variables of weekdays
X_j	Diamond characteristics	Dummy coded 4Cs of each diamond
W_{jt}	Daily competitiveness	Log of number of diamonds of the same grade, and of the neighboring grades, Residual from the price regression, % of price change from last period
p_{jt}	Daily price	Daily prices of each diamond (in 1000)
$\tilde{p}_{jt}$	Relative price index	Relative price of each diamond to the average price with same 4Cs
N_{jt}	In-degrees	Number of diamonds that are dominated by diamond j
	Out-degrees	Number of diamonds dominating diamond j

component as a function of the observed diamond attributes:

$$\psi_j(Z_t, X_j, W_{jt}, p_{jt}, \tilde{p}_{jt}) = \exp(Z_t\alpha_Z + X_j\alpha_X + W_{jt}\alpha_W + p_{jt}\beta_0 + \tilde{p}_{jt}\beta_1), \tag{9}$$

The third component consists of two parts according to our derivation: the fist part represents the probability of detecting the dominance relationship related to diamond j and the second part represents the AD effect, conditional on the detection of diamond j being a dominant. We call the first part the *detection probability* and the second part the *asymmetric dominance hazard*. In the reduced-form representation, we use $P_{jt}^{in}(N_{jt}, \tilde{p}_{jt})$ and $P_{jt}^{out}(N_{jt}, \tilde{p}_{jt})$ to model the probability that the representative consumer detects that diamond j is a dominant or is dominated, respectively. Similarly, we use $Q_{jt}^{in}(N_{jt}, \tilde{p}_{jt})$ and $Q_{jt}^{out}(N_{jt}, \tilde{p}_{jt})$ to model the conditional aggregate sales impact that comes from consumers detecting diamond j as a dominant or a decoy, respectively.[11] It is especially important to revisit that, in our setting, $Q_{jt}^{out}(N_{jt}, \tilde{p}_{jt}) = 0$. This is because when consumers detect a specific diamond to be a decoy, they would never purchase it, as they can always choose the dominant one. The existing literature (Huber et al., 1982) also verifies that fully-informed subjects would seldom make the "mistakes" of choosing the decoys in lab experiments. Following equation (8), the

[11] For ease of notation, we use $P_{jt}^{in}, P_{jt}^{out}, Q_{jt}^{in}, Q_{jt}^{out}$ hereafter to denote the corresponding functions that depend on variables N_{jt} and $\tilde{p}_{jt}$.

asymmetric dominance hazard can now be expressed as,

$$\begin{aligned}\phi_j(N_{jt}, \tilde{p}_{jt}) &= Pr(M_{ij}^{in} = \varnothing)Pr(M_{ij}^{out} = \varnothing) + Pr(M_{ij}^{in} \neq \varnothing)Pr(M_{ij}^{out} = \varnothing)q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in}) \\ &= (1 - P_{jt}^{in})(1 - P_{jt}^{out}) + P_{jt}^{in}(1 - P_{jt}^{out})Q_{jt}^{in},\end{aligned} \tag{10}$$

where we use P_{jt}^{in} and P_{ij}^{out} to approximate the true detection probabilities. Also $q_i(j, \mathbb{M}_j^o, \mathbb{M}_j^{in})$ is approximated by Q_{jt}^{in}.

As the notation suggests, we model the two components P_{jt} and Q_{jt} as functions of two variables: 1) how many diamonds dominate diamond j (N_{jt}^{out}) or how many diamonds are dominated by diamond j (N_{jt}^{in}); and 2) the relative price measurement $\tilde{p}_{jt}$. Huber et al. (1982) examined two factors that would potentially impact the salience of the asymmetric dominance effect: the "frequency effect," which measures the number of attributes that the dominant alternative is dominating, and the "range effect," which measures the degree of dominance in an attribute. In our context, because the model is built upon the sale hazard of each diamond, we do not directly measure the number of attributes that form strict dominance relationships. Instead, we aggregate the number of alternatives that a diamond is dominating/dominated by. This first measurement could be viewed as a proxy to the "frequency effect." The relative price variable, on the other hand, can be viewed as a close proxy for the "range effect.".

Formally, we model these decoy and dominance detection probabilities as follows:

$$P_{jt}^{in}(N_{jt}, \tilde{p}_{jt}) = I(N_{jt}^{in} > 0)\frac{\exp[\gamma_0^{in} + \gamma_1^{in} \ln N_{jt}^{in} + \gamma_2^{in} I(\tilde{p}_{jt} < 0)(-\tilde{p}_{jt})]}{1 + \exp[\gamma_0^{in} + \gamma_1^{in} \ln N_{jt}^{in} + \gamma_2^{in} I(\tilde{p}_{jt} < 0)(-\tilde{p}_{jt})]} \tag{11}$$

$$P_{jt}^{out}(N_{jt}, \tilde{p}_{jt}) = I(N_{jt}^{out} > 0)\frac{\exp[\gamma_0^{out} + \gamma_1^{out} \ln N_{jt}^{out} + \gamma_2^{out} I(\tilde{p}_{jt} > 0)\tilde{p}_{jt}]}{1 + \exp[\gamma_0^{out} + \gamma_1^{out} \ln N_{jt}^{out} + \gamma_2^{out} I(\tilde{p}_{jt} > 0)\tilde{p}_{jt}]}, \tag{12}$$

where $I(.)$ is the indicator function. Similarly, we model the asymmetric dominance hazard of Q_{jt} as:

$$Q_{jt}^{in}(N_{jt}, \tilde{p}_{jt}) = \exp[\delta_0^{in} + \delta_1^{in} \ln N_{jt}^{in} + \delta_2^{in} I(\tilde{p}_{jt} < 0)(-\tilde{p}_{jt})]. \tag{13}$$

Given the decoy and dominance detection probabilities and the conditional hazard function as specified above, equation (10) becomes the following:

$$\phi_j(N_{jt}, \tilde{p}_{jt}) = \begin{cases} 1, & \text{if } N_{jt}^{in} = 0 \ \& \ N_{jt}^{out} = 0 \\ (1 - P_{jt}^{in}) + P_{jt}^{in} Q_{jt}^{in}, & \text{if } N_{jt}^{in} > 0 \ \& \ N_{jt}^{out} = 0 \\ (1 - P_{jt}^{out}), & \text{if } N_{jt}^{in} = 0 \ \& \ N_{jt}^{out} > 0 \\ (1 - P_{jt}^{in})(1 - P_{jt}^{out}) + P_{jt}^{in}(1 - P_{jt}^{out}) \times Q_{jt}^{in}, & \text{if } N_{jt}^{in} > 0 \ \& \ N_{jt}^{out} > 0, \end{cases} \tag{14}$$

which are specified based on which of the four dominance groups a diamond belongs to. For the first cluster (neither decoy nor dominant), the proportional hazard is normalized to one. The second cluster (dominant but not decoy), the value of $\phi_j(N_{jt}, \tilde{p}_{jt})$ is the average of baseline hazard and asymmetric dominance hazard weighted by the detection probability. The value of $\phi_j(N_{jt}, \tilde{p}_{jt})$ for the third cluster (decoy but not dominant) is the probability that the diamond is not detected as a decoy. Finally, the value of $\phi_j(N_{jt}, \tilde{p}_{jt})$ for the fourth cluster (both decoy and dominant) is the average of baseline hazard and asymmetric dominance hazard weighted by the probability that it is not identified as neither dominant nor decoy and the probability that it is identified as a dominant but not a decoy.

After specifying all these components, our model is estimated using maximum likelihood based on the likelihood function defined in equation (4).

3.4 Model Identification

Before presenting our estimation results, it is worth discussing how we identify the parameters of our model. The central identification question is how we separately identify parameters in three components: 1) consumer search (reflected in detection probability) that forms the consideration set, 2) preference parameters conditional on consideration set, and 3) asymmetric dominance effect parameters.

We first develop a stylized example in Web Appendix B to show how such parameters could be non-parametrically identified from data variations in a simple setting. We assume that in the market, there are three types of diamonds A, B, and D, where D is strictly dominated by A but not B, and there is no dominance relationship between A and B. We assume a representative consumer would conduct simultaneous search with consideration set size of n, and define the choice probabilities of each diamond type under different combinations of diamonds in the consideration set. We also assume that once D is included in the set with A and B, the relative choice share of A would increase compared to the situation with diamonds types A and B only, i.e., the AD effect. Under these primitives, we generate the market shares of diamonds A, B, and D, under different search intensities ($n = 3$ and $n = 4$) and different dominance structures (ratio of D type diamonds being the same or twice as A and B). We then show detailed calculations about how the observed market share and dominance variation could help us recover each of the model parameters.

The basic intuition is as follows: first, the level and change of the market share of decoys under different dominance structures help us identify the search intensity level, as well as the baseline preference for the decoys when the dominants are not presented. Second, conditional on the identification of consumer search, the variations in the market share of the dominants under different dominance structures help us identify the baseline preference for the dominants when the decoys are not present, as well as the changes in the preference (AD effect) in the presence of decoys. Please refer to Web Appendix B for the details.

Now we apply the same intuition into our aggregate level hazard model framework. First, the average number of days it takes for a diamond to be sold gives us the estimate for parameters λ in the baseline hazard function $h_0(t)$. Second, the variations in the mean number of days to sell across "neither decoy nor dominnant" diamonds with different attributes help identify preference parameters $(\alpha_Z, \alpha_X, \alpha_W, \beta)$ in the proportional hazard part $\psi_j(.)$. The identification of parameters in the $\phi_j(.)$ component is our central focus in this paper. In terms of the detection probability parameters in equation (10), the identification of the probability that a decoy diamond is detected comes from the basic assumption that any rational consumer would not purchase the dominated diamond if she detects it as a decoy, i.e., $Q_{jt}^{out}(N_{jt}, \tilde{p}_{jt}) = 0$. Thus, in our data, the observations of diamond sales at the time that they are priced to be decoys give us estimates of the probability that those decoy diamonds are not discovered. In other words, the variation in decoy sales (the third case in equation (14)) across diamond grades and days help identify the parameters of $\gamma^{out} = (\gamma_0^{out}, \gamma_1^{out}, \gamma_2^{out})$. This completes the identification of the consumer search part for decoys. On the other hand, the parameters in the equation for detecting a dominant diamond $\gamma^{in} = (\gamma_0^{in}, \gamma_1^{in}, \gamma_2^{in})$ cannot be separately identified from the asymmetric dominance hazard part, the $\delta^{in} = (\delta_0^{in}, \delta_1^{in}, \delta_2^{in})$ parameters in equation (11). This can be seen from the second and fourth cases in equation (14), where P_{jt}^{in} and Q_{jt}^{in} are always bundled together in the form of $P_{jt}^{in} Q_{jt}^{in} + (1 - P_{jt}^{in})$. To separately identify γ^{in} from δ^{in}, we need to make an additional assumption: that is, $\gamma^{in} = \gamma^{out}$, i.e, the functional form for dominance detection is symmetric for decoys and dominants. This assumption is driven by our independence assumption on random consumer search. To clarify, for a listed diamond, the probability of it being included in the consideration set is independent from other diamonds being included or not. This implies that, all else equal, the probability of identifying a diamond with n decoys as a decoy diamond should be identical to the probability of identifying a diamond with n dominants as a dominant. In addition, since the dominance relationships are defined at the dyadic level, the probability of discovering one diamond dominating another is the flip side of discovering that one is dominated by the other. Thus, the parameters quantifying the detection probability should be same.[12]

Based on this symmetric detection assumption, and conditional on the detection probability being identified, the variations in the daily sales likelihood between diamonds in the "neither dominant nor decoy" group (first case in equation 14) and the strict dominant group (second case in equation 14) with variations in the number of in-degrees help identify the

[12] Our data limit us from testing whether they are empirically equal. Web browsing information from individual consumers would potentially help construct measurements to test this. Due to the stringent data requirement, we leave this exercise for future research.

δ^{in} parameters in the asymmetric dominance hazard part.

Also notice that we have put the same variables in both the detection probability equation and the asymmetric dominance hazard equation. This does not cause a problem in identification, because we are using different data observations to separate the effects of these variables in the two components: we use the sales information of strict decoys to identify the parameters γ; while we use the sales information of diamonds in the "strict dominants" and "both dominant and decoy" groups for the identification of δ.

4 Estimation Results

In our analysis, we use the log number of days each diamond is on the market to control for the diamond specific baseline hazard ($h_0^t(.)$). We model our proportional hazard component ($\psi_j(.)$) as a function of diamond characteristics X_j, daily demand proxies Z_t and daily competitiveness and attractiveness variables W_{jt}, daily prices, prices squared, percentage of price change from last period. For the asymmetric dominance hazard component ($\phi_j(.)$), our variables include an indicator of positive positive in- or out-degrees for each of the three diamond price segments; log of in- and out-degrees; and the relative price index.[13]

We report the estimation results in Table 7. The baseline hazard rate λ_0 differs across the three diamond price segments, with the high-price segment being the smallest. Days on the market negatively affects the baseline hazard, i.e., longer the diamond is unsold, the smaller the hazard is. For the first proportional hazard component, we find that the hazard decreases when a diamond has a larger carat weight. For the cut, color and clarity attributes, we observe an inverse U-shaped relationship—i.e., the sales hazard is the largest for diamonds with moderate attributes. Notice that our unit analysis is at each individual diamond level, thus the basic sales hazard would be determined by both potential consumer demand as well as the level of supply. This means that an inverse U-shape relationship does

[13]We estimate models with separate parameters for each of the diamond price segments on the variables of log in- and out-degrees and price index, as well. Results show that the estimates are not significantly different across diamond segments. In addition, likelihood ratio tests favor the model presented here.

not imply that "given price equal, a consumer does not prefer diamonds with better physical attributes." Note also that the setting here is different from classic market share models where the unit of analysis is defined at brand or product level and is not typically impacted by the supply level. Low sale likelihood of diamonds with low 4C levels might be explained by either their abundant supply, or low desirability due to their unattractive looks. Whereas, low sale likelihood of diamonds with high 4C levels might be explained by their high price premiums that may not justify their marginal benefit in quality compared to medium priced diamonds.

Cut is a very interesting attribute from the marketing perspective: most diamond advertising suggests that the cut is the most important attribute and thus consumers should purchase diamonds with the best cut level whenever possible. Our estimates indicate that, in general, as the cut of the diamond becomes superior, it becomes easier to sell the diamond. However, this is no longer true when a diamond's cut level further improves from "ideal" to "signature ideal". This could be the case due to two potential reasons: 1) the improvement in quality does not justify the price premium at that level, and 2) the retailer intentionally over supply "signature ideal" diamonds. Indeed, every diamond sold by this retailer has a certificate from diamond labs such as GIA and AGS. The lab certificates show the cut grade up to "ideal." While the "signature ideal" grade is created by the retailer for marketing purposes, with the only difference between "ideal" and "signature ideal" is that the latter has another private certificate from the retailer. Thus, our finding could be explained either by the motivation from the retailer to promote the "signature ideal" level diamonds with higher margins, or by the fact that consumers typically do not want to pay the significant price premium for this additional private certificate.

Table 7: Model Estimates

Variable	**Estimate**	**Std. Err.**
Baseline hazard λ		
Low Segment (2K-5K)	-2.756^{**}	0.092
Medium Segment (5K-10K)	-2.722^{**}	0.100
High Segment (10K-20K)	-2.832^{**}	0.126
ln(# Days on Market)	-0.330^{**}	0.003
Component X_j:		
ln(Carat)	-0.402^{**}	0.098
Cut: Poor	0.000	
Cut: Good	0.144^{*}	0.069
Cut: Very Good	0.439^{**}	0.068
Cut: Ideal	0.649^{**}	0.069
Cut: Signature Ideal	0.115	0.096
Color: J	0.000	
Color: I	-0.019	0.022
Color: H	0.062^{**}	0.024
Color: G	0.041	0.027
Color: F	0.035	0.030
Color: E	-0.156^{**}	0.033
Color: D	-0.192^{**}	0.037
Clarity: SI2	0.000	
Clarity: SI1	0.029	0.017
Clarity: VS2	0.073^{**}	0.022
Clarity: VS1	-0.004	0.026
Clarity: VVS2	-0.145^{**}	0.030
Clarity: VVS1	-0.316^{**}	0.035
Clarity: IF	-0.628^{**}	0.004
Clarity: FL	-0.620^{*}	0.291
Component Z_t:		
Google Search: "diamond"	0.217^{*}	0.107
Google Search: "diamond ring"	-0.712^{**}	0.064
Google Search: "wedding ring"	-0.047	0.057
Google Search: "engagement ring"	0.093^{**}	0.030
Google Search: retailer's name	0.172^{**}	0.020
Google Search: competitor's name	-0.635^{**}	0.063
Weekday Dummy: Monday	0.000	
Weekday Dummy: Tuesday	-0.072^{**}	0.014
Weekday Dummy: Wednesday	-0.118^{**}	0.014
Weekday Dummy: Thursday	-0.032^{**}	0.014
Weekday Dummy: Friday	-0.264^{**}	0.015
Weekday Dummy: Saturday	-1.828^{**}	0.026
Weekday Dummy: Sunday	-1.169^{**}	0.021

Continued on next page

Table 7: Model Estimates

Variable	**Estimate**	**Std. Err.**
Component W_{jt}:		
Price (in 1000)	0.068^{**}	0.016
Price Squared	-0.004^{**}	0.000
% Price Change from Last Period	-0.007	0.272
Residual from Price Regression	0.036	0.070
ln(# Diamonds of the Same Grade)	-0.003	0.011
ln(# Diamond of Neighboring Grades)	0.001	0.006
Detection Probability		
$N_{it}^{in} > 0$: Low Segment (2K-5K)	-1.519^{**}	0.166
$N_{it}^{in} > 0$: Medium Segment (5K-10K)	-2.327^{**}	0.142
$N_{it}^{in} > 0$: High Segment (10K-20K)	-2.688^{**}	0.832
$\ln(N_{it}^{in} + 1)$	0.158^{**}	0.032
$I(\tilde{p}_{it} < 0)(-\tilde{p}_{it})$	4.344^{**}	0.924
Asymmetric Dominance Hazard		
$N_{it}^{in} > 0$: Low Segment (2K-5K)	0.651^{**}	0.103
$N_{it}^{in} > 0$: Medium Segment (5K-10K)	1.110^{**}	0.117
$N_{it}^{in} > 0$: High Segment (10K-20K)	1.338^{**}	0.693
$\ln(N_{it}^{in} + 1)$	0.066^{**}	0.022
$I(\tilde{p}_{it} < 0)(-\tilde{p}_{it})$	-0.001	0.432
Log-likelihood	$-257{,}824.7$	

Note: Estimates with ** are significant at 0.05 level.

Estimates of our daily demand proxies suggest that Google search indexes for diamond-related keywords are significant proxies for the daily demand fluctuations. The daily sales hazards increase significantly when the Google search indexes on the keyword of “diamond”, “engagement ring” and the specific name of the retailer are high. However, if the search intensity is high on the competitor’s keyword, the diamonds’ sales hazards will decrease. Another interesting finding is that when more people are searching for the keywords “diamond ring” and “wedding ring,” the sales hazards decrease. One reason might be that the retailer is not able to get a premium position in the search results for those keywords and, thus, loses some potential consumers to its competitors. The sales hazards also differ significantly across weekdays, with Monday and Thursday being the best days for diamond sales, while

Saturday and Sunday are the worst days. One potential explanation might be that people tend to purchase diamonds on weekdays and then propose to their significant others on the weekends. It is also possible that people use the weekends to do research on diamonds, possibly go to brick-and-mortar stores and educate themselves about what they want to buy, and then place their orders online during the weekdays. Our results also show that the price effect has an inverse-U shape, with the medium priced diamonds having the highest hazards. The percentage price change from last period is not significant, suggesting that people might in general not tracking the prices of individual diamonds overtime. Other control variables such as the residual from price regression (measuring the relative price attractiveness) and log number of diamonds in the same grade and neighboring grades are insignificant.

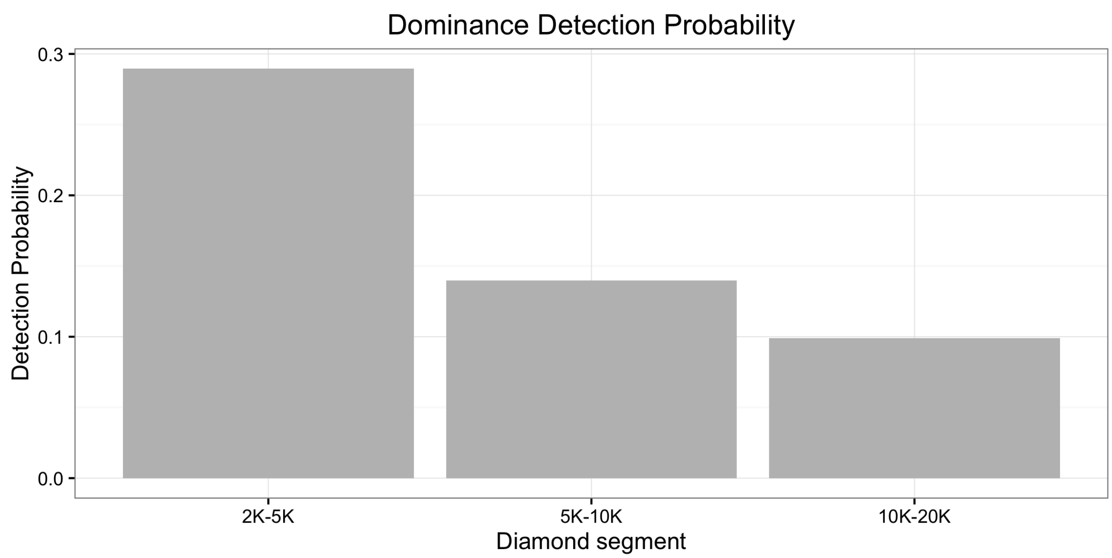

Figure 1: Mean Dominance Detection Probability Across Diamond Segments

We now discuss the estimation results on the detection probability and asymmetric dominance hazard, which are the most critical components of our model for addressing the paper's central research questions. First, regarding the detection probability, our results show that the base probability of discovering a decoy/dominant is significantly higher for diamonds in the low-price segment compared to those in the medium- and high-price segments; however, there is no statistically significant difference between the latter two segments. One potential

Table 8: The Distribution of Detection Probability and Asymmetric Dominance Hazard

	Min	**Q1**	**Median**	**Mean**	**Q3**	**Max**
Detection Probability						
2K-5K	0.20	0.23	0.27	0.29	0.33	0.88
5K-10K	0.10	0.11	0.13	0.14	0.16	0.83
10K-20K	0.07	0.08	0.09	0.10	0.11	0.51
Asymmetric Dominance Hazard						
2K-5K	2.00	2.16	2.29	2.30	2.44	3.16
5K-10K	3.18	3.32	3.51	3.52	3.69	4.55
10K-20K	3.99	4.09	4.33	4.38	4.57	5.78

reason might be that consumers of the low-price ($2K-$5K) segment are usually on tight budgets and are more likely to spend more time searching for better prices, thus, they are more to likely have larger consideration sets and more likely to detect decoys. The positive significant estimate of log of in-degrees/out-degrees (0.158) shows that when a diamond has more decoys/dominants, it is relatively easier for consumers to discover the dominance relationship. The positive significant estimate of the absolute value of the price index (4.344) shows that the further a decoy or dominant is priced from the average grade level price, the higher is the probability of dominance detection. We next calculate the decoy/dominant detection probabilities by using our model estimates. We compute the average of these probabilities and plot them across the three diamond price segments in Figure 1. In addition, a detailed summary table about the distribution across the three diamond segments are presented in Table 8. Interestingly, we find that when a diamond is a dominant, a decoy or both, the detection probabilities are quite low: 29% for the low-price segment, 14% for the medium-price segment and 10% for the high-price segment. Our findings show that our real-life choice scenario (with large number of choice alternatives defined on five attributes, with many decoys and dominants) greatly contrasts with the usual lab experiment settings (with few alternatives and one or couple of decoys), in which participants are typically aware of the dominance relationships by the construction of the experiment. Along this line, Frederick et al. (2014) shows that using stylized product representations where every product attribute is represented by numerical figures rather than pictorial depictions causes one to overestimate the significance of the AD effect. Yang and Lynn (2014) also shows that using qualitative-verbal descriptions instead of numerical depictions causes the same issue. Our study shows that even with numerical depictions of the product attributes, when products have large number of attributes and the number of choice alternatives are very large, the dominance relationships are hard to perceive as discussed in Huber et al. (2014).

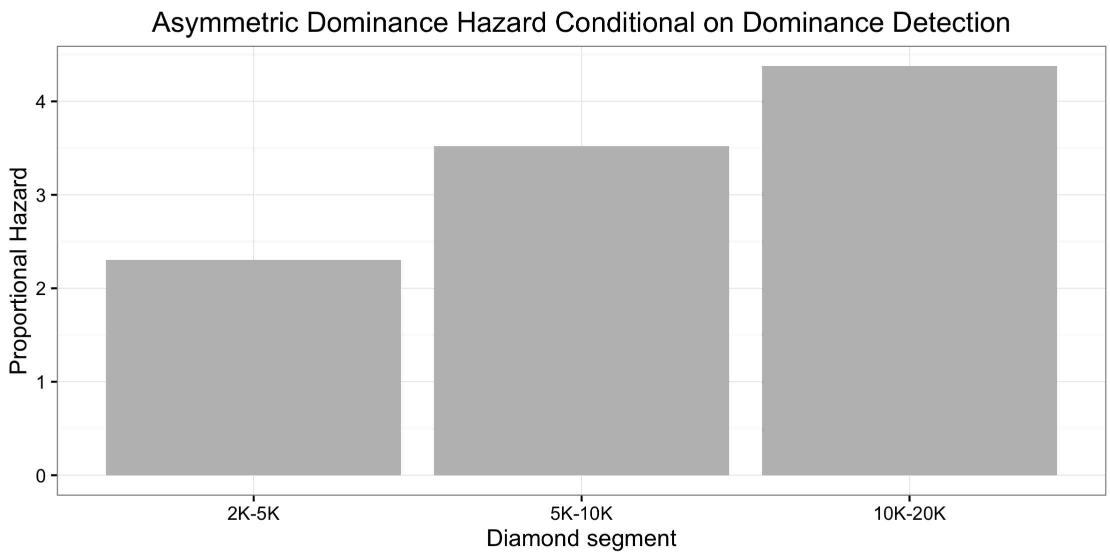

Figure 2: Mean Asymmetric Dominance Hazard Across Diamond Segments

Second, the estimates for the asymmetric dominance hazard component show that the baseline asymmetric dominance hazard for the low-price segment (0.651) is significantly lower than that of the medium- (1.110) and high-price (1.338) segments, while there is no statistical difference between the latter two. The results indicate that the AD effect is less effective in boosting demand in the low segment. The reason may be, as mentioned previously, that consumers with limited budgets will search more intensively for better prices and, therefore, are less responsive to the saving gained from a single dominant when they discover it—i.e., they may be more likely to continue to search. The parameter estimate for the log in-degree is positive and significant (0.066), indicating that having more decoys would further increase the effect of boosting dominants' attractiveness. The relative price index, on the other hand, is insignificant. We also plot the mean asymmetric dominance hazard effect across the three price segments in Figure 2. On average, conditional on discovering the dominance relationship, the asymmetric dominance hazard would increase by 130% for the low-price segment, 250% for the medium-price segment and 337% for the high-price segment. This finding is in line with Mourali et al. (2007) where they show that promotion focus (for less budget constrained buyers) would increase the attraction effect.

In summary, our estimation results suggest that it is generally difficult for consumers to figure out the dominance relationships in the online diamond marketplace. However, once an alternative is discovered to be a dominant, its sales hazard would be boosted significantly, especially in the medium- and high-price segments. Across the three segments, diamonds in the low-price segment are more likely to be discovered either as a decoy or as a dominant; however, the demand boost from this discovery turns out to be less significant. The opposite is true for diamonds in the medium- and high-price segments. Next, we use alternative model specifications to test the robustness of our results.

4.1 Robustness

We use a few alternative specifications to test our model's robustness. First of all, the literature has shown that consumers may overweight trivial attributes as they provide justifications for one's choice (Brown and Carpenter, 2000; Carpenter et al., 1994; Shafir et al., 1993; Simonson, 1989b). Even though these non-critical diamond attributes such as symmetry and polish do not justify a significant price premium (as shown through our price regression) during the choice process, consumers might still give importance to these attributes. For instance, a decoy diamond based on its 4Cs and price may not be considered by consumers as a decoy, if its polish level is better compared to its dominant. Along these lines, we want to test whether a diamond's non-critical attributes such as symmetry and polish would have significant impacts on the robustness of our results.

To test the effect of these non-critical attributes, we run three alternative models described below. In our first alternative specification, we include symmetry and polish into the construction of decoys and dominants. In other words, diamonds are coded as decoys only if they have the same 4Cs, symmetry and polish, but listed with the same or higher prices. It turns out that, 86.5% of the diamond-day observations would have the exact same dominance classification under this alternative decoy classification compared to our proposed one (with 4Cs only). Next, we run our model using data constructed based on this alternative decoy classification. The results are presented under column "Model II" in Table 9, along with "Model I"—the model used in our main estimation. Based on the estimates, both models yield qualitatively similar estimates, however based on the BIC criteria (BIC_{ModelI}=516,390 versus $BIC_{ModelII}$=516,501), our proposed model outperformed this first alternative specification. As a second alternative way to test the effects of non-critical attributes on the robustness of our results, we include the symmetry and polish levels as additional control variables and estimate our proposed model with these additional controls. We label this alternative model as Model III. Even though coefficient estimates for symmetry and polish turned out to be significant, both models yield qualitatively very similar results. In addition, our model outperformed this alternative model based on the BIC criteria ($BIC_{ModelIII}$=516,444). In a third test, we define the decoy-dominance relationships based only on the first part of our decoy definition: the diamonds differ in at least one of the 4Cs and the price for the inferior diamond should be larger or equal to the better one. In other words, we drop the definition of two diamonds with the same 4Cs, but with different prices to determine the dominance relationship between the two. This time, the alternative model yields a BIC value of 525,686, which is much worse than our proposed model.

Table 9: Model Robustness Check

Variable	**Model I**	**Model II**	**Model III**	**Model IV**
Symmetry: Very Good			0.220**(0.023)	
Symmetry: Excellent			0.243**(0.024)	
Polish: Very Good			0.181**(0.031)	
Polish: Excellent			0.176**(0.032)	
Detection Probability				
$N_{it}^{in} > 0$: (2K-5K)	-1.519**(0.166)	-1.456**(0.084)	-1.639**(0.118)	-1.542**(0.186)
$N_{it}^{in} > 0$: (5K-10K)	-2.327**(0.142)	-2.283**(0.144)	-2.737**(0.288)	-2.413**(0.121)
$N_{it}^{in} > 0$: (10K-20K)	-2.688**(0.832)	-2.641**(0.426)	-2.638**(0.362)	-2.735**(0.92)
$\ln(N_{it}^{in} + 1)$	0.158**(0.032)	0.164**(0.023)	0.163**(0.026)	0.122**(0.028)
$\ln(N_{it}^{in} + 1) \times \ln(N_{it}^{out} + 1)$				0.033(0.042)
$I(\tilde{p}_{it} < 0)(-\tilde{p}_{it})$	4.344**(0.924)	4.341**(0.528)	4.813**(0.548)	4.158**(1.023)
Proportional Hazard				
$N_{it}^{in} > 0$: (2K-5K)	0.651**(0.103)	0.645**(0.069)	0.639**(0.091)	0.645**(0.133)
$N_{it}^{in} > 0$: (5K-10K)	1.110**(0.117)	1.156**(0.117)	1.406**(0.245)	1.008**(0.135)
$N_{it}^{in} > 0$: (10K-20K)	1.338**(0.693)	1.358**(0.343)	1.332**(0.299)	1.256**(0.772)
$\ln(N_{it}^{in} + 1)$	0.066**(0.022)	0.064**(0.018)	0.061**(0.019)	0.056**(0.021)
$\ln(N_{it}^{in} + 1) \times \ln(N_{it}^{out} + 1)$				0.003(0.002)
$I(\tilde{p}_{it} < 0)(-\tilde{p}_{it})$	-0.001 (0.432)	-0.071(0.382)	0.348**(0.367)	0.005(0.389)
N. parameters	50	50	54	52
Log-likelihood	-257824.7	-257880.4	-257822.1	-257824.3

Note: Estimates with ** are significant at 0.05 level.

Second, we test whether the detection probability of diamonds in the both decoy and dominant category are jointly determined by the in-degrees and out-degrees, instead of being determined by either the in-degrees for being detected as dominants or out-degrees for being detected as decoys. In order to test this, we add an additional interaction term of $\ln N_{jt}^{in} \times \ln N_{jt}^{out}$ into our model. The results are presented under column "Model IV." Results yield that the coefficients for the proposed model estimates turned out to be very stable, while the additional interaction terms are small and insignificant.

In summary, through a series of alternative model specifications, we test the robustness of our results. These analyses yield that results in our proposed model is quite robust to different alternative operational definitions and specifications.

5 Managerial Implications

In order to demonstrate the substantive implications of our model, we use the estimated parameters and run policy simulations. First, we quantify the overall profit impact that is contributed by the AD effect. We also quantify the profit implication of the retailer's current pricing practice compared with a uniform pricing scheme. Second, we explore opportunities for the retailer to improve its profitability through modifying its strategies to change: 1) the number of dominants/decoys; 2) the degree of price dispersion; and 3) the baseline decoy/dominant discovery probabilities.

5.1 Effects of Dominants and Decoys on the Retailer's Profit

We now investigate the retailer's profit gain or loss from having decoy and dominant diamonds. The first method to check the profit impact due to asymmetric dominance is to calculate the profit under our current model estimates and compare it with a scenario where there is no such effect, i.e., the parameters δ^{in} are turned off. The retailer's expected profit for a given diamond j at time t is calculated as:

$$\pi_{jt} = \mathrm{Pr}_j(t|.) \times (p_{jt} - w_{jt}), \tag{15}$$

where p_{jt} is the price, and w_{jt} is the wholesale price, which can be easily calculated by subtracting out the retailer's mark-up of 18% (given in the retailer's annual report) from the observed daily retail prices. $\mathrm{Pr}_j(t|.) = 1 - \exp(-h_j(t|.))$ is the discrete time hazard, or the probability that diamond j would be sold in day t, conditional on it hasn't been sold until that day. The AD effect on profit comes from the differences in the sales probability represented by $\mathrm{Pr}_j(t|.)$ with and without the asymmetric dominance hazard component. The results are presented in Table 10. Without the AD effect, on average, each diamond would contribute \$20.49 in gross profit; while the contribution under the asymmetric dominance quantification becomes \$26.07. In other words, the AD effect contributes 21.40% of the retailer's gross profit. The contribution is quite similar across the three diamond price segments. Based on the financial information of the retailer, this percentage increase would translate into $15.4 million per year in absolute terms. This result shows that even though decoy/dominant detection probabilities are low in our real world scenario, the AD effect still have a very significant profit impact. Indeed, this profit impact is what really matters the most from the substantive point of view. This result addresses the questions (Frederick et al., 2014; Yang and Lynn, 2014) towards the practical validity and significance of the AD effect.

Table 10: The Impact of Asymmetric Dominance on Retailer's Gross Profit

Effect	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Avg Daily Revenue Per Diamond W/O AD	8.39	25.56	39.36	20.49
Avg Daily Revenue Per Diamond	11.00	32.60	49.37	26.07
% Revenue from AD Effect	21.54%	23.20%	20.80%	21.40%

Second, we investigate the impact of the AD effect on retailer's pricing strategy. Currently the suppliers decide on the wholesale prices of each diamond and the retailer adds a fixed profit margin over these prices. A potential pricing mechanism the retailer could use is a "uniform" pricing strategy in which the diamonds with identical attributes are always priced the same and diamonds with better attributes are priced higher than those inferior ones. This would eliminate the price dispersions as well as the dominance relations between diamonds.

Comparing with a uniform pricing strategy, the current decoy pricing practice with dominance relations would have different profit implications for decoys vs. dominants and for informed consumers (who detects the corresponding dominance relationships) and uninformed consumers. Table 11 illustrates the four scenarios. Decoy pricing strategy would on average increase prices for decoys while reduce prices for dominants. If an uninformed consumer purchases a decoy diamond, the retailer would gain extra profit due to the decoy's high price; while if an uninformed consumer purchases a dominant diamond, the retailer would lose some profit due to the dominant's low price. For informed consumers, because they will never purchase the decoy diamonds, the retailer would lose profit from those decoys; however, these consumers might be more likely to purchase the dominant diamonds and contribute more profit to the retailer, because the AD effect boosts the demand for dominants. We name the combined profit effect that comes from uninformed consumers the "information effect" and that from informed consumers the "asymmetric dominance effect." The information effect could be positive or negative, depending on how likely consumers would detect the dominance relations. The asymmetric dominance effect could be positive if the demand boosting from asymmetric dominance hazard is strong, and be negative if this effect is weak. We can also view the informed-decoy component as potential cannibalization and the informed-dominant component as potential market expansion.

Table 11: Profit Implication of Decoy Pricing vs. Uniform Pricing

	Decoy Diamond	**Dominant Diamond**
Uninformed Consumer	+	−
Informed Consumer	−	+

Note: Signs (+ or −) in the table represents the expected gain or loss under decoy pricing compared to a uniform pricing strategy.

The prices under the hypothetical uniform pricing strategy is calculated based on our regression analysis (Table 1) on the price equation, with the random errors being set to zero. Table 12 presents the profit impact in terms of percentage change in profit under decoy pricing. We find that the overall profit impact is positive: compared with the uniform pricing strategy, the current decoy pricing strategy led to an 19.04% increase in the retailer's gross profit. This positive effect is driven mainly by the asymmetric dominance effect, which contributes two thirds (12.96%), while the information effect contributes the other third of total profit increase. We also find significant differences in the profitability of decoy pricing across the three price segments. The retailer is marginally better off in the low- and medium-price segments, while the high-price segment profit increase is pretty significant (49.36%). The AD (information) effect is positive except the low-price (medium-price) segment. Overall, results suggest that the retailer should consider using the decoy pricing strategy, especially for diamonds in the relatively expensive domain; while it could maintain a uniform pricing strategy for diamonds in the less expensive segments.

Table 12: Impact of Current vs. Uniform Pricing on Retailer's Gross Profit

Effect	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Information Effect	2.19%	−9.13%	24.26%	6.33%
1).Uninformed—Decoy	4.71%	1.69%	27.41%	9.84%
2).Uninformed—Dominant	−2.53%	−10.82%	−3.15%	−3.51%
Asymmetric Dominance Effect	−0.98%	9.58%	25.44%	12.96%
3).Informed—Decoy	−22.73%	−9.96%	−6.53%	−11.81%
4).Informed—Dominant	21.75%	19.53%	31.98%	24.78%
Total Effect	1.36%	0.21%	49.36%	19.04%

Finally, we calculate the economic value that decoy pricing has contributed compared to uniform pricing. Translating the total effect into dollar terms, decoy pricing generates an additional $13.7 million yearly gross profit for the retailer compared to uniform pricing.

5.2 Further Profitability from Decoy Pricing

After showing the significant profit impact of decoy pricing, we next investigate how the retailer can further improve its profitability by effectively utilizing the AD effect. We look at three strategies the retailer could potentially adopt. The first strategy is to list more dominants or decoys. The second strategy is to manipulate the price dispersion levels while keeping the current dominance structure unchanged. Borrowing the terminology from the literature, we label the first strategy the "frequency effect" and the second strategy the "range effect." A third strategy the retailer could use is to change the baseline dominance detection probabilities for consumers. In practice, the retailer might achieve this by simply recommending dominants or decoys to consumers. We call this third strategy the "awareness effect."

For the frequency effect, we compare the profitability gains or losses when we add a few strict decoys or strict dominants. Results are presented in Table 13. Overall, the retailer can gain some additional profit when it adds dominants. For example, when the retailer adds one dominant for each of the diamonds that has at least one dominant in the current pricing schedule, it can gain an additional 0.61% profit, which translates into an additional \$440,000 yearly profit. Adding a second dominant further increases the retailer's profit by 0.51% (\$368,000). However, adding strict decoys would reduce the retailer's profitability.

Table 13: The Frequency Effect of Dominance Structure on the Retailer's Gross Profit

Dominance Structure	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Add 1 decoy	−0.36%	−0.23%	−0.17%	−0.23%
Add 1 dominant	0.51%	0.63%	0.64%	0.61%
Add 1 decoy and 1 dominant	0.16%	0.40%	0.47%	0.38%
Add 2 decoys	−0.65%	−0.42%	−0.31%	−0.42%
Add 2 dominants	0.96%	1.16%	1.17%	1.12%
Add 2 decoys and 2 dominants	0.30%	0.74%	0.86%	0.70%

In terms of the range effect, we change the price dispersion levels for the diamonds within the same grades. To achieve this, we simply enlarge or reduce the relative price index $\tilde{p}_{jt}$ for each diamond by a factor. For example, think about a diamond that is priced at \$11,000, with a calculated mean grade price of \$10,000. We change the price of this diamond to \$10,500 (dispersion factor 0.5), \$10,800 (dispersion factor 0.8), \$11,200 (dispersion factor 1.2) and \$11,500 (dispersion factor 1.5) in our simulation studies.[14] Table 14 reports the results. Overall, the retailer could make additional profits by reducing the price dispersion compared to the current pricing schedule in the low- and medium-price segments. This is because for those diamonds, the detection probability is relatively large, but the asymmetric dominance demand-boosting effect is not strong enough. On the other hand, the current pricing schedule for diamonds in the high-price segment seems to be already optimal. By changing the price dispersion by a factor of 0.5, the retailer could gain an additional 0.38% profit, which translates into an additional \$274,000 yearly profit.

The third strategy is to change the probability that a consumer would detect the diamond dominance structure. We achieve this by changing the estimated intercepts γ_0^{in} for the three price segments (see the model estimates table) and exploring the optimal values for the intercepts. In this exercise, we first generate a sequence of values between -4.0 and 4.0 with

[14]The mean price level is preserved in this exercise.

Table 14: The Range Effect of Dominance Structure on the Retailer's Gross Profit

Dispersion Factor	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
0.5	1.75%	1.28%	−0.83%	0.38%
0.8	0.84%	0.60%	−0.23%	0.26%
1.2	−1.04%	−0.72%	0.08%	−0.41%
1.5	−2.96%	−2.05%	−0.11%	−1.32%

the increments of 0.1, we then plug each value in this sequence to the estimated γ_0^{in}, and compute the corresponding expected profits. We compare across the conditions and get the optimal level in the intercepts that maximizes the expected profit. Table 15 reports the mean detection probabilities under the current awareness levels and under optimal awareness levels. We also report the additional profit impact when we move towards the optimal awareness levels. Interestingly, we find that the awareness levels at the medium- and high-price segments are lower than optimal levels; while for the low-price segment, the retailer should strongly discourage consumers from discovering the dominance relationships. This might be achieved by making the search cost higher in this segment. For the medium-price (high-price) segment, though, the retailer should increase the detection level from 14% to 29% (10% to 34%). The retailer might achieve this through personalized product recommendations. If the retailer could manage the awareness levels optimally, the overall profit impact would become very significant: with a 5.36% gross profit increase, the retailer could gain an additional \$3.9 million net profit annually.

Table 15: The Awareness Effect of Dominance Structure on the Retailer's Gross Profit

Awareness Level	**2K-5K**	**5K-10K**	**10K-20K**	**Total**
Current Mean Level	28.95%	13.97%	9.90%	20.66%
Optimal Mean Level	6.88%	28.50%	34.11%	18.77%
Profit Increase	7.53%	1.32%	7.10%	5.36%

In summary, our simulations show the possibility for the retailer to further increase the profitability by utilizing the AD effect quantified in this study. We find that the additional profit increase might be limited when the retailer manipulates the number of dominants and decoys (the frequency effect) and the price dispersion (the range effect). However, if the retailer can manage the consumers' awareness levels optimally, there is significant room to increase profit.

6 Conclusion

In this research, we empirically estimate the AD effect by using a unique panel data from a large online jewelry retailer. We first estimate a proportional hazard model that is derived from individual consumer primitives including consumer arrival process, consumer consideration set formation and conditional choice probabilities with embedded AD effects. Our model allows the daily sale likelihood of each diamond to depend on its inherent characteristics and price, daily demand fluctuations, competitive effects from other diamonds, and the observed dominance structure. We find that, in general, the probability of detecting decoys is low, especially for the medium- and high-priced diamonds, but this detection probability would increase as the number of dominating diamonds increases. More importantly, we confirm that once a diamond is discovered to be a decoy, it would have a strong impact on boosting the sale likelihood of the corresponding dominant diamond. Thus, we empirically verify that the AD effect exists in a real business environment beyond lab settings.

In addition, we contribute to the substantive issue of measuring the overall profit impact of decoy pricing. We quantify the overall profit impact of asymmetric dominance using model estimates and find that it contributes about 21.4% of the retailer's gross profit. We also find that the existing decoy pricing in the diamond market improves the retailer's overall gross profit by 19%, compared to a uniform pricing strategy where no dominance relationship exists. Next, we explore various strategies that the retailer can adopt to improve its profitability through further utilizing the asymmetric dominance effect. We test the implications of three strategies: listing more decoys/dominants (frequency effect); changing the price dispersion of the listed diamonds (range effect); and changing the baseline decoy/dominant detection probabilities through recommending diamonds to consumers (awareness effect). From these analyses, we find that the third strategy turns out to be the most effective among the three yielding an additional 5.36% profit to the retailer.

Our study is the first empirical attempt to quantify the robustly documented AD effect in the judgment and decision making domain by using a real world panel data. It is exciting to apply the well-documented context dependent choice theory to real-life data and to empirically explore its managerial implications. Several directions might be pursued to extend the understanding of this topic in future research. One direction is to jointly model demand for and supply of diamonds. We are less concerned with the diamond suppliers' optimal pricing decisions in our application. Modeling the suppliers' pricing decisions and investigate whether they have strategically taken the AD effect into the decisions might be an avenue for future study. This requires knowledge about pricing decisions at individual supplier level. A second direction is to model the AD effect with other context effects, such as compromise and similarity effects. We face great identification challenges in jointly estimating multiple effects in our context. Future research could potentially address this issue when we have consumer search data. Finally, a third direction is to model the competition between our focal retailer and the other online retailers in the diamond market because consumers might search diamonds from different online stores. This will require data of consumers not only from the focal retailer, but also from the other online stores.

References

Bettman, James R, Mary Frances Luce, John W Payne. 1998. Constructive consumer choice processes. *Journal of consumer research* **25**(3) 187–217.

Brown, Christina L, Gregory S Carpenter. 2000. Why is the trivial important? a reasons-based account for the effects of trivial attributes on choice. *Journal of Consumer Research* **26**(4) 372–385.

Burdett, Kenneth, Kenneth L Judd. 1983. Equilibrium price dispersion. *Econometrica: Journal of the Econometric Society* 955–969.

Carpenter, Gregory S, Rashi Glazer, Kent Nakamoto. 1994. Meaningful brands from meaningless differentiation: The dependence on irrelevant attributes. *Journal of Marketing Research* 339–350.

Frederick, Shane, Leonard Lee, Ernest Baskin. 2014. The limits of attraction. *Journal of Marketing Research* **51**(4) 487–507.

Heath, T B, S Chatterjee, K R France. 1995. Mental accounting and changes in price: the frame dependence of reference dependence. *Journal of consumer research* **22** 90–97.

Hong, Han, Matthew Shum. 2006. Using price distributions to estimate search costs. *The RAND Journal of Economics* **37**(2) 257–275.

Honka, Elisabeth. 2014. Quantifying search and switching costs in the us auto insurance industry. *The RAND Journal of Economics* **45**(4) 847–884.

Honka, Elisabeth, Pradeep K Chintagunta. 2015. Simultaneous or sequential? search strategies in the us auto insurance industry. *Working paper* .

Huber, J, J W Payne, C Puto. 1982. Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of consumer research* **9**(1) 90–98.

Huber, J, C Puto. 1983. Market boundaries and product choice: Illustrating attraction and substitution effects. *Journal of consumer research* **10** 31–44.

Huber, Joel, John W Payne, Christopher P Puto. 2014. Let's be honest about the attraction effect. *Journal of Marketing Research* **51**(4) 520–525.

Kamakura, Wagner A, Rajendra K Srivastava. 1984. Predicting choice shares under conditions of brand interdependence. *Journal of Marketing Research* 420–434.

Khan, Uzma, Meng Zhu, Ajay Kalra. 2011. When Trade-Offs Matter: The Effect of Choice Construal on Context Effects. *Journal of Marketing Research* **48**(1) 62–71.

Kim, Jun B, Paulo Albuquerque, Bart J Bronnenberg. 2010. Online demand under limited consumer search. *Marketing science* **29**(6) 1001–1023.

Kivetz, Ran, Oded Netzer, V Srinivasan. 2004. Alternative models for capturing the compromise effect. *Journal of marketing research* **41**(3) 237–257.

Lehmann, Donald R, Yigang Pan. 1994. Context effects, new brand entry, and consideration sets. *Journal of Marketing Research* 364–374.

Luce, R Duncan. 1959. *Individual Choice Behavior*. John Wiley & Sons, Inc, New York.

Luce, R Duncan. 1977. The choice axiom after twenty years. *Journal of Mathematical Psychology* **15** 215–233.

Mourali, M, U Böckenholt, M Laroche. 2007. Compromise and attraction effects under prevention and promotion motivations. *Journal of consumer research* **34** 234–247.

Müller, Holger, Victor Schliwa, Sebastian Lehmann. 2014. Prize decoys at work—new experimental evidence for asymmetric dominance effects in choices on prizes in competitions. *International Journal of Research in Marketing* **31**(4) 457–460.

Orhun, A Yesim. 2009. Optimal product line design when consumers exhibit choice set-dependent preferences. *Marketing Science* **28**(5) 868–886.

Pinna, Fabio, Stephan Seiler. 2016. Estimating search benefits from path-tracking data: Measurement and determinants .

Ratneshwar, S, A D Shocker, D W Stewart. 1987. Toward understanding the attraction effect: The implications of product stimulus meaningfulness and familiarity. *Journal of consumer research* **13** 520–533.

Rooderkerk, Robert P, Harald J Van Heerde, Tammo HA Bijmolt. 2011. Incorporating context effects into a choice model. *Journal of Marketing Research* **48**(4) 767–780.

Royle, Jone R, David J. O'Connor, Gareth M. Reynolds, Paul A. Bottomley. 1999. The robustness of the asymmetrically dominated effect: Buying frames, phantom alternative, and instore purchases. *Psychology and Marketing* **16**(3) 225–243.

Shafir, Eldar, Itamar Simonson, Amos Tversky. 1993. Reason-based choice. *Cognition* **49**(1-2) 11–36.

Simonson, I. 1989a. Choice based on reasons: The case of attraction and compromise effects. *Journal of consumer research* **16** 158–174.

Simonson, Itamar. 1989b. Choice based on reasons: The case of attraction and compromise effects. *Journal of consumer research* **16**(2) 158–174.

Simonson, Itamar. 2014. Vices and virtues of misguided replications: The case of asymmetric dominance. *Journal of Marketing Research* **51**(4) 514–519.

Tversky, A. 1972. Elimination by aspects: A theory of choice. *Psychological review* **79** 281–299.

Wedell, Douglas H. 1991. Distinguishing among models of contextually induced preference reversals. *Journal of Experimental Psychology: Learning, Memory, and Cognition* **17**(4) 767–778.

Yang, Sybil, Michael Lynn. 2014. More evidence challenging the robustness and usefulness of the attraction effect. *Journal of Marketing Research* **51**(4) 508–513.

Web Appendices

A Test of Price Dispersion from Consumer Search

In this section, we describe a simple statistical test method that would help us understand whether the observed price dispersion in the data could be purely explained by consumer search behavior; and if not, whether the test results would be consistent with our proposed AD effect.

When consumers search for price, Burdett and Judd (1983) proves that price dispersion could arise in equilibrium even for homogeneous products. The intuition is that because of consumer search cost, not every option would be discovered by consumers, and thus the high-priced options would still have positive sale likelihoods. Combining the sales likelihood and profit margin at different price points, one would expect, in equilibrium, each price point observed in the marketplace would generate the same expected profit. Hong and Shum (2006) uses this mixed pricing equilibrium idea to recover the consumer search cost distribution purely from the observed market price dispersions for textbooks—a typical homogeneous good.

We borrow this idea here, and use it in our test. For diamonds with identical attributes (i.e., the same grade), denoted by the set J, we observe two types of price dispersions: 1) across diamonds in the set J within the same day t, 2) within the same sku across days. We use p_{jt} to denote the price of diamond j on dat t. We denote the corresponding conditional sale likelihood as $Ph_j(t|p_{jt})$. Because the retailer adds a fixed margin ($1 - r = 18\%$) in our data, the wholesale price from suppliers become $w_{jt} = rp_{jt}$. We also denote the marginal cost for the suppliers as c_{jt}.

Assume the market price dispersion is purely driven by consumer search, i.e., there is no AD effect in the consumer response function ($Ph_j(t|p_{jt})$). Under this assumption, for a supplier, maximizing the total expected profit from a set of diamonds becomes equal to maximizing the expected profit for each individual diamond. However, when there exists the AD effect, this no longer holds, because the existence of decoy diamonds would boost the demand of their dominants, i.e., the decoys bring positive externality to the profit of dominants. Due to that, we would expect the expected profit from dominants to be higher than the decoys. In other words, if the AD effect is there in addition to search, each price point in the support of the observed price distribution would no longer yield the same expected profits, i.e., dominants will have higher expected profits compared to the decoys.

The supplier's expected profit is:

$$\pi_{jt} = (rp_{jt} - c_{jt}) \times Ph_j(t|p_{jt})$$

Under the no AD effect assumption, assume the suppliers have priced optimally, then, maximizing the individual profit function gives us $\frac{\delta \pi_{jt}}{\delta p_{jt}} = 0$. This holds for any price observed in the marketplace, because under mixed pricing equilibrium, each price point generates the same optimal profit. The equation yields the following marginal cost:

$$c_{jt} = rp_{jt}(1 + \frac{1}{\eta_{jt}(p_{jt})}) \tag{A.1}$$

where $\eta_{jt} = \frac{\delta Pr_j(t|p_{jt})}{\delta p_{jt}} \frac{p_{jt}}{Pr_j(t|p_{jt})}$ is the price elasticity at price p_{jt}.

However, when there is AD effect, this relationship does not hold anymore, because the decoys serve as "loss-leaders" and will generate less profit than their dominants. Consequently, for high priced decoys, the true elasticity at these price points will be larger in absolute values (more elastic) than if they would generate the same profits as the low priced dominants. Therefore, using equation (A.1) would lead us to a relationship where the calculated cost c_{jt} increases with the observed price p_{jt}, for identical diamonds.

Now this leads to our proposed tests. In the first test (Test I), we assume that the supplier' marginal costs of diamonds with identical attributes are the same, i.e, $c_{jt} = c, \forall j \in J, \forall t$. It might a reasonable assumption in this particular industry, because globally diamonds are supplied by only a few dominant manufacturers. Both Burdett and Judd (1983) and Hong and Shum (2006) also use the same assumption. We proceed with the following steps:

1. Use a proportional hazard model to fit the demand function $Ph_j(t|p_{jt})$, with polynomials of p_{jt} (we use linear, quadratic, and cubic forms), diamond characteristics, days on market, and day fixed effects entering the equation to control for local demand effects.

2. Calculate the implied cost $\hat{c}_{jt}$ using equation (A.1) for each observed price point, under our null hypothesis that there is only search effect.

3. Regress $\hat{c}_{jt}$ over the relative price index $\tilde{p}_{jt} = \frac{p_{jt} - \bar{p}_{jt}}{\bar{p}_{Jt}}$ ($\bar{p}_{Jt}$ is the average price of diamonds in J on day t), and other control variables such as diamond characteristics and day effects.

4. If the coefficient for $\tilde{p}_{jt}$ is insignificant, then the test favors the null hypothesis that price dispersion could be explained purely based on consumer search; if the coefficient is positive and significant, we would reject the null hypothesis, and the results would be consistent with the AD effect story along with the consumer search.

In the second test, we relax the cost assumption that states $c_{jt} = c$. Instead, we impose the following assumption: for the same diamond j, the cost for the supplier would be the same over time, i.e., $c_{jt} = c_j, \forall t$. In other words, diamonds in the same grade might have different costs, but this cost is time-invariant. We use the within-diamond over time price variation to test our hypothesis. The test follows the same steps as in the first test, except that in step 3, we run the regressions using diamond sku-level fixed effects as controls and test whether the coefficient for $\tilde{p}_{jt}$ is significant.

We run the tests for each of the three price segments (low-, medium- and high-end) and report the results in the following table. Both tests reject the null hypothesis, and support the AD effect to exist along with consumer search. In addition, consistent with our main findings, the effects are stronger for higher price segments.

Table A1: Test of price Variation from Consumer Search

Variable	**2K-5K**	**5K-10K**	**10K-20K**
Test I			
Controls		diamond characteristics (4C), $\bar{p}_{Jt}$, day effects	
$\tilde{p}$	1.314**(0.001)	3.163**(0.004)	6.073**(0.007)
Adj. R-squared	0.960	0.965	0.965
Test II			
Controls		diamond fixed effects	
$\tilde{p}$	2.349**(0.024)	2.965**(0.051)	4.440**(0.143)
Adj. R-squared	0.960	0.963	0.946

Note: Estimates with ** are significant at 0.05 level. Dependent variable—estimated cost—is in 1000 dollars.

B Stylized Example on Model Identification

In this section, we use a stylized example to show how the preference parameters, search parameters and asymmetric dominance effect can be separately identified. We first generate market shares under different market conditions and then we use the shares to show how we recover these underlying model primitives.

Assume that there are three types of diamonds A, B and D, where D is a decoy to A, but not B; and B is neither decoy nor dominant to A. There are numbers of N_A, N_B, and N_D of A, B, and D type diamonds, respectively. In addition, assume that consumers in the market searches for n diamonds simultaneously before making their choices of which diamond type to purchase. If the minimum of N_A, N_B and N_D is very large (that is mostly the case in our data), we can use a sampling with replacement framework in calculating all the probabilities in forming the consideration sets. Since we have three types of diamonds (A, B, and D), in terms of the consideration sets with distinct elements, there will be seven unique combinations: $\{A\}$, $\{B\}$, $\{D\}$, $\{A,B\}$, $\{A,D\}$, $\{B,D\}$, and $\{A,B,D\}$. Corresponding probabilities of observing each of these seven combinations are given as follows.

$$Pr(\{A\}) = \left[\frac{N_A}{N}\right]^n, \; Pr(\{B\}) = \left[\frac{N_B}{N}\right]^n, \; Pr(\{D\}) = \left[\frac{N_D}{N}\right]^n,$$

$$Pr(\{A, B\}) = \sum_{k=1}^{n-1} \binom{n}{k} \left[\frac{N_A}{N}\right]^k \left[\frac{N_B}{N}\right]^{n-k},$$

$$Pr(\{A, D\}) = \sum_{k=1}^{n-1} \binom{n}{k} \left[\frac{N_A}{N}\right]^k \left[\frac{N_D}{N}\right]^{n-k},$$

$$Pr(\{B, D\}) = \sum_{k=1}^{n-1} \binom{n}{k} \left[\frac{N_B}{N}\right]^k \left[\frac{N_D}{N}\right]^{n-k},$$

$$Pr(\{A, B, D\}) = \sum_{k=1}^{n-2} \sum_{l=1}^{n-k-1} \binom{n}{k} \binom{n-k}{l} \left[\frac{N_A}{N}\right]^k \left[\frac{N_B}{N}\right]^l \left[\frac{N_D}{N}\right]^{n-k-l}.$$

where $N = N_A + N_B + N_D$. If the consideration set contains only one type of diamond, then the conditional choice probability or market share for that type equals to 1, i.e., $s_{A|\{A\}} = s_{B|\{B\}} = s_{C|\{C\}} = 1$. If the consideration set contains types A and B, the conditional choice probabilities become $s_{A|\{A,B\}} > 0$ and $s_{B|\{A,B\}} > 0$ where $s_{A|\{A,B\}} + s_{B|\{A,B\}} = 1$. If the consideration set contains types A and D, then the conditional choice probabilities become $s_{A|\{A,D\}} = 1, s_{D|\{A,D\}} = 0$, because D type is decoy to A. If the consideration set contains types D and B, then the conditional choice probabilities become $s_{D|\{B,D\}} > 0, s_{B|\{B,D\}} > 0$ where $s_{D|\{B,D\}} + s_{B|\{B,D\}} = 1$. Finally, if the consideration set contains types A, B and D, without the asymmetric dominance effect, the conditional choice probabilities become $s_{A|\{A,B,D\}} = s_{A|\{A,B\}}$ and $s_{B|\{A,B,D\}} = s_{B|\{A,B\}}$ and $s_{D|\{A,B,D\}} = 0$; with the AD effect, the probabilities become $s_{A|\{A,B,D\}} = s_{A|\{A,B\}} + \delta$ and $s_{B|\{A,B,D\}} = s_{B|\{A,B\}} - \delta$, $\delta > 0$. δ reflects the magnitude of AD effect. Given this set-up, each diamond type's (A, B or D) market share (S) can be calculated by summing the products of corresponding consideration set probabilities and conditional choice probabilities. For example, $S_D = Pr(\{A\}) \times 0 + Pr(\{A,B\}) \times 0 + \Pr(\{D\}) \times 1 + Pr(\{A,D\}) \times 0 + Pr(\{B,D\}) \times s_{D|\{B,D\}} + Pr(\{A,B,D\}) \times 0$.

We now consider a few examples and calculate the corresponding market share for each diamond type, both with and without the AD effect. In the scenarios below, we use $N_A : N_B : N_C$ to denote the ratio of the number of diamonds, and we use two different variations in dominance structure, 1 : 1 : 1 and 1 : 1 : 2 . In each of the scenarios, we fix the preference parameters to be $s_{A|\{A,B\}} = \frac{1}{2}, s_{B|\{B,D\}} = \frac{2}{3}, \delta = \frac{1}{3}$. We summarize the results in the following table:

Table A2: Market Shares Under Different Scenarios

	Without AD Effect			With AD Effect		
Scenario	A	D	B	A	D	B
$N_A : N_B : N_D = 1:1:1$ & $n = 3$	0.481	0.111	0.407	0.556	0.111	0.333
$N_A : N_B : N_D = 1:1:2$ & $n = 3$	0.438	0.219	0.344	0.500	0.219	0.281
$N_A : N_B : N_D = 1:1:1$ & $n = 4$	0.494	0.070	0.436	0.642	0.070	0.288
$N_A : N_B : N_D = 1:1:2$ & $n = 4$	0.469	0.146	0.385	0.594	0.146	0.260

In these scenarios, we vary the proportion of decoys to other diamonds, as well as the search intensity from consumers. In our empirical setting, we observe significant variations in terms of the number of decoy and dominant classifications as well as the purchase intensity of each type of diamonds. This example resembles the empirical setting along that line. Our objective is to separately identify three sets of parameters based on the observed market structure and market outcome: the search parameter n, the preference parameters $s_{A|\{A,B\}}, s_{B|\{B,D\}}$, and the AD effect parameter δ. We first discussion the intuition behind model identified, and then provide detailed calculations to show how exactly the parameters could be recovered.

We observe that the decoy diamond's market share remain constant for both with and without AD conditions, but vary across different market structure and search intensity. Because of (imperfect) search, its market share is still positive. The level (0.111 vs. 0.070) and change (0.219-0.111 vs. 0.146-0.070) for the market share of D under different market structure help identify the preference for D ($s_{B|\{B,D\}}$) as well as search n. Conditional on the identification of $s_{B|\{B,D\}}$ and n, the levels (0.556 vs. 0.500) of the share of A (or B) across the market structure help identify the preference for A without D ($s_{A|\{A,B\}}$), and the change for the preference with D (δ), i.e., a two-equation two-unknowns problem.

Putting this identification reasoning into our specific context, we now show exactly how the numbers can be calculated. Suppose what we observe is the market shares under the first two scenarios in the table under "with AD effect" condition, i.e., $N_A : N_B : N_D = 1 : 1 : 1 \rightarrow (0.556, 0.111, 0.333)$ and $N_A : N_B : N_D = 1 : 1 : 2 \rightarrow (0.500, 0.219, 0.281)$. We identify the parameters in the following two steps:

Step 1: identification of $s_{B|\{B,D\}}$ and n.

For aggregate market share of D, S_D: $S_D = Pr(\{D\}) \times 1 + Pr(\{B, D\}) \times (1 - s_{B|\{B,D\}})$

- if $n = 3$:

$$0.111 = \frac{1}{27} + \frac{6}{27} \times (1 - s_{B|\{B,D\}})$$
$$0.219 = \frac{8}{64} + \frac{18}{64} \times (1 - s_{B|\{B,D\}})$$

these two equations will consistently yield the solution of $s_{B|\{B,D\}} = \frac{2}{3}$.

- if $n = 4$:

$$0.111 = \frac{1}{81} + \frac{14}{81} \times (1 - s_{B|\{B,D\}})$$
$$0.219 = \frac{16}{256} + \frac{64}{256} \times (1 - s_{B|\{B,D\}})$$

the first equation would yield $s_{B|\{B,D\}} = \frac{3}{7}$, and the second equation would yield $s_{B|\{B,D\}} = \frac{3}{8}$, a conflict.

Thus, we conclude that $n = 3$, and $s_{B|\{B,D\}} = \frac{2}{3}$.

Step 2: identification of $s_{A|\{A,B\}}$ and δ conditional on n.

For market share of A: $S_A = Pr(\{A\}) \times 1 + \mathrm{Pr}(\{A, D\}) \times 1 + Pr(\{A, B\})s_{A|\{A,B\}} + Pr(\{A, B, D\})s_{A|\{A,B,D\}} = Pr(\{A\}) + \mathrm{Pr}(\{A, D\}) + Pr(\{A, B\})s_{A|\{A,B\}} + Pr(\{A, B, D\})(s_{A|\{A,B\}} + \delta)$

Given $n = 3$, we now have the following:

$$0.556 = \frac{1}{27} + \frac{6}{27} + \frac{6}{27}s_{A|\{A,B\}} + \frac{6}{27}(s_{A|\{A,B\}} + \delta)$$
$$0.500 = \frac{1}{64} + \frac{18}{64} + \frac{6}{64}s_{A|\{A,B\}} + \frac{12}{64}(s_{A|\{A,B\}} + \delta)$$

Solving the above equations gives us the results as $s_{A|\{A,B\}} = \frac{1}{2}$, and $\delta = \frac{1}{3}$. We have recovered all the parameters.

Through this stylized example, we illustrate how we can empirically identify the parameters of the consumer preferences, search process and the AD effect from the observed variation of the decoy structure and market shares over time. We are aware that our domain is significantly more complicated than this stylized example, but we believe that one can still use this observed variation of decoys over time to separate search from the AD effect.

C Decoy Pricing vs. Uniform Pricing

Now we discuss in detail how the different effects under the decoy pricing strategy vs. the uniform pricing strategy are computed. Under the uniform pricing strategy, the retailer's expected profit for a given diamond j at time t becomes the following:

$$\pi_{jt}^{U} = Ph_j(t|p_{jt}^{U}) \times (p_{jt}^{U} - w_{jt}),$$

where p_{jt}^{U} is the uniform price for diamond j at time t, and w_{jt} is the wholesale price of diamond j at time t, which can be easily calculated by subtracting out the retailer's fixed mark-up from the observed daily retail prices. $Ph_j(t) = 1 - \exp(-h_j(t))$ is the probability that diamond j would be sold in time period t, conditional on it remaining unsold until that moment. Therefore, the total profit effect, $\Delta\pi_{jt}^{Total}$, for the retailer due to selling decoys and dominants can be calculated as follows:

$$\begin{aligned}\Delta\pi_{jt}^{Total} &= \pi_{jt} - \pi_{jt}^{U} \\ &= Ph_j(t|p_{jt}) \times (p_{jt} - w_{jt}) - Ph_j(t|p_{jt}^{U}) \times (p_{jt}^{U} - w_{jt}).\end{aligned}$$

We now decompose this total effect into each of the individual components outlined in the decomposition table as follows:

- Uninformed consumer–decoy diamond (for $N_{jt}^{out} > 0$):

$$\begin{aligned}\Delta\pi_{jt}^{Un-Decoy} =& [1 - e^{-(1-P_{jt}^{in}(.|p_{jt}))(1-P_{jt}^{out}(.|p_{jt}))h_j^{o}(t|p_{jt})}] \times (p_{jt} - w_{jt}) \\ &- [1 - e^{-(1-P_{jt}^{in}(.|p_{jt}))(1-P_{jt}^{out}(.|p_{jt}))h_j^{o}(t|p_{jt}^{U})}] \times (p_{jt}^{U} - w_{jt})\end{aligned}$$

- Uninformed consumer–dominant diamond (for $N_{jt}^{in} > 0$):

$$\begin{aligned}\Delta\pi_{jt}^{Un-Dominant} =& [1 - e^{-(1-P_{jt}^{in}(.|p_{jt}))(1-P_{jt}^{out}(.|p_{jt}))h_j^o(t|p_{jt})}] \times (p_{jt} - w_{jt}) \\ & - [1 - e^{-(1-P_{jt}^{in}(.|p_{jt}))(1-P_{jt}^{out}(.|p_{jt}))h_j^o(t|p_{jt}^U)}] \times (p_{jt}^U - w_{jt})\end{aligned}$$

- Informed consumer–decoy diamond:

$$\Delta\pi_{jt}^{In-Decoy} = 0 - [1 - e^{-P_{jt}^{out}(.|p_{jt}))h_j^o(t|p_{jt}^U)}] \times (p_{jt}^U - w_{jt})$$

- Informed consumer–dominant diamond:

$$\begin{aligned}\Delta\pi_{jt}^{In-Dominant} =& [1 - e^{-P_{jt}^{in}(.|p_{jt})(1-P_{jt}^{out}(.|p_{jt}))h_j^o(t|p_{jt})Q_{jt}^{in}(.|p_{jt})}] \times (p_{jt} - w_{jt}) \\ & - [1 - e^{-P_{jt}^{in}(.|p_{jt})(1-P_{jt}^{out}(.|p_{jt}))h_j^o(t|p_{jt}^U)}] \times (p_{jt}^U - w_{jt})\end{aligned}$$

where in the above equation, $h_j^o(t) = h_0(t) \times \psi_j(.)$ is the normalized hazard for detecting the diamond neither as a decoy nor as a dominant. The total information effect equals $\Delta\pi_{jt}^{info} = \Delta\pi_{jt}^{Un-Decoy} + \Delta\pi_{jt}^{Un-Dominant}$ and the total AD effect equals $\Delta\pi_{jt}^{AD} = \Delta\pi_{jt}^{In-Decoy} + \Delta\pi_{jt}^{In-Dominant}$. In the paper, we apply the above calculations to all the diamonds observed in the market every day and take the mean value across the diamond-days to 1) compute the overall profit impact and decompose this overall impact into each of the four components.